Energy Efficiency: Value Added to Properties & Loan Performance

ROBERT ARGENTO, XIAN FANG BAK, LARIECE M. BROWN

Freddie Mac
Single-Family

Contents

Energy Efficiency: Value Added to Properties and Loan Performance

ROBERT ARGENTO, XIAN FANG BAK, LARIECE M. BROWN

1. INTRODUCTION

The Housing and Economic Recovery Act of 2008 established for Freddie Mac a duty to help preserve affordable housing for families with very low, low, and moderate incomes. Improving the energy efficiency of single-family homes is one important way to achieve preservation. Less than 1% of mortgages are related to energy efficiency features (Kaza et al., 2015); this suggests that the market is underserved, with opportunity for growth. We conducted this analysis to understand the value and the loan performance associated with energy-efficient homes to support the consideration of energy efficiency in mortgage underwriting practices.

One might expect energy-efficient homes to sell for higher prices due to the added value of energy efficiency features, along with the energy savings and comfort they bring. Furthermore, one might expect energy-efficient homes to incur lower utility bills, resulting in more disposable income for homeowners to pay their mortgages (Kaza et al., 2014). In other words, energy-efficient homes could have higher collateral value and could impose less financial stress on their owners; combined, these factors could potentially justify flexibility during the underwriting process.

This paper compares the property sale price and loan default rates between energy efficiency rated and unrated homes, as well as better-rated and lessor-rated homes. Descriptive analysis shows that homeowners choosing to have their homes rated are different from the general population, and rated homes have different characteristics from unrated homes. We identified a comparable unrated group for the rated group by accounting for differences in property attributes as well as borrower and loan characteristics in our regression analysis.

Summary of Findings

Using a national random sample, we conducted an analysis of energy-efficient homes rated between 2013 and 2017 and found:

- From the property value analysis, rated homes are sold for, on average, 2.7% more than comparable unrated homes
- Better-rated homes are sold for 3-5% more than lesser-rated homes.
- From the loan performance analysis, the default risk of rated homes is not, on average, different from unrated homes, once borrower and underwriting characteristics are considered.
- Loans in the high debt-to-income (DTI) bucket (45% and above) that have ratings, however, appear to have a lower delinquency rate than unrated homes.

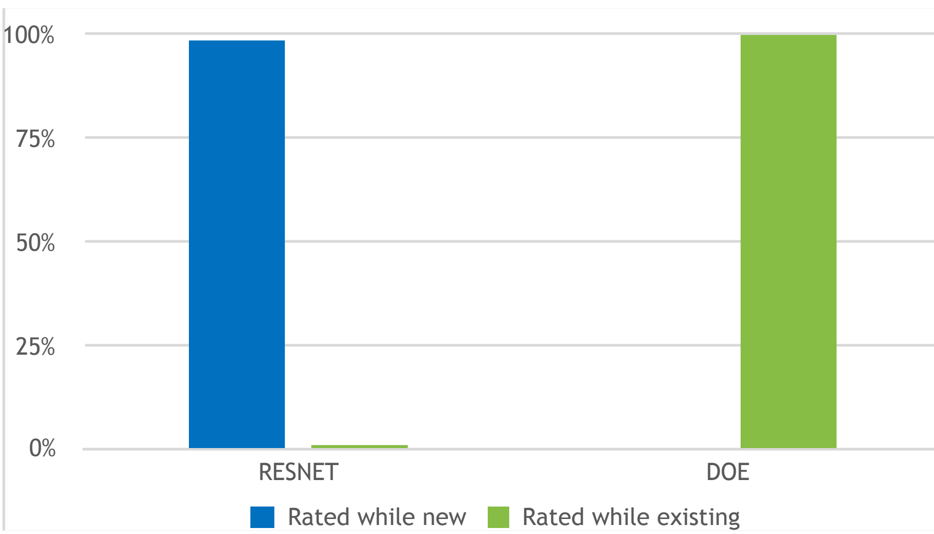
2. RATINGS BACKGROUND

We studied two widely used energy efficiency rating systems: (1) Home Energy Rating System (HERS) Index by the Residential Energy Services Network (RESNET); and (2) Home Energy Score (HES) by the Department of Energy (DOE). The two ratings vary in many ways, especially in terms of their main requesters for ratings, the reference home used in the rating process, and their geographic locations.

2.1 Main Requesters and Age of Rated Properties

Historically, the main requesters for a RESNET rating have been builders, with more home sellers participating in recent years. As a result, most of the RESNET-rated homes are rated when they are newly built or built within two years of the construction (Exhibit 1). In contrast, the main requesters for the DOE rating are home owners of existing homes. As a result, DOE-rated homes are not typically rated while new; the average property age for DOE-rated homes is around 45 years old at the time of the rating[1]. Accordingly, the pools of RESNET-rated and DOE-rated homes have different property and homeowner attributes.

Exhibit 1. Share of homes rated as new and existing



Note: Year built and year of rating were used for identifying newness of the properties at rating. Homes missing the year built or rating are excluded. Homes were rated between 2013 and 2017. New is defined as 0~2 years after building.

2.2 Rating Scales and References

RESNET's HERS Index ranges from negative to positive infinity, mostly concentrated between 1 and 100. The index reflects a relative scale obtained by comparing the rated home to a reference home designed to be of a similar size, shape and type that is a standard new home built to the International Energy Conservation Code. A score of 100 refers to the energy use level for the reference home. A score of 80 indicates 20% less energy consumption than the reference home. A typical resale home scores 130, indicating 30% more energy use than its reference home. Thus, a higher score indicates less energy efficiency. Most RESNET-rated homes in our sample have a HERS Index of less than 85, meeting industry standards (such as ENERGY STAR certification) for being energy efficient.

DOE's HES uses a 1-to-10 scale, where higher scores indicate higher energy efficiency levels. For example, a score of 1 generally indicates that the home's energy usage is in the top 10%, while a score of 10 indicates that the home's energy usage is in the bottom 10%. According to DOE, the 10 levels account for location climate by "mapping the zip code for the house address to the nearest weather station. Each weather station has its own definition of Score ranges based on local weather" (HES Scoring Methodology, 2017). Property size is not considered when assessing the level of energy use. Therefore, all other things being equal, larger homes will receive a lower HES energy efficiency rating, given the fact that larger homes are likely to use more energy.

[1] Exhibit A1 in the Appendix describes the age distribution when homes receive DOE rating.

2.3 Locations of Rated Homes

Geographically, RESNET-rated homes are relatively spread out, but they do not reflect each state's share of the housing market (Exhibit 2). For example, California is underrepresented given its large total housing stock[2]. The Midwest-Great Lakes and Northeastern states have wide geographic coverage of RESNET-rated homes while the county level counts are low. Counties in Texas, Arizona and southern Nevada have the greatest concentration of RESNET-rated homes. The 10 counties with the most RESNET-rated homes represent 24% of the total RESNET market nationwide (see Exhibit A2 in the Appendix). In contrast, DOE-rated homes are very concentrated in certain areas, such as Northeastern states including Connecticut and New Jersey (Exhibit 3). The 10 counties with the most DOE-rated homes encompass about 70% of all DOE-rated homes nationwide (see Exhibit A3 in Appendix).

