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Creditworthiness and buildings' energy efficiency in the Italian mortgage market*

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Abstract

Energy efficiency represents one of the key planned actions aiming at reducing greenhouse emissions and the consumption of fossil fuel to mitigate the impact of climate change. In this paper, we investigate the relationship between energy efficiency and the borrower's solvency risk in the Italian market. Specifically, we analyze a residential mortgage portfolio of four financial institutions which includes about 70,000 loans matched with the energy performance certificate of the associated buildings. Our findings show that there is a negative relationship between a building's energy efficiency and the owner's probability of default. Findings survive after we account for dwelling, household, mortgage, market control variables, and regional and year fixed effect. Additionally, a ROC analysis shows that there is an improvement in the estimation of the mortgage default probability when the energy efficiency characteristic is included as a risk predictor in the model.

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1 Introduction

Energy efficiency represents one of the key planned actions aiming at reducing greenhouse emissions and the consumption of fossil fuel to mitigate the impact of climate change. According to the European Commission[1], buildings represent 40% of the total energy consumption and are responsible for 36% of the total CO2 emissions in Europe. Currently, only 25% of the stock of European buildings is considered energy efficient. In the 2030 climate & energy framework, the European Commission has set as a minimum target of the improvement in the energy efficiency by 32.5%. The process of making buildings energy efficient reveals several advantages also in terms of economic stimuli (e.g., the construction of buildings is a driving force component of the GDP) and in terms of investment opportunities since it provides an increase in the property value. Furthermore, energy efficiency seems to be an attractive market segment also for lenders in the mortgage market. Recent literature has started to investigate whether energy efficiency is related to a lower solvency risk for owners and consequently, whether it reduces the lending risk for banks and other financial institutions. Most of these studies conclude that there is a negative association between buildings' energy efficiency and owners' default. For instance, Kaza *et al.* (2014) provide evidence that the US energy efficient residential buildings–measured by the ENERGY STAR certificate–have a lower probability of default. Guin and Korhonen (2020) focus on the UK residential mortgages and find that energy efficient buildings show less payment arrears than the inefficient ones. An and Pivo (2020) investigate the commercial mortgage-backed securities market and find that the green buildings have a lower default risk thanks to a lower contemporaneous loan-to-value ratio with respect to the non-green counterpart. Billio *et al.* (2021) investigate the Dutch residential market and find that mortgages on energy efficient buildings have a lower probability of default. In addition to the borrower's individual factors, the authors show that there exists an economic channel (e.g., savings coming from reduced energy costs) that mitigates even further the probability of default of borrowers in lower-income groups. Current regulatory credit risk scoring models, such as the standardized approach produced by the Basel Committee on Banking Supervision, do not include energy efficiency features. If energy efficiency represents a significant predictor of mortgage default, it should be included in credit-scoring models of financial intermediaries along with the usual determinants such as applicant's demographic (e.g., age) and financial information (e.g., income level), and loan-specific characteristics (e.g., loan-to-value ratio). However, most of the studies that have attempted to analyze the European market have encountered several

[1]For more details, see `https://ec.europa.eu/info/news/new-rules-greener-and-smarter-buildings\-will-increase-quality-life-all-europeans-2019-apr-15_en`.

data availability issues. For instance, the non-compulsory disclosure of energy-efficient investments, the heterogeneity among the energy labels in the union, and the General Data Protection Regulation (GDPR) requirements. Therefore, further empirical investigations for the European Union are certainly welcome. In this paper, we investigate the relationship between energy efficiency and the borrower's solvency risk in the Italian market. Specifically, we analyze a residential mortgage portfolio of four financial institutions which includes about 70,000 loans matched with the energy performance certificate of the associated buildings.[2] In the analysis, we adopt the logit model and the Cox model to test for the relationship between energy efficiency and the likelihood of default of a mortgage. The logit regression is suitable to model binary outcomes (the dependent variable takes the value of one in the presence of default and zero otherwise), while the Cox regression allows distinguishing between "healthy" and "non-healthy" mortgages (i.e., non-defaulted vs. defaulted) over time. Our findings show that there is a negative relationship between a building's energy efficiency and the owner's probability of default. Findings survive after we account for dwelling, household, mortgage, market control variables, and regional and year fixed effect. Additionally, a receiver-operating characteristic (ROC) analysis shows that there is an improvement in the estimation of the mortgage default probability when the energy efficiency characteristic is included as a risk predictor in the model. Finally, results indicate that the degree of energy efficiency has also an impact and that the higher the energy efficiency, the lower is the risk of default. The remainder of the paper is structured as follows. Section 2 introduces the Italian residential mortgage data and the associated energy performance certificates, then Section 3 presents the implemented methodologies. Section 4 illustrates the empirical analysis and our major results. Finally, Section 5 concludes.

2 Portfolio Analysis

In the following, we employ Italian residential mortgage data that was provided by CRIF s.p.a as part of the Energy Efficient Mortgages Initiative, for the project "Energy efficiency Data Protocol and Portal" (cf. EeDaPP 2020). The original sample was narrowed based on the following criteria. Complete information on the borrower's creditworthiness must be available for each loan. The time period of the sample is restricted to 2012 through 2019, during which mortgage loans were originated. The loan-to-value (LTV) ratio is capped at 1.1 to eliminate outliers. Borrower type is "individual," with each borrower holding a single

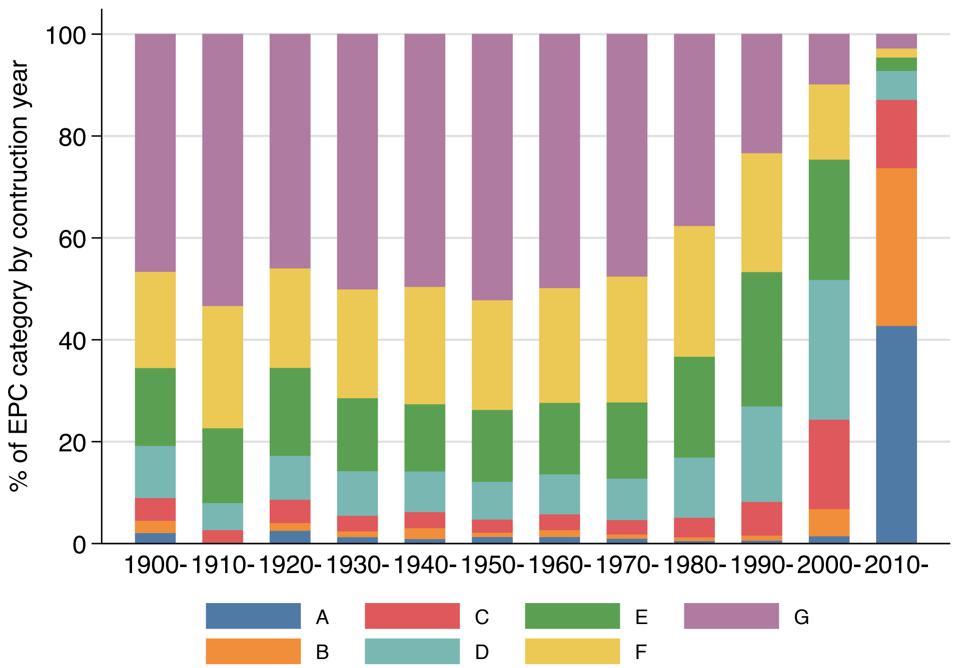
[2]The dataset has been made available to Ca' Foscari University of Venice by CRIF S.p.a and is part of the Energy efficiency Data Protocol and Portal (EeDaPP) project funded by the European Commission on the H2020 Programme (H2020-EE-2017-CSA-PPI).

mortgage. Either "apartment" or "house" must be selected as the property type. The status of the property falls into one of the following three categories: new/retrofit, used, or to be renovated. The years of construction of the buildings range from 1900 to 2019 and each borrower is required to be associated with exactly one building/apartment and vice versa. Our final dataset contains 70,666 individual mortgage loans after applying the above selection criteria.

2.1 Energy Efficiency

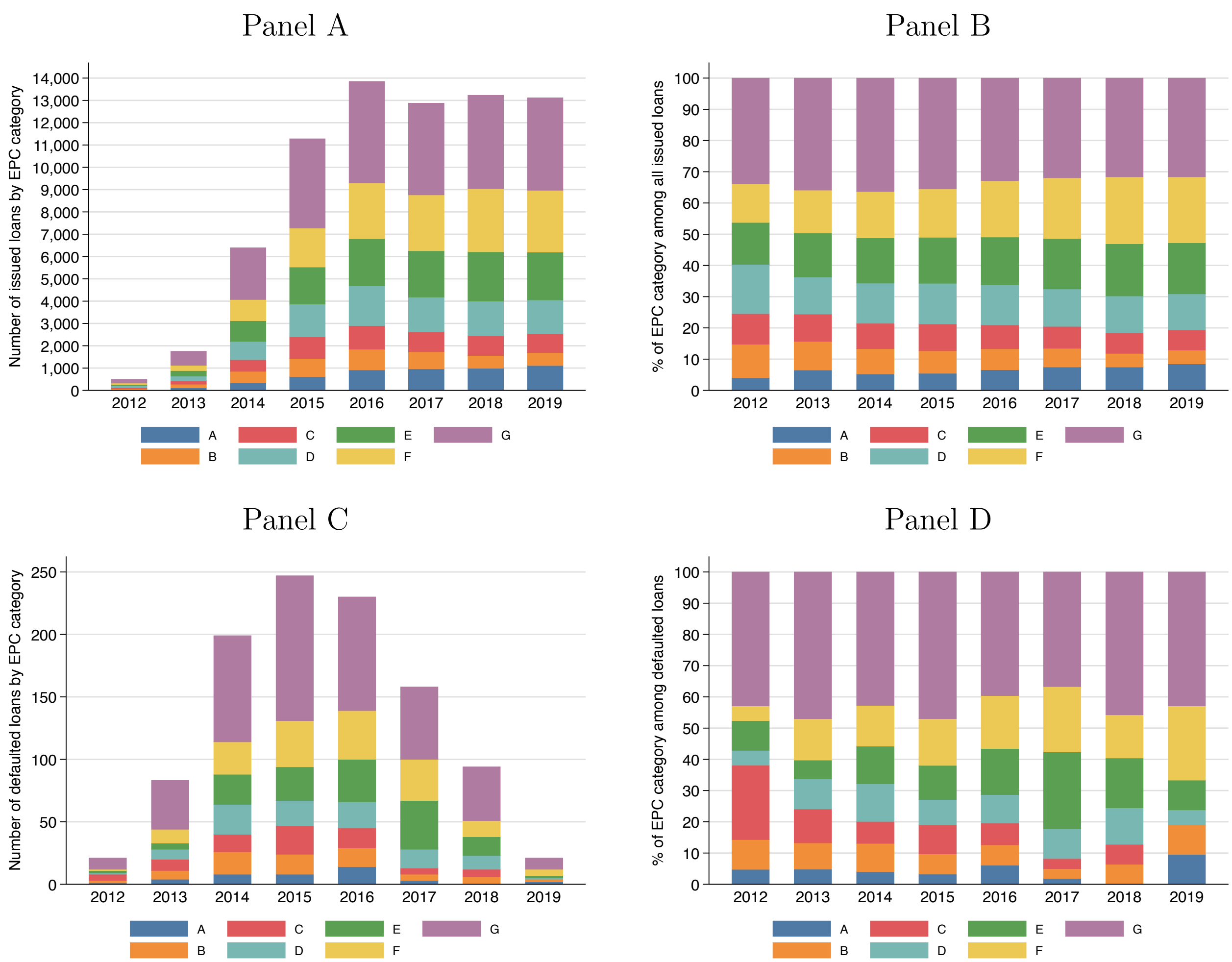
We use Energy Performance Certificates (EPC) of buildings to classify them into different energy efficiency categories. Figure 1 depicts the EPC distribution within 10-year buckets of building construction years. From the bar charts, we can observe that energy efficiency has improved significantly over time, with the most energy efficient buildings built after 2010.

Figure 1: Energy ratings by construction year. This figure presents the rating distribution across construction years. The construction years are categorised into 10-year buckets. The EPC rating categories fall into categories A (best) to G (worst energy efficiency).



The distribution of EPCs by year of loan origination is shown in Figure 2. Panel A shows the total number of mortgages granted, while Panel B shows the percentage of each EPC category by year of loan origination. According to the latter, between 12 and 15% of loans were originated for buildings with an EPC rating of A or B. Panels C and D deal exclusively with loans in arrears. The first time a borrower is more than 90 days delinquent, the loan is considered in default. As shown in Panel C, the absolute number of delinquent loans decreases with the year of loan origination. Panel D reports the percentage share of each rating within the year of origination.

Figure 2: Energy Rating (EPC) distribution of all (Panels A and B) defaulted (Panels C and D) mortgages by year of mortgage origination. The right (left) panels present the percentage share (absolute number) of each rating category given the origination years ranging from 2012 to 2019.



The rating distribution of all buildings in the sample is shown in Table 1, while the building distribution across Italian provinces is presented in Table 2. Less efficient buildings, especially G-rated buildings, represent the largest share in the sample, whereas A- and B-rated buildings account for roughly 13.1 percent. The percentage of defaulted mortgages in each rating class is shown in Column 3 of Table 1. In this regard, it's worth noting that the highest percentage of defaults is linked to the poorest energy efficiency rating G, whereas the lowest share of default is associated with the EPC rating A. Defaulted mortgages account for 1.31% of all mortgages.