Exhibit 2. County level counts of RESNET-rated single-family homes between 2013 and 2017

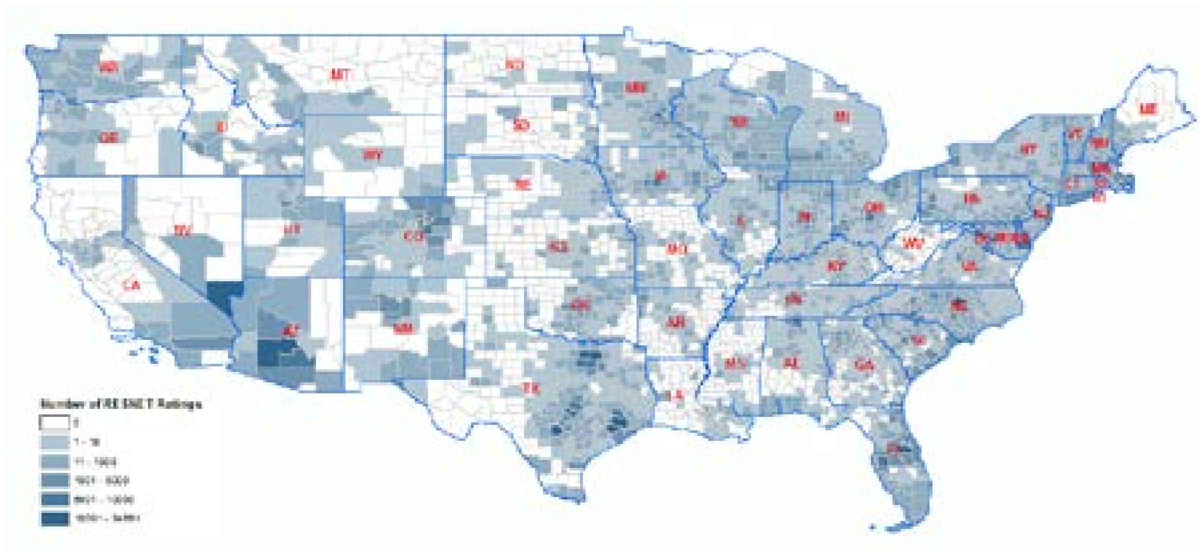
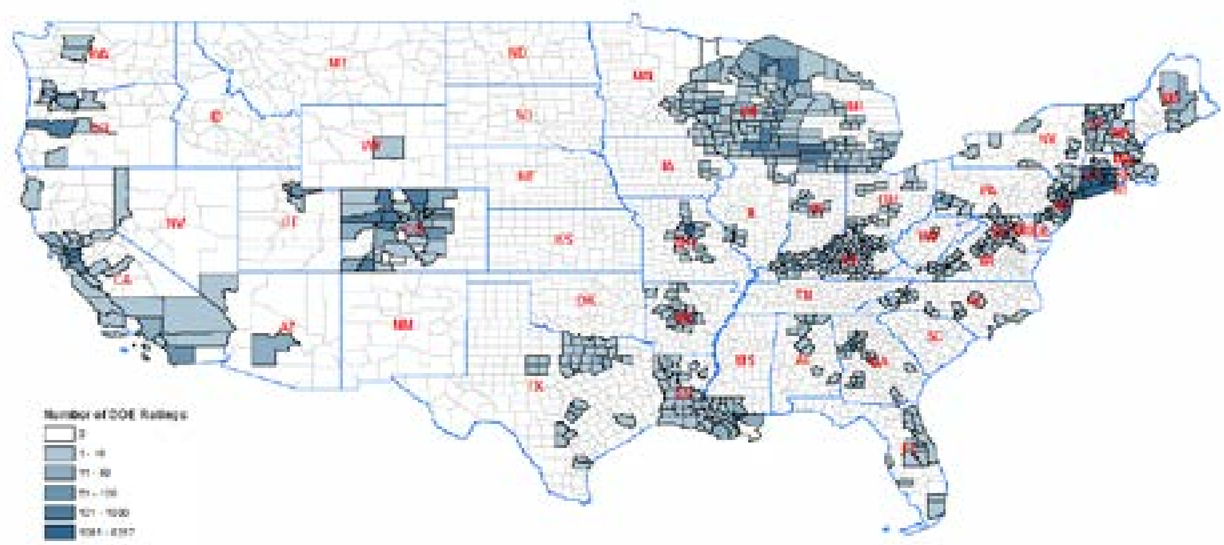


Exhibit 3. County level counts of DOE-rated single-family homes between 2014 and 2017



[2] The number of homes HERS rated in California does not include homes rated under the California Energy Commission's (CEC) Title 24. Title 24 includes an Energy Design Rating (EDR), modeled on the RESNET HERS Index. RESNET standards recognizes a state rating program if mandated by state law. With the EDR, the governing body is the CEC not RESNET. RESNET and CEC have been working on harmonizing the California rating system with RESNET's.

3. DATA AND METHODOLOGY

3.1. Data Sources

We acquired energy efficiency rating data collected between 2013 and 2017[3] from RESNET and DOE. The datasets included rating scores and home features related to energy consumption that were assessed during energy auditing. We received data regarding about 789,000 RESNET-rated and 65,000 DOE-rated single-family homes in total. From that universe, we used random sampling to select 70,000 RESNET-rated homes and 6,500 DOE-rated homes for analysis[4].

To appropriately protect homeowner privacy, we collaborated with a major credit bureau to gather additional data that would take care to protect homeowners' privacy. For each of the randomly selected homes, the credit bureau used its property records database to form a comparison dataset by randomly selecting five unrated homes from the pool of single-family owner-occupied properties within the same census tract. This helped minimize the differences in neighborhood characteristics and essentially excluded geographic outliers that would be less appropriate comparable homes for the rated properties. We eventually obtained a dataset on a total of about 450,000 properties (about 76,500 rated, plus 5 comparable unrated for each rated). For these 450,000 homes, we procured the latest sale price and property attributes through the credit bureau's property record database. Property attributes included number of bedrooms and bathrooms, square footage, acreage, year built, location in terms of census tract, and year of sale.

From the credit bureau's database, we also obtained anonymized characteristics on the approximately 670,000 borrowers associated with the properties in our dataset, as well as information on mortgage underwriting factors and loan performance[5]. These variables included: mortgage payment history, debt-to-income (DTI) ratio, loan amount, loan type, as well as borrowers' income, credit score, age and education level[6]. Except for mortgage payment history, which is recorded monthly, other variables for each account are examined in December each year between 2012 and 2016. To get the variable values closest to the moment of originations, we linked the December values in the year prior to the loan origination date to use as the numbers at the origination.

3.2. Methodology

3.2.1. Comparison Groups

We used two specifications to explore the effects of energy efficiency. In the first specification, we compared rated homes to unrated homes. We first investigated the differences in property sale prices between rated and unrated groups while accounting for differences in property attributes. We then investigated the differences in loan performance while controlling for differences in borrower and loan attributes. Because differences between rated and unrated homes in terms of property and borrower characteristics may signal sample selection bias related to the choice of rating, further techniques are needed to reduce that bias. As a result, we applied propensity score matching[7] techniques to select unrated homes that were most comparable to rated homes, mimicking the process of selecting a home for rating. The goal was to select unrated homes that had a similar probability of being rated but were not in the sample that were rated. In the second specification, we classified rated homes into different energy efficiency levels based on their rating scores. With this specification, we could test whether and how much energy efficiency levels impact house value and whether there is a threshold at which energy efficiency effects become apparent.

[3] DOE has very little data for 2013 (only 6 homes rated), since DOE's HES rating program began in 2012.

[4] On average, it's based on 1-in-11 random sample selection for RESNET and 1-in-10 for DOE. We applied larger sample rates for earlier years than later years to keep more homes with longer loan performance period for evaluation.

[5] The matching process was completed by the credit bureau to protect the privacy of the consumers in the data. We did not access individual private information.

[6] Loan-to-value (LTV) ratio is not available from the purchased dataset. We calculated our own by dividing the loan amount at origination using the sale price closest to the origination time.

[7] More details on matching are in the Appendix Exhibit A4.

3.2.2. Model Specifications and Variables

To assess the value of energy efficiency added to home sale price, we used a standard hedonic model to compare the sale prices of rated and unrated homes, as well as of more energy-efficient homes and less energy-efficient homes. In the hedonic model, the house price is explained by a set of property and neighborhood characteristics. Energy efficiency is an element in the property attribute set and contributes to the explanation of the house price. Our hedonic model specification is:

$$\ln P_{ijt} = c + \alpha E_{ijt} + \beta X_{ijt} + \sigma_t + \delta_j + \varepsilon_{ijt} \quad (1).$$

$\boldsymbol{P_{ijt}}$ is the price of house i in census tract j sold in year-quarter t; $\boldsymbol{E_{ijt}}$ is the energy efficiency variable (can be dummy variables indicating rated or not, or continuous energy efficiency rating scores, or a set of discrete rating level dummies to indicate different efficiency levels); $\boldsymbol{X_{ijt}}$ is a set of property characteristics; $\boldsymbol{\delta_j}$ is census tract fixed effect to capture neighborhood characteristics; $\boldsymbol{\sigma_t}$ is year by quarter fixed effect to capture year and seasonal effects in the housing market.