Table 1: Rating distribution for all and defaulted mortgages. Column 2 presents the % share of each rating category given the total sample of mortgages. Column 3 indicates the share of defaulted loans within each rating category. The number of unique mortgages is 70,666.

Rating category	All	Defaulted
A	7.01	0.71
B	6.06	1.33
C	7.44	1.20
D	12.37	1.05
E	15.80	1.19
F	18.77	1.12
G	32.55	1.73
Total	100	1.31

Table 2 shows that mortgages are not evenly distributed throughout Italian regions, with Lombardy (46.20 %) and Emilia Romagna (29.04%) accounting for the biggest shares. The A-rated buildings represent between 2.4% and 24.2% of all buildings within individual regions. In all regions, the share of defaulted energy-efficient (EE) mortgages is lower than the share of defaulted non-EE mortgages.

In the analysis, we define the energy efficiency characteristic by creating a binary variable EE_i that equals 1 if a building i is A-rated (e.g., the top-notch in the EPC classification) and zero, otherwise.

2.2 Descriptive Statistics

The covariates for the correlation analysis are chosen such that mortgage-, dwelling-, and borrower-specific effects are accounted for. We use total loan amount, loan-to-value ratio, and mortgage term at the time of loan origination as mortgage controls. The total number of monthly installments divided by twelve gives the mortgage term, measured in years.[3] Dwelling-specific controls are property type and status, as well as age of the dwelling at loan origination. The majority of mortgages in the sample is issued for apartment purchases (97.8%), while only a small fraction was used to acquire a house (2.2%). The status of the dwelling is one of three types: new/renovated (32.8%), used (65.6%), or to-be-renovated (1.6%). Borrower-specific controls are the borrower's age at the time of loan origination and his or her credit score rating. We use the quarterly Italian unemployment rate (at the NUTS1 macroregional level), the monthly inflation rate (year-on-year change in the consumer price index), and the quarterly growth in the house price index (year-on-year change, at the NUTS1 macroregional level) to account for overall macroeconomic conditions.

[3] The total number of monthly installments is calculated by transforming all reported periodicities (i.e., monthly, quarterly, semi-annually, and annually) into monthly.

Table 2: Loans distribution (all and defaulted) conforming to the NUTS 2 classification for Italy. Column 2 shows the % share of each region within the total. Column 3 indicates the share of energy-efficient buildings (defined as A-rated buildings) within each region. Column 4 (Column 5) presents the percentage share of defaulted non-energy efficient (energy-efficient) mortgages with a region. The total number of mortgages is 70,666.

	All		Defaulted	
Property Region	By region	EE within region	non-EE	EE
ABRUZZO	0.45	18.50	1.57	0.00
BASILICATA	0.16	18.75	1.79	0.00
CALABRIA	0.22	18.59	0.64	0.00
CAMPANIA	0.33	10.59	1.27	0.00
EMILIA ROMAGNA	29.04	7.60	1.09	0.07
FRIULI VENEZIA GIULIA	0.23	11.32	0.00	0.00
LAZIO	0.82	10.21	2.08	0.00
LIGURIA	0.84	2.18	2.18	0.00
LOMBARDIA	46.20	6.56	1.31	0.05
MARCHE	0.58	5.10	2.67	0.00
MOLISE	0.05	24.24	0.00	0.00
PIEMONTE	9.05	4.44	1.06	0.00
PUGLIA	0.31	15.60	1.38	0.00
SARDEGNA	0.73	12.16	0.77	0.00
SICILIA	4.82	2.67	2.05	0.06
TOSCANA	2.33	3.82	1.58	0.06
TRENTINO ALTO ADIGE	0.74	15.49	0.38	0.00
UMBRIA	0.06	18.60	0.00	0.00
VALLE D'AOSTA	0.35	2.44	2.03	0.41
VENETO	2.68	19.40	0.90	0.11
Total	100	6.93	1.39	0.05

The variables were obtained from Istat, the Italian national statistical office.[4] Summary statistics on key borrower, property, and mortgage characteristics are reported in Table 3. The table distinguishes between non-defaulted (Panel A) and defaulted (Panel B) mortgages. Furthermore, we also distinguish between energy-efficient (EE = 1) and energy-inefficient (EE = 0) dwellings in both panels. We stress again that the energy efficiency indicator EE is set to one if a dwelling's EPC rating is A, and it is zero otherwise. In terms of borrower characteristics, there does not appear to be a significant difference in age at origination between EE and non-EE mortgages. However, defaulted loans exhibit a slightly higher average age than non-defaulted loans in the sample. In terms of creditworthiness, the less creditworthy borrowers are more likely to default. Defaulted non-EE mortgages have the highest average loan-to-value ratio. Borrowers appear to default more often on mortgages with a higher loan amount, higher property values, and an earlier year of construction.

The distribution of mortgages by construction year (Panel A), granted loan amount (Panel B), and mortgage origination year (Panel C) is shown in Figure 3. Starting from the 1950s, the dataset is well distributed in terms of construction year, but the earlier years are sparsely represented. The average loan amount is EUR 118,032, with only 1% of issued loans exceeding a value of EUR 400,000. The loan sample is relatively new, with 0.68% of loans originated as recently as 2012.

In terms of macroeconomic indicators, the average quarterly total unemployment rate for adults aged 15 and older was 11.18 percent between Q1 2012 and Q4 2019. During the same period, the average inflation rate was 1.01%, while the house price index decreased on average by 2.3% across regions.

In summary, the portfolio analysis of Italian mortgages indicates that the dataset contains a sizeable amount of defaulted loans, although defaulted EE mortgages represent only a small part of the sample. This might be attributed to the fact that the mortgage sample is relatively recent and defaults typically occur after ten or more years from the date of origination. However, the sample size is large enough to run a comprehensive analysis and the presented control variables for borrower, mortgage and dwelling characteristics will be used to isolate the relationship between EE and the probability of mortgage default.

3 Methodology

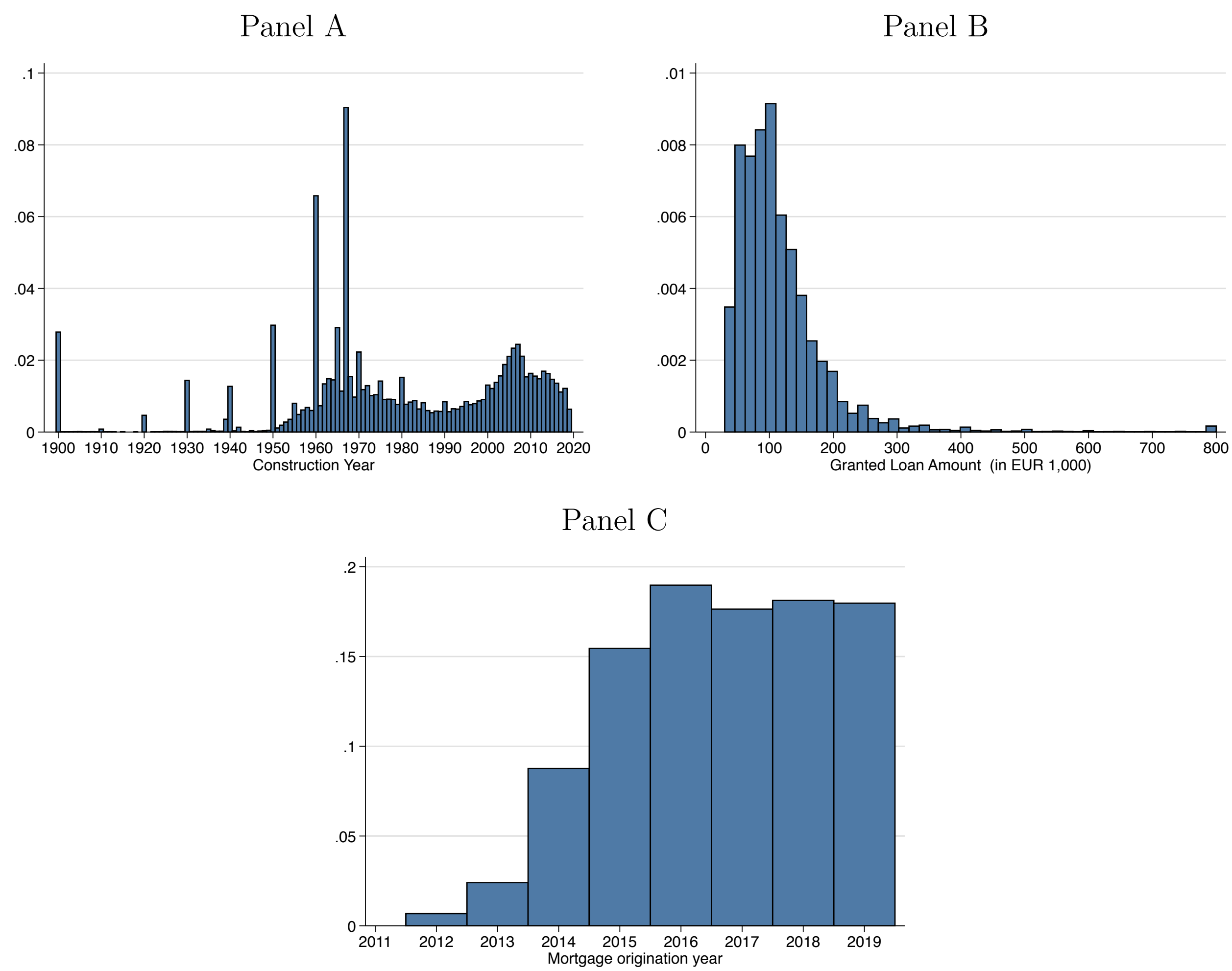
Logit regression and survival analysis are two statistical approaches that are commonly used for credit risk evaluation, and we choose to use both for robustness considerations. Our decision is based on the fact that logit regressions are commonly used for cross-sectional

[4] For more information, visit www.istat.it.

Table 3: Summary statistics for loan and borrower characteristics. Panel A (Panel B) provides the statistics for non-defaulted (defaulted). Column 2 discriminates between energy-efficient (EE=1) and energy-inefficient (EE=0) buildings.

Panel A: Non-defaulted							
	EE	Mean	Median	Std.	Min	Max	N
Borrower age at	0	40.4	39.0	10.1	18.0	87.0	64,823
origination	1	40.0	39.0	9.9	18.0	79.0	4,916
Credit score	0	516.7	521.0	42.0	167.0	598.0	64,823
	1	520.2	524.0	38.1	204.0	598.0	4,916
Granted loan amount	0	109,755	98,000	68,420	30,009	3,000,000	64,823
	1	158,486	140,000	121,434	32,000	4,100,000	4,916
Loan-to-Value	0	0.65	0.69	0.19	0.04	1.09	64,823
	1	0.60	0.63	0.20	0.06	1.09	4,916
Mortgage term	0	20.69	20.08	6.58	3.00	40.33	64,823
(in years)	1	21.61	20.08	6.55	4.00	40.08	4,916
Construction year	0	1977	1974	25	1900	2019	64,823
	1	2009	2015	19	1900	2019	4,916
Property value	0	181,319	152,000	126,179	32,000	5,310,000	64,823
	1	279,919	240,000	216,434	44,000	6,028,000	4,916
Panel B: Defaulted							
	EE	Mean	Median	Std.	Min	Max	N
Borrower age at	0	41.8	41.0	10.8	20.0	78.0	892
origination	1	43.1	41.0	12.1	27.0	79.0	35
Credit score	0	456.2	485.0	89.3	172.0	579.0	892
	1	433.2	469.0	102.9	179.0	558.0	35
Default since origination	0	26.3	23.0	16.4	5.0	95.0	892
(in months)	1	25.3	23.0	14.1	5.0	62.0	35
Granted loan amount	0	109,994	94,023	118,985	30,722	3,000,000	892
	1	358,305	155,000	1,158,114	38,000	7,000,000	35
Loan-to-Value	0	0.66	0.72	0.20	0.07	1.09	892
	1	0.61	0.64	0.21	0.18	0.99	35
Mortgage term	0	21.84	20.63	6.69	3.08	40.00	892
(in years)	1	23.72	25.08	6.10	10.50	30.58	35
Construction year	0	1976	1972	24	1900	2018	892
	1	2007	2013	22	1900	2016	35
Property value	0	184,735	145,000	199,071	38,000.00	4,054,000.00	892
	1	577,571	254,000	1,651,266	111,000	10,000,000	35

Figure 3: Distribution by construction year and original balance. Panel A indicates the relative frequency of construction year for the considered buildings. Panel B shows the relative frequency of total mortgage original balance. Panel C provides the frequency of the earliest mortgage origination year.



datasets, but survival models account for the time dimension, in which the hazard of an event occurring (i.e., default) increases with time. As a result, survival analysis appears to be a good complement to the more static Logit regression. In addition, the Cox model takes into account truncation and censoring in the data. The two subsections that follow give further information on the approaches used and their unique characteristics.

3.1 Logit Regression

Logistic regression is a typical method for examining the link between borrower-level loan information and the likelihood of default (see, e.g., Altman and Saunders 1997, Qi *et al.* 2020). This regression allows to model a binary outcome variable associated to a group of potential determinants. The dependent variable in our example is a dichotomous variable that indicates whether a borrower has defaulted or not. The simplicity of such a model contributes to its popularity and is derived from the function $f(z)$, which takes a range of values between 0 and 1, and is defined as:

$$f(z) = \frac{1}{1+\exp(-z)}. \tag{1}$$

Figure 4 shows that as z tends to $-\infty$, the logistic function $f(z)$ approaches zero and as z goes to $+\infty$ the value of the function $f(z)$ approaches one. Therefore, the logistic function represents an ideal candidate to model (default) probabilities that lie between 0 and 1.