To assess the loan performance associated with energy efficient homes, we used a default risk model to compare the delinquency rate between rated and unrated homes, as well as between more energy efficient and less energy efficient homes. In the default risk model, the delinquency is explained by a set of mortgage origination factors associated with the borrower and loan. Particularly, we compared the probabilities of owners of rated homes against unrated homes (or more energy efficient homes against less energy efficient homes) becoming ever 90-day late on their payments (ever 90-day delinquent), while controlling for other factors that could affect delinquency. The default risk model is written in the form of logistic regression:

$$logit\ (D_{ijt} = 1) = c + \alpha E_{ijt} + \beta X_{ijt} + \sigma_t + \delta_j + \varepsilon_{ijt} \quad (2).$$

D_{ijt} is the outcome variable of mortgage i in state j originated in year t; like model specification (1), $\boldsymbol{E_{ijt}}$ is energy efficiency variable with the same option as for specification (1); X_{ijt} is a set of explanatory variables related to mortgage termination, including mortgage underwriting variables such as the borrower's FICO score, income, loan-to-value ratio (LTV), DTI, loan characteristics (such as loan amount and term), as well as census tract income. σ_t represents vintage fixed effects capturing the differences in the origination year of loans. δ_j is fixed effects at the state level to make comparisons of the rated and unrated homes within the state.

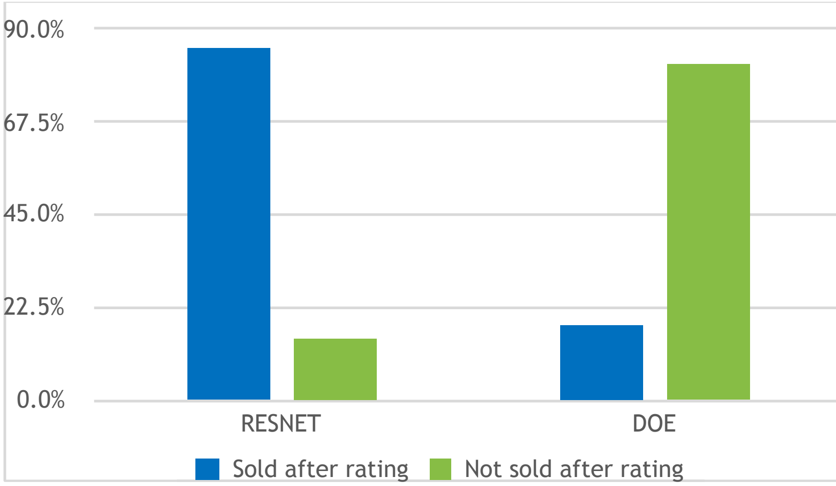
4. RATING SYSTEMS AND THEIR CONSUMERS

Before conducting the regression analysis, we studied the homeowners behind the demand of energy efficiency ratings and compared them with the general population. Exhibit 4 shows that about 85% of RESNET-rated homes were sold after they were rated, while no sales were observed for about 80%[8] of DOE-rated homes after their ratings and before the end of our study period (May 1, 2018). Accordingly, the typical consumers were new homebuyers in the RESNET sample and existing homeowners in the DOE sample. This could also signal the original purpose of rating: either a marketing tactic to differentiate home features and drive higher sale prices (likely the RESNET sample) or a technique purely for energy use information and understanding potential energy efficiency improvements (likely the DOE sample).

The remainder of Section 4 focuses on studying these major segments of consumers (blue bar for RESNET and green bar for DOE in Exhibit 4) in each rating sample.

[8] This is not unreasonable, given that existing home sales are about 6% annually. Assuming DOE homes are rated either all in 2013 or all in 2017, simple math tells us that there will roughly be 36% or 12% of them sold by 2018. The sales rate of 20% observed in our data falls reasonably in the range of 12%-36%, when DOE homes are rated over the years between 2013 and 2017.

Exhibit 4. Share of homes with or without observed sales after rating



Note: Rating date and sale date are used for identifying this temporal relationship. Homes with missing rating date or sale date are excluded. Homes were rated between 2013 and 2017.

4.1. Income Distribution of Homeowners of New and Existing Energy Efficiency-rated Homes

Due to the different geographic concentrations of RESNET- versus DOE-rated homes, for ease of comparison, homeowner incomes were converted into relative income by dividing them with area median income (AMI) at the county level. We did not see a large difference in the relative income distributions between RESNET- and DOE-rated homes; more than 40% of the homeowners earned more than 120% AMI and the rest were distributed in lower income buckets (Exhibit 5). Interestingly, the income distributions for both RESNET- and DOE-rated homes both showed fewer high-income households (>120% AMI) and more very low-income households (≤50% AMI) compared to the general mortgage origination market, using the 2016 Home Mortgage Disclosure Act (HMDA) data.

Exhibit 5. Homeowners' relative income

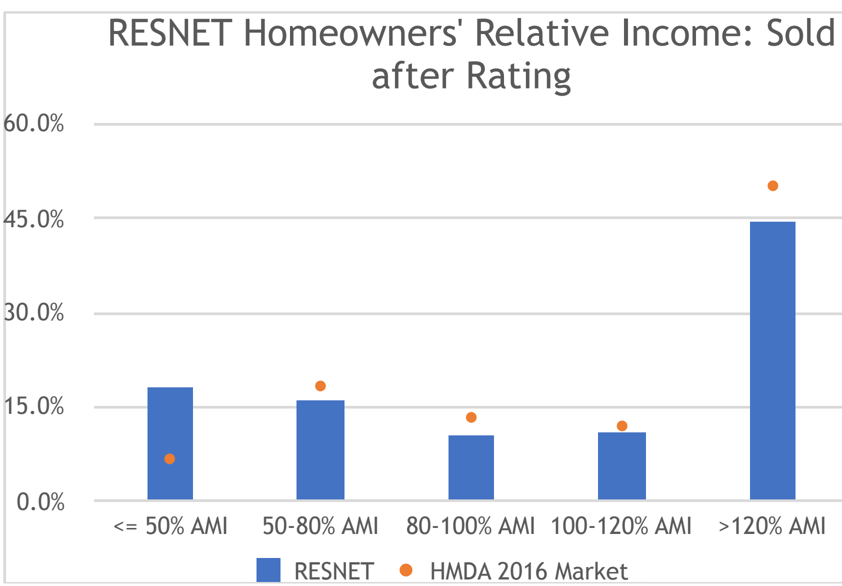
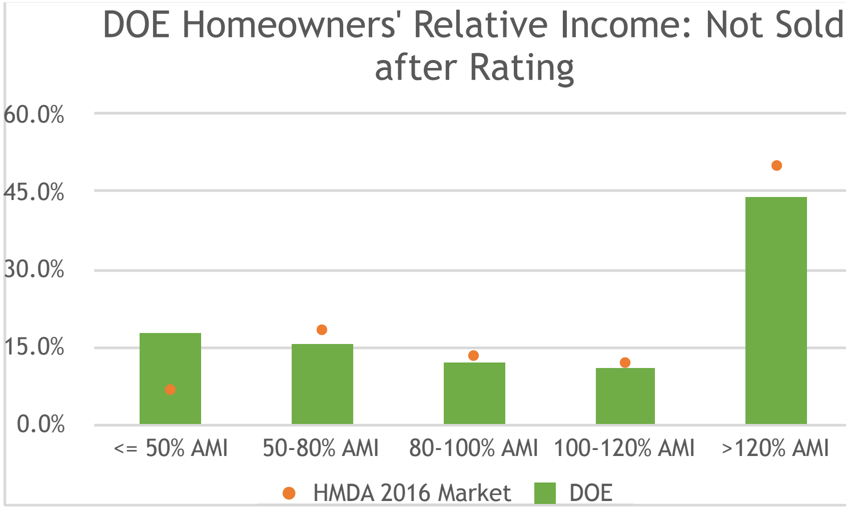


Exhibit 5. Homeowners' relative income

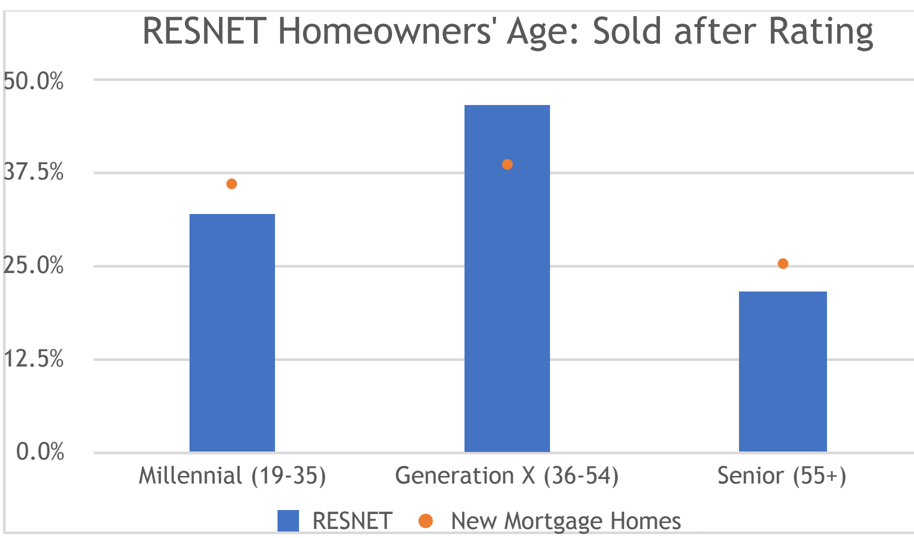


Note: Household income is shown relative to the area median income at the county level. Homes were rated between 2013 and 2017. "RESNET" refers to RESNET-rated homes that were sold after rating. "DOE" refers to DOE-rated homes that were not sold after rating (no sale transactions observed before May 1,2018). "HMDA 2016 Market" refers to HMDA 2016 owner-occupied single-family and manufactured housing originations and purchases, excluding redundant loans.

4.2. Age Distribution of Homeowners of New and Existing Energy Efficiency-rated Homes

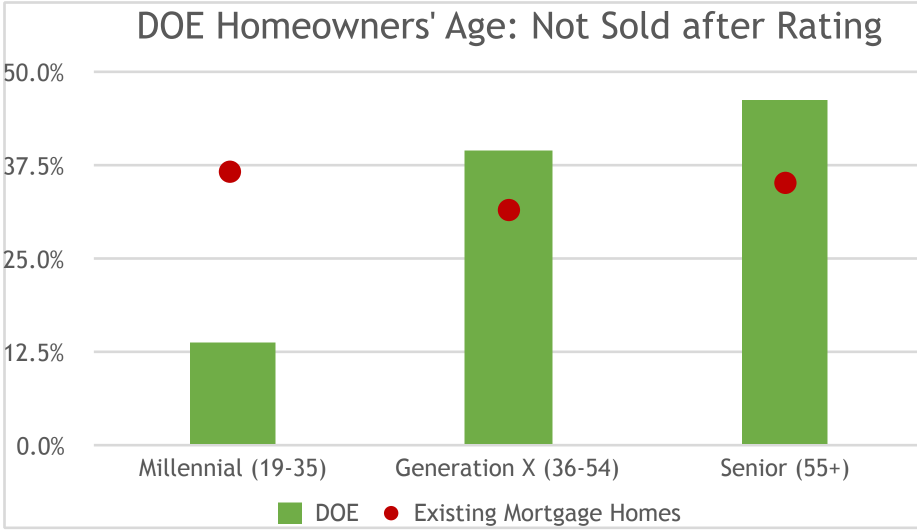
Compared to their corresponding benchmark populations, RESNET-rated homes are slightly more likely to be owned by Generation Xers (36-54 years old as of 2016)[9] and fewer Millennials (19-35 years old as of 2016). DOE-rated households, on the other hand, decisively skew older; Generation Xers and Baby Boomers plus earlier generations (those at age 55 or over as of 2016; identified as "Seniors" through the rest of the paper) are overrepresented relative to the general population, at the expense of Millennials (Exhibit 6).

Exhibit 6. Homeowners' age



[9] There are small variations in generation definitions in different studies. Our definitions of generations are close to those in Urban Institute *(https://www.urban.org/sites/default/files/publication/98729/millennial_homeownership.pdf)*. Millennials are born between 1981 and 1997; Generation Xers are born between 1962 and 1980 (1965-1980 in Urban Institute study). Further, we define all those born in and before 1961 as the Senior.

Exhibit 6. Homeowners' age



Note: Ages in brackets were as of 2016. Homes were rated between 2013 and 2017. "RESNET" refers to RESNET-rated homes that were sold after rating. "DOE" refers to DOE-rated homes that were not immediately sold after rating (no sale transactions observed before May 1,2018). "New Mortgage Homes" and "Existing Mortgage Homes" refer to anonymized individual credit bureau data from September 2016; the former is where there was no mortgage in 2012 but one in 2016 and the latter is where there was a mortgage in both years.

4.3. Education Levels of Homeowners of New and Existing Energy Efficiency-rated Homes

For both RESNET-rated and DOE-rated homes, about 50% of owners have a least a bachelor's degree. These percentages are higher than their corresponding benchmarks (35% for RESNET and 23% for DOE, as shown in Exhibit 7).

Exhibit 7. Homeowners' education levels

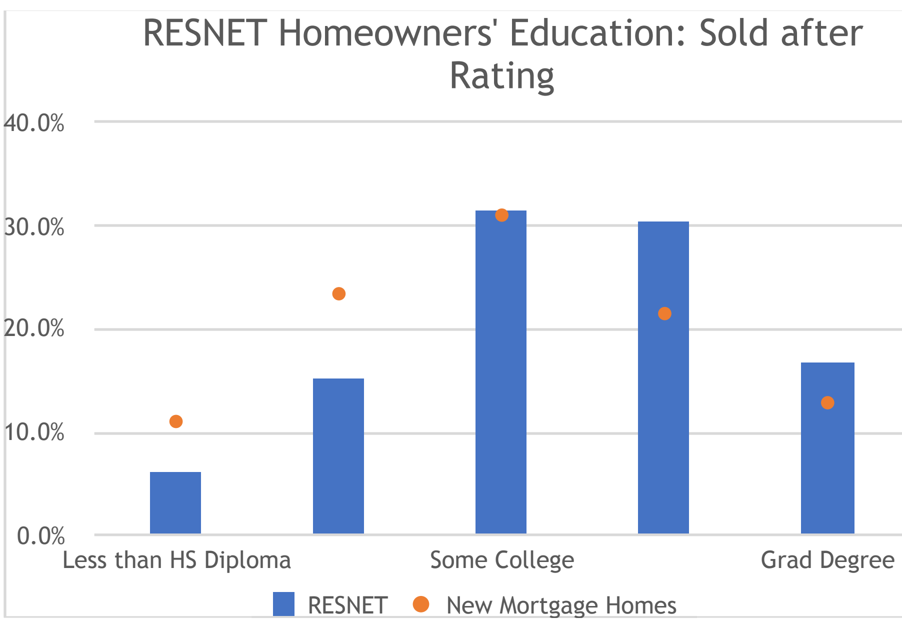
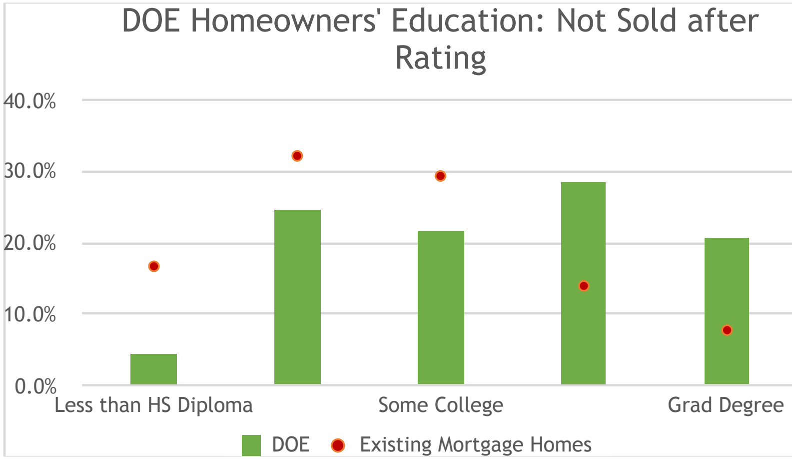