Figure 4: The figure illustrates the bounds of the logistic function $f(z)$.

$0\frac{1}{2}1\longleftarrow -\infty 0{+}\infty \longrightarrow z f(z)$

By defining z as the sum of a linear combination of p covariates x, i.e., $z = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p$, the logistic regression model is obtained by substituting z into $f(z)$:

$$\mathbb{P}(Y^i = 1 | x_1, x_2, \ldots, x_p) = \frac{1}{1+\exp(-(\alpha + \sum_{l=1}^{p} \beta_l x_l))} = G(\beta^i \mathbf{X}^i), \tag{2}$$

where α and β_l represent the parameters to be estimated. Therefore, the function $f(z)$ represents the conditional probability of the binary outcome variable Y of a subject i given a set of observed factors $x_1, x_2, \ldots, x_p$. The log-likelihood function is expressed as

$$\log L = \sum_{i=1}^{n} [Y^i \log G(\beta^i \mathbf{X}^i) + (1 - Y^i) \log(1 - G(\beta^i \mathbf{X}^i))]. \tag{3}$$

The likelihood is maximized by applying numerical methods such as the Newton-Raphson method to the first order condition in Equation 3. Estimates from logistic and the logit regressions are equivalent since both are retrieved using the maximum likelihood estimator and the logistic function is the inverse of the logit function:

$$\text{logit}^{-1}(\beta^i \mathbf{X}^i) = \text{logistic}(\beta^i \mathbf{X}^i) \tag{4}$$

For easier reading, we consider the logit model instead of the logistic since in the latter, the estimates as reported as odds ratios.

3.2 Cox Proportional Hazards Model

The Cox Proportional-Hazards Model (Cox 1972) is one of the most commonly used survival models because it allows for the inclusion of a number of variables and scales them with a baseline hazard rate. The model is defined as follows:

$$h(t, X) = h_0(t) \exp\left(\sum_{l=1}^{p} \beta_l x_l\right), \tag{5}$$

where $h_0(t)$ is the baseline hazard function, p is the number of independent variables X, and β_l is the parameter that has to be estimated for lth covariate.

The baseline hazard is a function of time t and does not depend on the set of covariates, which is a key property of the Cox model. In contrast, the exponential function, which does not use the time dimension t, involves only the set of covariates X. This means that the standard formulation of the Cox model reduces to $h_0(t)$ when all covariates x are zero.

The hazard ratio (HR) is defined as the ratio of hazards for two subjects that are included in a study. Assume $t_k^i(t_k^j)$ refers to observation time of subject i (subject j), then we can write the hazard ratio as the estimate of $h(t_k^i, X^i)$ divided by the estimate of $h(t_k^j, X^j)$:

$$\widehat{HR} = \frac{\hat{h}(t_k^i, X^i)}{\hat{h}(t_k^j, X^j)}, \tag{6}$$

where X^i and X^j are the subjects' respective covariate values. From Equation 6, we can observe that it is possible to estimate the parameters β even if the baseline hazard rate is not specified. Namely, HR can be rewritten as

$$\widehat{HR} = \frac{\hat{h_0}(t_k^i) \exp(\sum_{l=1}^{p} \hat{\beta}_l x_l^i)}{\hat{h_0}(t_k^j) \exp(\sum_{l=1}^{p} \hat{\beta}_l x_l^j)} = \exp\left(\sum_{l=1}^{p} \hat{\beta}_l (x_l^i - x_l^j)\right) = \theta, \tag{7}$$

where θ is a time-independent constant. The proportional hazard assumption states that for the risk of one person to be proportional to that of another, the HR formulation must remain constant over time. This means that the final expression of the hazard ratio does not include the time variable and that once the values of X^i and X^j are determined, the value of the exponential function becomes time-invariant, as shown in the equation above. This is the formal expression of the proportional hazards assumption. The relation between two subjects can, consequently, be written as $\hat{h}(t_k^i, X^i) = \theta\hat{h}(t_k^j, X^j)$.

A visualization of empirical survival functions can shed light on whether the proportional hazards assumption is valid. The empirical survival function is usually shown using the approach proposed in Kaplan and Meier (1958). The assumption of this non-parametric methodology is that censoring time does not depend on the individual's behaviour. The function is defined as

$$\hat{S}_{t_m} = \prod_{i=1}^{m} \mathbb{P}(T > t_i | T \geq t_i) = \hat{S}(t_{m-1})\mathbb{P}(T > t_i | T \geq t_i), \tag{8}$$

where t_m represents ordered event times and the probabilities are approximated by the frequency distribution in the dataset.

Since the observation period in survival analyses is often limited to a certain period of time, it is crucial to distinguish between (i) the date when a subject first takes a risk, (ii) the period when a subject is under observation, and (iii) the date when a subject experiences failure. If the date on which an individual first takes a risk is before the start of the observation period, we speak of left truncation. In the context of mortgage analysis, left truncation applies to mortgages that were originated before the first observation date. In general, left-censored subjects can be included in the analysis, but it is critical to consider the subject's time of risk exposure when they enter the observation (i.e., the age of the credit at the start of the study). If the time of default is not observable due to the subject's early exit from the study or early termination of the study, the subject is said to be right-censored. For example, it is not possible to consider the future default of a loan that is still ongoing at the end of the period considered in the survival study. The censoring date for a loan that was honoured during the period under investigation, on the other hand, is the date of the last payment, since (theoretically) a default might happen at any time in the future if only the loan term was long enough. The use of a dummy variable for censored observations is a common approach to correct for censoring.

4 Results

4.1 Estimates from the logit regression

As discussed in the previous section, the logit regression model is suitable for modeling binary outcomes like default, where the dependent variable is equal to one if a default occurs, and zero otherwise. Table 4 shows the regression estimates. Model (1) provides the findings by only including the EE indicator and mortgage-related parameters in the model such as the borrower's credit score, loan-to-value at mortgage origination, and loan term. The regression coefficient of -0.5712 for the EE dummy indicates that energy efficiency is significant and negatively associated to the likelihood of mortgage default. Given that this finding could be masked by building or household characteristics, we provide further specifications and include additional control variables in models (2) and (3). Model (2) includes dwelling age as a proxy for a building's general condition. Since more recent buildings are likely to require less renovation costs, the age might influence the borrower's ability to repay the debt. Additionally, model (3) takes into account the borrower's age at the time of origination to assess the borrower's attitude toward debt and ability to repay a loan. Models (4) and (5) involve region fixed effects at NUTS 1 level[5] and origination year. Fixed effects of origination year account for the fact that newer loans are less likely to default than older ones as highlighted in the descriptive statistics. Region fixed effects account for regional heterogeneity such as cultural attitude and economic strengths. Finally, model (6) controls for the macroeconomic condition of the economy at the date of loan origination and includes the inflation rate, the unemployment rate, and the house price index growth rate. The latter two variables are available at the NUTS 2 regional level. It's important to note that the EE is significant and negatively related to the borrower's risk of default in all the considered specifications.

To investigate whether the inclusion of building's energy efficiency information improves the model's prediction accuracy, we continue with model (6) of Table 4 as the baseline specification and perform a receiver-operating characteristic (ROC) analysis. The ROC analysis is a useful tool for evaluating the accuracy of a statistical model that classifies subjects into one of two categories (Metz 1978, Zweig and Campbell 1993). In our case, the Logit model classifies the loans into the categories defaulted and non-defaulted. To measure if this classification improves in precision as the explanatory variable EE is included in the

[5]The Nomenclature of Territorial Units for Statistics (NUTS) represents standard references for geographical coordinates for the classification of countries for statistical purposes. Three NUTS levels are established by Eurostat. The NUTS 1 codes refer to the least granular region specification. In the case of Italy, the NUTS 1 regions are: (i) North-East, (ii) North-West, (iii) Centre, (iv) South, and (v) Islands.

Table 4: Logit regression results to assess the relationship between buildings' energy efficiency and the default risk of the borrowers. The dependent variable is binary indicating whether a mortgage is in default (e.g., at least three months in arrears) or not. The dummy variable EE equals to one if a building‘s energy efficiency rating is A-rated and zero otherwise. Mortgage controls are borrower's credit score, loan-to-value, and loan term (in years). Dwelling control is building age at loan origination. Borrower control is borrower‘s age at loan origination. Market controls are monthly Italian inflation rate (change in the consume price index to previous year's value in the same month), quarterly unemployment rate at regional level, quarterly house price index growth at regional level. Origination year and NUTS1-region fixed effects (FE) are included where indicated. Standard errors (reported in square brackets) are robust. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level, respectively.

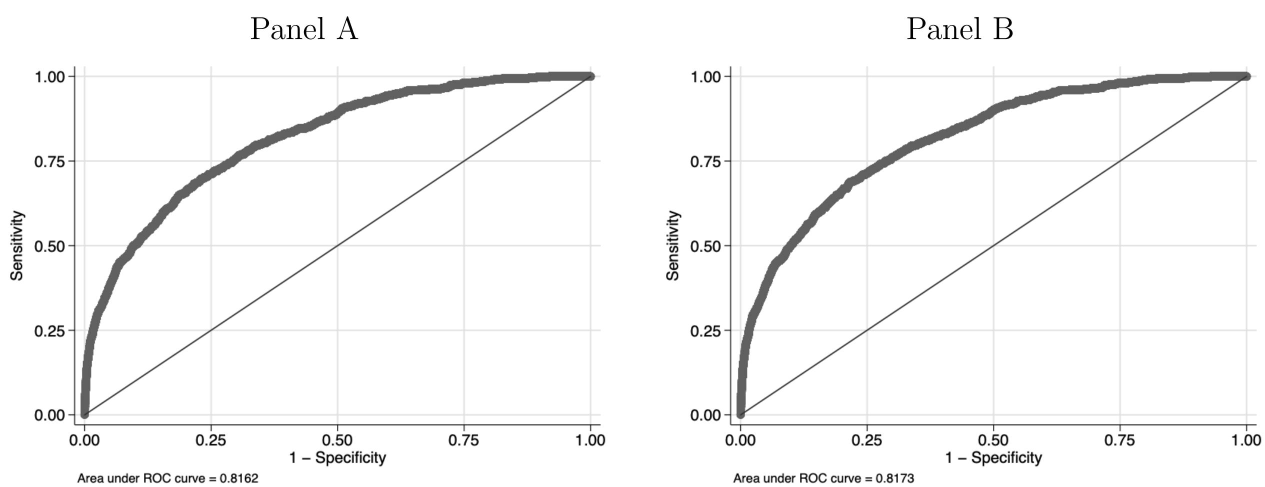
Dependent variable: Default dummy

	(1)	(2)	(3)	(4)	(5)	(6)
EE (A rating)	-0.5712***	-0.5589***	-0.5711***	-0.3988**	-0.3700**	-0.3609**
	[0.1724]	[0.1771]	[0.1769]	[0.1755]	[0.1764]	[0.1763]
Credit score	-0.0159***	-0.0159***	-0.0156***	-0.0151***	-0.0151***	-0.0152***
	[0.0004]	[0.0004]	[0.0004]	[0.0004]	[0.0004]	[0.0004]
Loan-to-Value	0.3284*	0.3280*	0.3798*	0.9951***	0.9773***	0.9709***
	[0.1994]	[0.1993]	[0.1995]	[0.2127]	[0.2146]	[0.2147]
Loan term	0.0346***	0.0346***	0.0413***	0.0426***	0.0408***	0.0410***
	[0.0058]	[0.0058]	[0.0060]	[0.0060]	[0.0061]	[0.0061]
Building age		0.0004	0.0001	0.0028**	0.0025*	0.0024*
		[0.0013]	[0.0013]	[0.0013]	[0.0013]	[0.0013]
Borrower age			0.0126***	0.0140***	0.0135***	0.0134***
			[0.0037]	[0.0037]	[0.0037]	[0.0037]
Inflation						13.3975
						[11.0935]
Unemployment						4.2248
						[2.6423]
HPI growth						-2.8562
						[3.8312]
Observations	70,666	70,666	70,666	70,666	70,666	70,666
Dwelling controls	No	Yes	Yes	Yes	Yes	Yes
Household controls	No	No	Yes	Yes	Yes	Yes
Market controls	No	No	No	No	No	Yes
Mortgage controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	No	Yes	Yes
Origination Year FE	No	No	No	Yes	Yes	Yes
SE	Rob.	Rob.	Rob.	Rob.	Rob.	Rob.
Pseudo R-squared	0.114	0.115	0.116	0.159	0.162	0.163

model, we compute the area under the ROC curve (AUC) for both cases, with and without EE. The higher the AUC, the better the model is at predicting defaulted loans as defaulted and the non-defaulted loans as non-defaulted. For model (6), the AUC yields a value of 0.8173. The exclusion of the EE variable results in an AUC equal to 0.8162 (cf. Panels A and B in Figure 5). These results indicate that EE improves the model's prediction accuracy.