Exhibit 7. Homeowners' education levels



Note: Homes were rated between 2013 and 2017. "RESNET" refers to RESNET-rated homes that were sold after rating. "DOE" refers to DOE-rated homes that were not immediately sold after rating (no sale transactions observed before May 1,2018). "New Mortgage Homes" and "Existing Mortgage Homes" refer to anonymized individual credit bureau data from September 2016; the former is where there was no mortgage in 2012 but one in 2016 and the latter is where there was a mortgage in both years.

5. NEW HOMES (RESNET SAMPLE)

Sections 5 and 6 convey our analysis of new homes and existing homes separately. The new home study relied on the RESNET-rated sample while the existing home study relied on the DOE-rated sample. Also, from section 4, we know that RESNET data is more appropriate for analyzing the impact of energy efficiency on sale price and loan performance because of the prevalence of sale transactions. DOE data, on the other hand, is more useful for understanding existing homes and their owners who request ratings to inform themselves about the potentiality for energy efficiency improvements or retrofits.

5.1. Property Valuation Analysis

5.1.1 Summary Statistics

Descriptive analysis showed that the characteristics of RESNET-rated homes were different from those of unrated homes. Exhibit 8 shows the average house characteristics for unrated and RESNET-rated homes. Compared to unrated homes, RESNET-rated homes were sold for higher prices on average. At the same time, rated homes were larger and newer. Among all RESNET-rated homes, better-rated homes (higher quartiles) were sold for higher prices partially related to their larger sizes. We needed to account for these differences to discover the difference energy efficiency made in sale prices.

Exhibit 8. Average house characteristics for unrated and RESNET-rated

			Higher quantiles indicate better energy efficiency rating			
	Unrated	RESNET	Quartile 1	Quartile 2	Quartile 3	Quartile 4
HERSIndex - RESNET		62.7	72.5	65.0	60.1	53.0
Price	263,304	320,092	252,617	306,224	352,300	371,522
Square feet	2,354	2,674	2,289	2,662	2,859	2,909
Acres	0.4	0.3	0.2	0.2	0.3	0.3
Year built	1996	2013	2013	2014	2014	2013
Year sold	2011	2015	2015	2015	2015	2015
Age (at sale)	14.2	1.1	1.4	0.9	0.9	1.1
New (at sale)	18%	51%	49%	51%	52%	53%
Number of bedrooms	3.5	3.7	3.5	3.8	3.8	3.8
Number of bathrooms	2.6	2.9	2.6	2.8	2.9	3.1
Energy use (mbtu/yr)		87.5	78.3	85.0	91.9	97.1
Energy cost($/yr)		1,732	1,802	1,731	1,731	1,664
Number of observations	306,387	51,301	12,979	13,185	12,184	12,953

Note: RESNET-rated homes were rated between 2013 and 2017, and unrated homes were selected from nearby neighborhoods. Quartiles were constructed based the value of 100-HERSIndex, and each quartile contains about one fourth of all RESNET-rated homes in the sample.

5.1.2. Regression Analysis

To measure the relationship between house prices and RESNET rating, we first compared rated homes to unrated homes, controlling for property attributes and neighborhood differences. In Exhibit 9, columns 1 and 3 used the unmatched sample as native comparisons to our preferred results in columns 2 and 4 using the matched sample.

After accounting for property characteristics in the price regression analysis, we found RESNET-rated homes were sold for 4.3% more when all unrated homes were used and 2.7% more when more comparable unrated homes were used in the matched sample (Columns 1 and 2 in Exhibit 9). When grouping rated homes into four energy efficiency quartile levels, we found that homes in the first quartile (least energy efficient group with an average HERS Index of 72.5) did not sell for a statistically different price than unrated homes (Column 4 in Exhibit 9). However, as the energy efficiency level rises in each quartile, sale prices also rise (2.6-4.4%) relative to comparable unrated homes. This indicates a threshold (at least Quartile 2 rating) for the market value of energy efficiency to be realized. It also shows the importance of matching, since the estimates in Column 3 are over-estimated for most quartiles without using matched samples.

The price premium associated with RESNET-rated homes can be interpreted in several ways. First, being RESNET-rated may reflect high energy efficiency because more than 90% of RESNET homes in our sample had a score less than 85 (which also qualifies them for ENERGY STAR® certification). In other words, being RESNET-rated is overall a good proxy for energy efficiency. Second, because RESNET ratings typically are requested by builders, those builders may highlight the ratings when marketing the properties to differentiate those homes from other properties and achieve a pricing premium as a result. Third, in addition to the value added by the energy efficient features of RESNET-rated homes, the simple fact that the homes were rated could signal added value to the homebuyers.

To tease out the signaling effect, we repeated our regression analysis using only RESNET-rated homes. If there are signaling effects, then all RESNET homes would reflect them and could be cancelled out when comparing rated homes with each other. If we further assume similar marketing effectiveness among rated homes at different energy efficiency levels, then the RESNET-only sample is closer to capturing the price premium that is only associated with energy efficiency. Comparing homes in the higher quartiles to those in Quartile 1, we again found 3-5% higher sale prices associated with homes of higher energy efficiency levels, as shown in Column 6 of Exhibit 9.

Exhibit 9. Regression estimation results for the effect of energy efficiency on sale prices

Variables	Rated vs. Unrated				RESNET only	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent: log(price)	All unrated	Matched (n=1)	All unrated	Matched (n=1)	Score	Score buckets
RESNET-rated (Yes=1)	0.043***	0.027***				
	(0.003)	(0.004)				
Quartile 1			0.035***	0.008		
			(0.004)	(0.005)		
Quartile 2			0.050***	0.026***		0.030***
			(0.004)	(0.005)		(0.005)
Quartile 3			0.051***	0.034***		0.044***
			(0.004)	(0.005)		(0.007)
Quartile 4			0.035***	0.044***		0.052***
			(0.006)	(0.007)		(0.010)
100-HERS Index					0.002***	
					(0.001)	
Observations	312,222	72,464	312,222	72,464	45,028	45,028
Adjusted R-squared	0.690	0.652	0.690	0.652	0.697	0.697

Note: Columns 1 and 3 include all unrated homes in our sample, and columns 2 and 4 restrict the unrated homes to the nearest matched homes based on propensity scores. Control variables include square footage, acres, age of the property at sale and its square term, as well as census tract and year-quarter fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.2. Loan Performance Analysis

5.2.1. Summary Statistics

From an underwriting perspective, there are notable differences between rated and unrated homes[10]. Exhibit 10 shows that RESNET-rated homes have lower delinquency rates than unrated homes, both in terms of becoming ever 60 days and ever 90 days delinquent. Among rated homes, some trends in the changes of loan factors are evident at different levels of energy efficiency. Better-rated homes (higher quartiles) had lower delinquency rates. At the same time, better-rated homes also had better profiles in general: owners with higher average credit scores (FICO), lower LTV ratios at origination, higher origination unpaid principal balances (UPB), higher owner incomes, and higher neighborhood incomes at the census tract level.