As discussed in Section 2.1, the presented results involve the tightest definition of the variable EE which includes only A-rated buildings. In the Appendix we relax the previous definition and consider also B-rated buildings as energy-efficient (see, Billio *et al.* 2021). Results show that, even if the EE variable is still negatively associated with mortgage default risk, the statistical significance does not survive in all the specifications that include additional control variables. This highlights that only A-rated buildings have a lower probability of default.

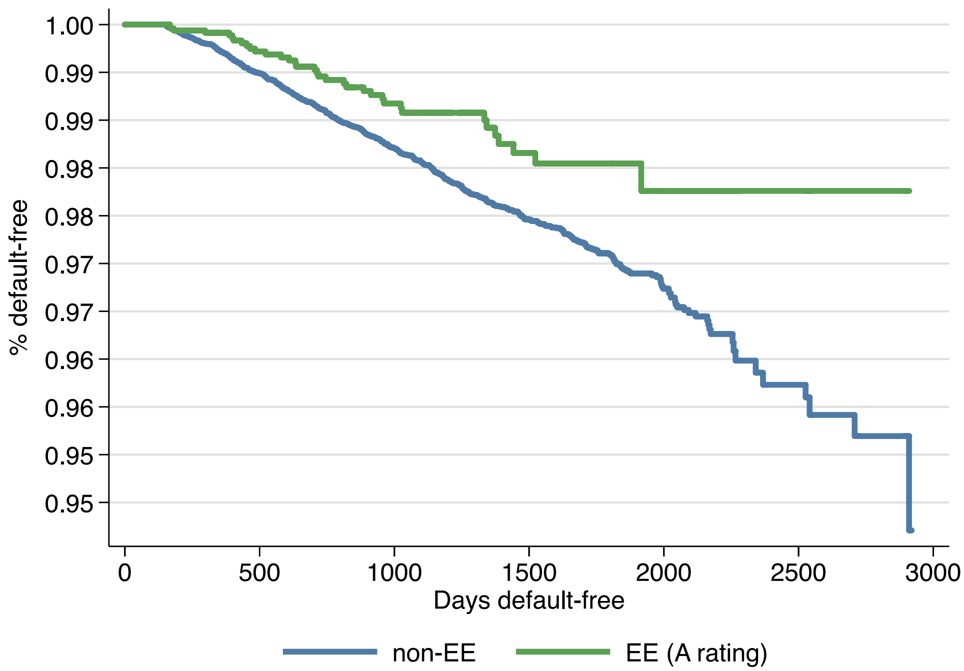
Figure 5: Panel A (B) depicts the ROC excluding (including) the EE, using the model specification (6).



4.2 Estimates from the Cox regression

As discussed in the previous section, the Cox model is typically applied in survival studies. For a correct application of the model, it is necessary to test if the proportional hazards assumption holds. Figure 6 shows the empirical survivor functions for energy-efficient and non-energy efficient mortgages, respectively. The plot reveals that the two curves do not intersect or diverge excessively, implying that the proportionality assumption is valid. According to this finding, the hazard ratio for any two loans may be expected to be constant across time. Furthermore, the survival curves show that energy-efficient mortgages, on average, survive longer than non-efficient counterparts, as seen by the growing difference between the two curves. This also underlines the fact that mortgages on energy-efficient buildings are less likely to fail.

Figure 6: Survivor Functions. This figure shows the Kaplan-Meier survival curves for two mortgage groups: mortgages on energy-efficient (A-rated) and non-energy-efficient buildings. The Log-rank statistical test assesses the equality of survivor functions and in this case, yields a p-value of 0.0019. Therefore, the null hypothesis of equality of the two survivor function is not accepted.



Similar to the logit regression, we estimate the Cox regression to analyse the relationship between energy efficiency and survival time. Results are presented in Table 5. Model (1) provides the findings by just including mortgage-related characteristics in the model, such as the borrower's credit score, loan-to-value at mortgage origination, and loan length. The EE indicator's regression coefficient is negative and significant (-0.4016), corroborating the results of the Logit regression. Accounting for household, dwelling, and market control variables does not affect the primary finding on EE, as shown in model specifications (2) to (6).

Analogously to the Logit regression, if we extend the EE definition and include also B-rated, the EE variable is still negatively associated with mortgage default risk, but again the statistical significance fails after considering additional control variables. Also, in this case, A-rated buildings are associated with lower default risk.

Table 5: Cox regression results to assess the relationship between buildings' energy efficiency and the default risk of the borrowers. The dependent variable is binary indicating whether a mortgage is in default (e.g., at least three months in arrears) or not. The dummy variable EE equals to one if a building's energy efficiency rating is A-rated and zero otherwise. Mortgage controls are borrower's credit score, loan-to-value, and loan term (in years). Dwelling control is building age at loan origination. Borrower control is borrower's age at loan origination. Market controls are monthly Italian inflation rate (change in the consume price index to previous year's value in the same month), quarterly unemployment rate at regional level, quarterly house price index growth at regional level. Origination year and NUTS1-region fixed effects (FE) are included where indicated. Standard errors (reported in square brackets) are robust. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level, respectively.

Dependent variable: Default dummy

	(1)	(2)	(3)	(4)	(5)	(6)
EE (A rating)	-0.4016**	-0.3124*	-0.3237*	-0.3358*	-0.3076*	-0.3009*
	[0.1724]	[0.1762]	[0.1758]	[0.1766]	[0.1773]	[0.1773]
Credit score	-0.0143***	-0.0143***	-0.0140***	-0.0140***	-0.0140***	-0.0140***
	[0.0004]	[0.0004]	[0.0004]	[0.0004]	[0.0004]	[0.0004]
Loan-to-Value	0.8688***	0.8725***	0.9276***	0.8850***	0.8563***	0.8473***
	[0.2058]	[0.2053]	[0.2046]	[0.2067]	[0.2087]	[0.2087]
Loan term	0.0319***	0.0326***	0.0398***	0.0398***	0.0378***	0.0382***
	[0.0055]	[0.0055]	[0.0058]	[0.0058]	[0.0059]	[0.0059]
Building age		0.0030**	0.0026**	0.0025**	0.0022*	0.0022*
		[0.0012]	[0.0012]	[0.0012]	[0.0013]	[0.0013]
Borrower age			0.0137***	0.0136***	0.0130***	0.0128***
			[0.0036]	[0.0036]	[0.0036]	[0.0036]
Inflation						7.6548
						[11.0186]
Unemployment						3.5620
						[2.5977]
HPI growth						2.0283
						[3.8225]
Observations	70,642	70,642	70,642	70,642	70,642	70,642
Dwelling controls	No	Yes	Yes	Yes	Yes	Yes
Household controls	No	No	Yes	Yes	Yes	Yes
Market controls	No	No	No	No	No	Yes
Mortgage controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	No	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
SE	Rob.	Rob.	Rob.	Rob.	Rob.	Rob.
Pseudo R-squared	0.0560	0.0563	0.0571	0.0575	0.0587	0.0588