Exhibit 10. Average borrower and loan characteristics for unrated and RESNET-rated homes

			Higher quartiles indicate better energy efficiency rating			
	Unrated	RESNET	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Ever D60	3.6%	3.1%	4.4%	3.3%	2.5%	2.4%
Ever D90	2.5%	2.3%	3.3%	2.4%	1.9%	1.7%
Credit scores (FICO)	734	741	730	737	748	753
Government loan	40.3%	35.4%	47.2%	37.3%	28.6%	25.7%
Loan-to-value at origination	86.0%	86.0%	88.6%	86.6%	84.7%	83.5%
Debt-to-income	28.7%	28.1%	27.9%	28.5%	28.0%	28.2%
Borrowers' age	41.33	41.68	41.69	41.4	41.63	41.71
UPB at origination	261,432	275,398	217,063	260,484	298,727	317,933
Income(self reported)	87,684	89,912	80,563	88,142	94,287	96,255
AMI (area median income)	75,677	76,843	72,770	74,843	78,399	81,611
Ratio of income to AMI	117%	119%	112%	119%	122%	120%
Tract income	98,878	97,223	86,082	96,665	103,622	103,010
Number of observations	18,541	28,065	8,441	8,602	7,644	7,706

Note: Sample size presented in this exhibit is smaller than in Exhibit 8 because the loan performance dataset in this exhibit is a subset of the property dataset in Exhibit 8. All homes were restricted to those with primary mortgage accounts, with at least two years of loan performance, and originated after January 2013 and before August 2016. Unrated homes were further restricted to those built after 2013. Quartiles were constructed by 100-HERS Index.

5.2.2. Regression Results for Default Risk

In our analysis of the default risk, when underwriting factors were accounted for, however, we did not find the loan performance of RESNET-rated homes to be different from unrated homes (Columns 1 and 2 in Exhibit 11). Also, better scores did not translate to better loan performance among rated homes (Columns 3-6 in Exhibit 11). A few possible reasons might explain the absence of the effect of energy efficiency on loan performance. First, our analysis period has low levels of overall delinquency. The small number of delinquent events in the dataset may not be enough for drawing statistical conclusions. Second, the savings on energy bills may be too small to resolve difficulties in mortgage repayment. Extra disposable income could put households at a better financial condition; however, the degree of relief may not be enough to cancel out financial shocks caused by traumatic events such as a major illness, income reduction or unemployment, divorce or death of a spouse. Third, savings on energy bills may have been used instead for purposes besides mortgage payments, such as paying off other types of debts (credit cards, for example) or purchasing items not previously included in the household budget. Consumers are different in prioritizing the types of debts they have, as well as positioning non-debt related consumptions over debts.

[10] The unrated homes used for loan performance analysis were selected by the year built (after 2013) rather than the propensity matching process. Together with other restrictions imposed on mortgage data (see note related to Exhibit 12), this returns a sample of unrated homes smaller than the RESNET-rated home sample, which is not appropriate for applying the propensity matching method.

Exhibit 11. Logistic regression results for the effect of energy efficiency on delinquency

Variables	Rated vs. Unrated		RESNET only			
Dependent: D90(Yes=1)	(1)	(2)	(3)	(4)	(5)	(6)
	All	Conventional	ALL	ALL	Conventional	Conventional
RESNET-rated (Yes=1)	-0.034	-0.049				
	(0.070)	(0.167)				
Quartile 2				0.085		-0.683**
				(0.117)		(0.310)
Quartile 3				-0.009		-0.537
				(0.144)		(0.337)
Quartile 4				-0.057		-0.398
				(0.163)		(0.360)
100-HERS Index			-0.004		-0.018	
			(0.007)		(0.018)	
Observations	46,035	27,711	27,715	27,715	15,382	15,382
Pseudo R-squared	0.256	0.294	0.265	0.266	0.303	0.306

Note: Control variables included buckets of FICO, LTV, DTI, relative income, unpaid principle balance, loan term, as well as census tract income, vintage fixed effects, and state fixed effects. The loan performance dataset is a subset of the property dataset. All homes were restricted to those with primary mortgage accounts, with at least two years of loan performance, and originated after January 2013 and before August 2016. Quartiles were constructed by 100-HERS Index. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2.3. Loans in High Debt-to-income (DTI) Bucket

Because of our focus on access to credit, we also looked at how potential energy savings impact delinquency rates for loans with different DTI buckets. Based on both summary statistics and the regression analysis, RESNET-rated homes have a lower delinquency rate than unrated homes in the highest DTI bucket (45% and above).

Exhibit 12 presents the average values of an ever 60-day delinquency rate for conventional loans by LTV and DTI buckets. The top panel represents RESNET-rated homes and the bottom panel shows the unrated homes. As expected, within each group, higher DTI or higher LTV was associated with higher delinquency rates. Comparing rated and unrated homes, the average values of delinquency rate at more than 45% DTI buckets were smaller for RESNET-rated homes than for unrated homes (Exhibit A5 in the Appendix presents a similar pattern for the ever 90-day delinquency rate and Exhibit A6 presents the loan counts by DTI and LTV buckets).

We next test statistically whether the impact of energy efficiency on loan performance matter differently for homes at different DTI levels. To do this, we included interaction terms between the existence of an energy efficiency rating (rating dummy variable) and DTI buckets. After we controlled for other differences in underwriting between the rated and unrated homes, the reduced delinquency associated with energy efficiency ratings in the high DTI buckets remained. Exhibit 13 presents estimates derived from a linear probability model, and this model was chosen over a logit model (in Exhibit 11) for easier calculation and interpretation on estimates of the interaction terms. Estimates in Exhibit 13 are the sum of coefficients of RESNET-rated dummy and coefficients of interaction terms (rating dummy * DTI buckets). By reviewing the ever 60-day delinquency model results for conventional loans in the third column, we observed the estimate indicates the delinquency rate for RESNET-rated homes was 170 basis points lower than for unrated homes in the above-45% DTI bucket. These differences are also statistically significant in ever 60-day and ever 90-day delinquency models for all loans (government and conventional loans).

Exhibit 12. Ever 60-day delinquency rate for conventional loans by LTV and DTI buckets

RESNET - Ever D60 - Conventional Grid

DTI Buckets	80% and Under	Above 80% to 95%	Above 95%	Total
0% under 30%	0.5%	0.7%	2.3%	0.6%
30% under 45%	1.2%	1.4%	2.4%	1.3%
45% and above	2.5%	2.5%	4.0%	2.6%
Total	0.8%	1.2%	2.6%	1.0%

Non-RESNET - Ever D60 - Conventional Grid

DTI Buckets	80% and Under	Above 80% to 95%	Above 95%	Total
0% under 30%	0.6%	0.9%	1.8%	0.7%
30% under 45%	1.0%	1.3%	2.6%	1.2%
45% and above	4.0%	2.7%	9.0%	4.2%
Total	1.0%	1.3%	3.1%	1.1%

Note: Data includes households with a first-lien mortgage reported in a major credit bureau data originated between January 2013 and September 2016 on houses built since 2013. Credit records with highly unusual values likely to result from reporting errors are excluded.

Exhibit 13. Derived estimates of differences in delinquency rates between RESNET-rated and unrated homes by DTI buckets

DTI Buckets	D60-All	D90-All	D60-Conventional	D90-Conventional
30% under 45%	0.003	0.004	0.002	0.003
p-value	0.321	0.088	0.101	0.027
45% and above	-0.018	-0.006	-0.017	-0.006
p-value	0.011	0.079	0.004	0.105

Note: Highlighted coefficients are significant at the 5% or 10% level. Control variables include buckets of FICO, LTV, DTI, relative income, UPB, loan term, as well as loan type, census tract income, vintage fixed effects, state fixed effects, and interactions terms of DTI buckets with dummy variable of rating. This table presents estimates derived from linear probability model. Specifically, coefficients of energy efficiency rating dummy + coefficients of (rating dummy * DTI buckets). DTI<30% is omitted. Linear probability model was used for easier calculation and interpretation on estimates of the interaction terms.

6. EXISTING HOMES (DOE SAMPLE)

6.1. Summary Statistics for the Property Dataset

DOE-rated homes have average sale prices similar to unrated homes. However, DOE-rated homes are smaller and much older than the unrated homes (Exhibit 14). It is also important to note that the most recent year-of-sale for DOE-rated and unrated homes are very different. The average year of sale is 2005 for the DOE-rated group and 2011 for the unrated group. Given that rated homes in our sample are rated after 2013, this indicates homeowners requesting DOE ratings are not seeking a rating for purposes of an immediate sale after a rating but are interested in energy retrofits. Therefore, the DOE dataset may be less appropriate for sale price analysis given the absence of price information after rating. Furthermore, among all DOE-rated homes, more energy-efficient homes are less expensive, smaller, use less energy, and generate lower utility bills.

Exhibit 14. Average house characteristics for unrated and DOE-rated homes

			Higher quantiles indicate better energy efficiency rating			
	Unrated	DOE	Quartile 1	Quartile 2	Quartile 3	Quartile 4
HEScore - DOE		5.0	2.0	4.5	6.0	7.9
Price	263,304	263,987	315,052	270,053	244,236	221,440
Square feet	2,354	2,064	2,502	2,102	1,901	1,706
Acres	0.4	0.6	0.9	0.7	0.5	0.4
Year built	1996	1970	1960	1971	1975	1977
Year sold	2011	2005	2004	2004	2005	2005
Age (at sale)	14.2	32.4	41.5	30.9	28.7	27.7
New (at sale)	18%	7%	5%	8%	8%	9%
Number of bedrooms	3.5	3.2	3.6	3.3	3.1	2.9
Number of bathrooms	2.6	2.3	2.6	2.5	2.2	2.1
Energy use (mbtu/yr)		112.6	151.2	113.4	99.7	83.1
Energy cost($/yr)		2,986	4,156	2,992	2,544	2,130
Number of observations	306,387	4,852	1,324	1,364	710	1,454

Note: DOE-rated homes were rated between 2014 and 2017, and unrated homes were selected from nearby neighborhoods. Quartiles were constructed based on the value of Home Energy Score (DOE), and each quartile contains about one fourth of all DOE-rated homes in the sample. Higher quartiles indicate better energy efficiency ratings.

6.2. Summary Statistics for the Loan Dataset

On average, compared to unrated homes, DOE-rated homes have higher delinquency rates, as shown in Exhibit 15. However, the consumers in DOE-rated homes also have mortgages with slightly higher LTVs and DTIs. This contrasts with the RESNET sample, where rated homes tend to show lower delinquency rates with less credit-favorable profiles. Furthermore, in the DOE-rated sample, a better energy efficiency rating was not associated with better loan performance, when looking only at the DOE-rated homes by energy efficiency quartiles. In contrast to the RESNET-rated sample, there is also little pattern in loan characteristics as the energy efficiency level changes, except for that loans on homes with better DOE ratings had lower DTI, comprise a higher percentage of government loans, and were in neighborhoods with lower incomes.

Exhibit 15. Average borrower and loan characteristics for unrated and DOE-rated homes

			Higher quantiles indicate better energy efficiency rating			
	Unrated	DOE	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Ever D60	2.4%	3.0%	2.0%	3.7%	2.6%	4.3%
Ever D90	1.7%	1.7%	1.0%	2.6%	0.5%	2.9%
Credit scores (FICO)	743	748	748	750	748	745
Government loan	28.9%	26.1%	22.6%	24.6%	28.7%	29.3%
Loan-to-value at origination	83.8%	84.1%	84.6%	85.6%	81.6%	84.6%
Debt-to-income	27.7%	28.0%	29.2%	27.9%	27.5%	27.4%
Borrowers' age	40.86	40.28	40.22	39.72	39.91	41.63
UPB at origination	256,816	246,672	288,962	261,869	206,938	221,172
Income(self reported)	91,119	90,593	92,425	91,964	86,011	92,695
AMI (area median income)	82,128	91,780	91,966	91,990	91,621	91,452
Ratio of income to AMI	112%	99%	101%	100%	93%	102%
Tract income	105,642	103,144	112,275	105,098	96,625	96,578
Number of observations	17,394	725	199	191	195	140

Note: Sample size presented in this Exhibit are smaller than Exhibit 14, because the loan performance dataset in this Exhibit is a subset of the property dataset in Exhibit 14. All homes are restricted to homes with primary mortgage accounts, with at least two years of loan performances. Unrated homes are further restricted to those built after 2013. Quartiles are constructed by Home Energy Score. Higher quartiles indicate better energy efficiency rating.

7. CONCLUSIONS

The two energy efficiency rating systems used for this study reveal two distinct markets for energy efficiency: buyers of new homes versus owners of existing homes. Across both markets, households who choose homes with energy efficiency ratings generally receive more advanced degrees than the benchmark populations. Existing homes with energy efficiency ratings are favored by the households older than 55 years of age, while new homes with ratings are favored by Generation Xers (36-54 years old as of 2016). Interestingly, there are also fewer high income (>120% AMI) and more low income (<=50% AMI) households in both energy efficiency-rated markets as compared to the general population. The interest in energy efficiency in the low-income cohort suggests that energy-efficient home improvements may be a means to support low-income consumers.

Using the sample of energy efficiency-rated new homes (RESNET sample) with energy efficient features, we found a sale price premium associated with energy efficiency rating. New homes with RESNET ratings were sold for 2.7% more than comparable unrated homes on average. The higher price associated with energy efficient features could be offset by future utility bill savings and resale value. Furthermore, we observed a loan performance bump for energy efficiency-rated homes in the high DTI buckets (≥45%). This could suggest that potential energy savings associated with energy-efficient homes offer greater benefits to debt-stretched consumers. In underwriting, allowing certain flexibility in loan amount and DTI ratios could be contemplated to reflect the higher collateral value and lower default risk in the high DTI segment.

In contrast, data for energy efficiency in the market of existing homes is more limited. Measuring the impact of energy efficiency on the sale prices of existing homes is more challenging than on new homes because existing homeowners often request ratings to help decide whether to make energy efficiency improvements rather than to better position their homes for sale. As rating requests continue to grow over time, a larger data sample of energy efficient existing homes could be available for the price analysis.[11]

[11] More localities and states are taking actions to incentivize energy efficiency in homes. For example, the City of Portland, Oregon has required all single-family home sellers to order and disclose energy audits since January 1, 2018. See www.portlandoregon.gov/bps/71421.

APPENDIX

Exhibit A1.

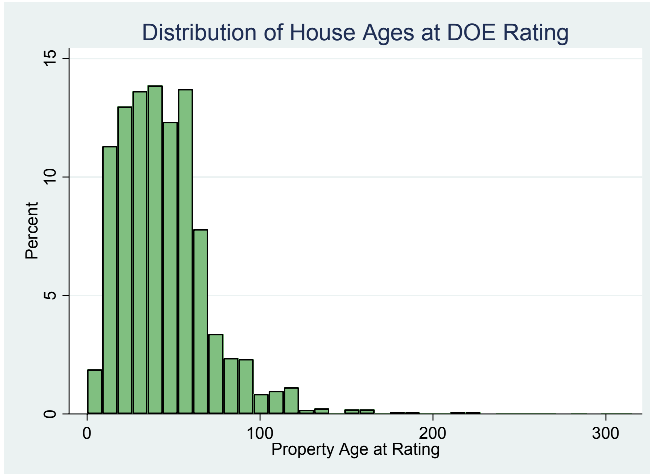


Exhibit A2.

County Name	State	Counts of Rated Homes	Share in the Country
Top 10 Counties with Most RESNET-rated Homes			
Harris	TX	34,991	4.4%
Maricopa	AZ	31,833	4.0%
Clark	NV	19,082	2.4%
Collin	TX	18,772	2.4%
Fort Bend	TX	17,723	2.2%
Bexar	TX	16,524	2.1%
Denton	TX	15,061	1.9%
Wake	NC	14,145	1.8%
Orange	FL	11,124	1.4%
Montgomery	TX	9,907	1.3%
	Total	189,162	24.0%

Exhibit A3.

County Name	State	Counts of Rated Homes	Share in the Country
Top 10 Counties with Most DOE-Rated Homes			
Hartford	CT	8,317	12.9%
New Haven	CT	6,615	10.2%
Fairfield	CT	6,585	10.2%
Monmouth	NJ	6,131	9.5%
Ocean	NJ	5,836	9.0%
Boone	MO	3,791	5.9%
Suffolk	NY	3,560	5.5%
Jefferson	KY	1,952	3.0%
Nassau	NY	1,708	2.6%
New London	CT	1,643	2.5%
	Total	46,138	71.5%

Exhibit A4a. Linear probability regression results for the choice of rating

This exhibit presents the regression results for the choice of rating. In column 1, property characteristics are used as the explanatory, assuming property attributes can predict the likelihood of a home being rated. In column 2, both property and homeowners' characteristics are used, assuming homeowners' information is also associated with the choice of rating. Even though the requesters for RESNET ratings are likely to be developers rather than homeowners, developers could have targeted the potential buyers' preference based on buyers' characteristics. Propensity score calculations are based on column 2's specification.

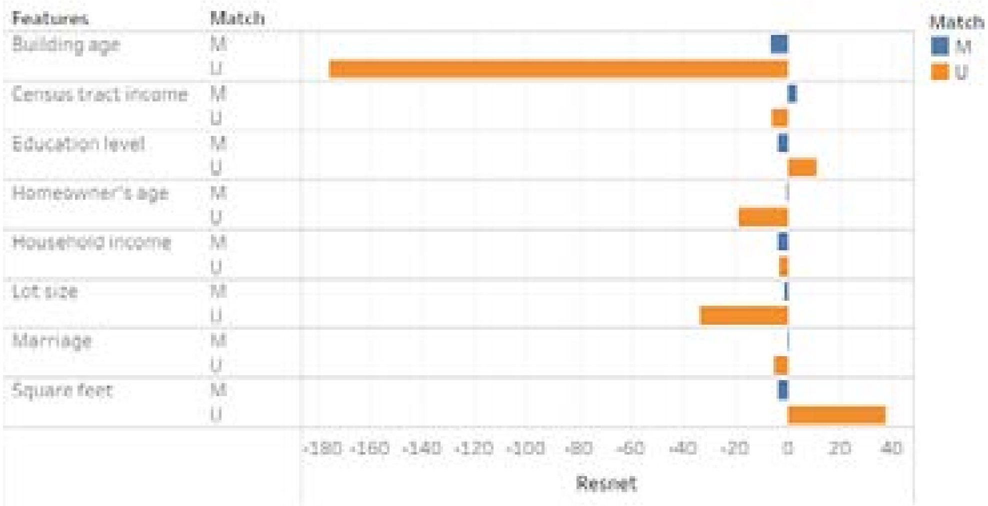
Based on the propensity scores, we conducted matching with the nearest neighbor (n=1), as well as three and five nearest neighbors. Final results are not much different from each other and we only present the matching results with the nearest neighbor (n=1) in Exhibit 9 in the paper.

Linear probability regression results for the choice of rating

Variables	1	2
Dependent: RESNET-rated (Yes=1)	Property Characteristics	Property+Borrower Characteristics
Square feet	0.000***	0.000***
	(0.000)	(0.000)
Site size	-0.207***	-0.187***
	(0.019)	(0.021)
Building age (3~5)	0.700***	0.676***
	(0.016)	(0.018)
Building age (5~10)	-1.726***	-1.743***
	(0.018)	(0.020)
Building age (10~15)	-7.375***	-7.328***
	(0.165)	(0.177)
Building age (15~20)	-6.817***	-6.772***
	(0.180)	(0.193)
Building age (20~30)	-6.607***	-6.662***
	(0.172)	(0.193)
Building age (30~40)	-6.041***	-6.158***
	(0.165)	(0.190)
Building age (40~50)	-6.084***	-6.011***
	(0.205)	(0.214)
Building age (>50)	-3.759***	-3.829***
	(0.047)	(0.052)
Census tract income	-0.000***	-0.000***
	(0.000)	(0.000)
Borrower's income		0.000***
		(0.000)
Borrower's age		0.001
		(0.001)
Marriage status = Single		-0.041
		(0.028)
Marriage status = Unknov		-0.005
		(0.020)
Education = Unknown		0.089
		(0.105)
Education = HS Diploma		-0.031
		(0.035)
Education = Some College		0.065**
		(0.033)
Education = Bach Degree		0.141***
		(0.033)
Education = Grad Degree		0.190***
		(0.036)
Constant	-0.059**	-0.084*
	(0.027)	(0.048)
Observations	331,218	267,391
Pseudo R-squared	0.480	0.482

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Exhibit A4b. Reduction in the dissimilarityof variables after matching



Note: The X axis shows the standardized % bias across covariates, a metric to capture the difference between the rated and unrated groups. M = homes matched to rated homes; U = homes not matched to rated homes. Figure presents the nearest match (n=1) in the matching group. Variables included in the logistic regression for calculating propensity scores are square feet, lot size, building age buckets, as well as borrower's income, age, marriage status, education, and neighborhood income.

Exhibit A5. Ever 90-day delinquency rate for conventional loans by LTV and DTI buckets

RESNET - Ever D90 - Conventional Grid

DTI Buckets	80% and Under	Above 80% to 95%	Above 95%	Total
0% under 30%	0.3%	0.5%	1.8%	0.4%
30% under 45%	0.7%	1.1%	2.0%	0.9%
45% and above	1.5%	2.3%	3.0%	1.8%
Total	0.5%	0.9%	2.0%	0.7%

Non-RESNET - Ever D90 - Conventional Grid

DTI Buckets	80% and Under	Above 80% to 95%	Above 95%	Total
0% under 30%	0.4%	0.7%	1.4%	0.5%
30% under 45%	0.7%	0.5%	1.0%	0.7%
45% and above	1.5%	2.7%	7.7%	2.4%
Total	0.6%	0.8%	2.2%	0.7%

Note: Data includes households with a first-lien mortgage reported in a major credit bureau data originated between January 2013 and September 2016 on houses built since 2013. Credit records with highly unusual values likely to result from reporting errors are excluded.

Exhibit A6. Loan counts by LTV and DTI buckets for conventional loans

Loan Counts				
	LTV Buckets			
DTI Buckets	80% and Under	Above 80% to 95%	Above 95%	Total
0% under 30%	8,891	2,478	434	11,804
30% under 45%	2,993	1,485	251	4,729
45% and above	962	514	100	1,576
Total	12,866	4,483	793	18,143

Non-RESNET - Loans Counts - Conventional Grid

Loan Counts				
	LTV Buckets			
DTI Buckets	80% and Under	Above 80% to 95%	Above 95%	Total
0% under 30%	5,527	1,215	278	7,021
30% under 45%	2,083	765	191	3,039
45% and above	668	257	78	1,004
Total	8,287	2,237	549	11,075

REFERENCES

Home Energy Score Scoring Methodology, 2017: https://betterbuildingssolutioncenter.energy.gov/sites/default/files/attachments/Home%20Energy%20Score%20Methodology%20Paper%20v2017.pdf

Kaza, Nikhil, Quercia, Roberto G., and Tian, Chao Yue. "Home energy efficiency and mortgage risks." Cityscape 16, no. 1 (2014): 279-298.

Kaza, N., Quercia, R. G., & Tian, C. Y. (2015). Energy Efficiency and Mortgage Risks: Implications for the Northeast. Communities & Banking, 22.

Walls, Margaret, Gerarden, Todd, Palmer, Karen, and Bak, Xian Fang. "Is energy efficiency capitalized into home prices? Evidence from three US cities." Journal of Environmental Economics and Management 82 (2017): 104-124.

Freddie Mac
Single-Family