4.3 Additional findings

In the presented analyses, we have focused on the existence of the relationship between a building's energy efficiency and the probability of mortgage default. Given the above findings, we extend the analysis to have a more granular representation of energy efficiency. As in Kaza *et al.* (2014), we investigate the relationship between a degree of energy efficiency and the likelihood of default by assuming that the higher the energy efficiency of a building, the lower is risk of default. To carry out the new analysis, we build a set of new indicator variables by aggregating the EE ratings into four efficiency classes. Hence, efficiency class 1 involves ratings A and B, class 2 includes ratings C and D, class 3 is assigned to ratings E and F, and class 4 is identified by G-rated buildings. All the previously defined control variables remain unchanged. Table 6 includes the regression results for Logit (models (1) to (3)) and Cox regressions (models (4) to (6)). There are two major implications from the regression estimates for efficiency classes 1 to 3. First, all three regression coefficients are negative and significant, implying that G-rated buildings have the highest risk of mortgage default. Second, across all model settings, the regression coefficients show a diminishing trajectory with the degree of energy efficiency. This indicates that more energy-efficient buildings have stronger mitigation in the likelihood of default, implying that the degree of energy efficiency matters. As a result, the risk of default is reduced when a building renovation improves the EPC rating by one or two notches (from E to C). These findings remain unchanged by the inclusion of additional control variables. Based on these results, we may deduce that mortgages guaranteed by energy efficient residential buildings have a reduced risk of default. Additionally, the results indicate that degree of energy efficiency matters and is correlated with a reduced probability of default.

5 Conclusion

Studies on energy efficiency and residential mortgages are crucial in establishing future energy regulations (Billio *et al.* 2021). These findings provides intriguing implications also in risk management since a reduced risk of insolvency for energy efficient buildings should induce alternative pricing for the borrower, such as lower interest rates. In this paper, we contribute to this growing body of literature by analyzing the relationship between building energy efficiency and the risk of default on an Italian portfolio of residential mortgages. Our results indicate a negative and significant association between buildings' energy efficiency and the probability of mortgage default. " A receiver-operating characteristic (ROC) analysis confirms that the inclusion of energy efficiency information improves the measurement of the

Table 6: Degree of Energy Efficiency estimates to assess the likelihood of default on mortgages backed by buildings with different degrees of energy efficiency. Logit regression estimates are included from columns 1 to 3, and Cox regression from columns 4 to 6, respectively. The dependent variable is binary indicating whether a mortgage is in default (e.g., at least three months in arrears) or not. The EE dummy variables are built on the four energy efficiency categories: (i) one if the building's rating is A or B, (ii) one if the rating is C or D, (iii) one if the rating is E or F, and (iv) one if G and zero otherwise. The latter represents the reference case, that is, the omitted category in the regressions. Mortgage controls are borrower's credit score, loan-to-value, and loan term (in years). Dwelling control is building age at loan origination. Borrower control is borrower's age at loan origination. Market controls are monthly Italian inflation rate (change in the consume price index to previous year's value in the same month), quarterly unemployment rate at regional level, quarterly house price index growth at regional level. Origination year and NUTS1-region fixed effects (FE) are included where indicated. Standard errors (reported in square brackets) are robust. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level, respectively.

Dependent variable: Default dummy

	Logit model			Cox model		
	(1)	(2)	(3)	(4)	(5)	(6)
A/B rating	-0.4013***	-0.3772***	-0.3804***	-0.3919***	-0.3166**	-0.3203**
	[0.1148]	[0.1316]	[0.1316]	[0.1179]	[0.1297]	[0.1295]
C/D rating	-0.3349***	-0.3336***	-0.3503***	-0.3405***	-0.2803***	-0.2952***
	[0.0953]	[0.1055]	[0.1056]	[0.0966]	[0.1037]	[0.1036]
E/F rating	-0.3736***	-0.2346***	-0.2416***	-0.2292***	-0.2077**	-0.2154***
	[0.0808]	[0.0852]	[0.0852]	[0.0805]	[0.0834]	[0.0835]
Credit score	-0.0161***	-0.0151***	-0.0151***	-0.0142***	-0.0139***	-0.0140***
	[0.0004]	[0.0004]	[0.0005]	[0.0004]	[0.0004]	[0.0004]
Loan-to-Value	0.3857*	0.9739***	0.9649***	0.8568***	0.8494***	0.8381***
	[0.1980]	[0.2157]	[0.2157]	[0.2076]	[0.2100]	[0.2100]
Loan term	0.0299***	0.0414***	0.0417***	0.0330***	0.0384***	0.0388***
	[0.0056]	[0.0061]	[0.0061]	[0.0055]	[0.0059]	[0.0059]
Building age		0.0008	0.0006		0.0008	0.0006
		[0.0014]	[0.0015]		[0.0014]	[0.0014]
Borrower age		0.0135***	0.0133***		0.0130***	0.0128***
		[0.0037]	[0.0037]		[0.0036]	[0.0036]
Inflation			13.3941			7.7655
			[11.1310]			[11.0023]
Unemployment			5.4038**			4.4800*
			[2.7096]			[2.6457]
HPI growth			-2.4965			2.3931
			[3.8339]			[3.8120]
Observations	71,011	70,666	70,666	70,642	70,642	70,642
Dwelling controls	No	Yes	Yes	No	Yes	Yes
Household controls	No	Yes	Yes	No	Yes	Yes
Market controls	No	No	Yes	No	No	No
Mortgage controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
SE	Rob.	Rob.	Rob.	Rob.	Rob.	Rob.
Pseudo R-squared	0.124	0.163	0.164	0.0569	0.0592	0.0594

borrower's default risk. Finally, we show that the degree of energy efficiency also matters, i.e. buildings with higher energy efficiency ratings are associated with a relatively lower risk of default. These findings allow us to better understand if and to what extent energy efficiency is desirable in the European mortgage market.

References

Altman, E. I., Saunders, A. (1997), Credit risk measurement: Developments over the last 20 years, *Journal of Banking & Finance*, 21(11), 1721–1742.

An, X., Pivo, G. (2020), Green Buildings in Commercial Mortgage-Backed Securities: The Effects of LEED and Energy Star Certification on Default Risk and Loan Terms, *Real Estate Economics*, 48(1), 7–42.

Billio, M., Costola, M., Pelizzon, L., Riedel, M. (2021), Buildings' energy efficiency and the probability of mortgage default: The dutch case, *The Journal of Real Estate Finance and Economics*, .

Cox, D. R. (1972), Regression models and life-tables, *Journal of the Royal Statistical Society. Series B (Methodological)*, 34(2), 187–220.

EeDaPP (2020), 'Energy efficiency data protocol and portal'.

Guin, B., Korhonen, P. (2020), Does energy efficiency predict mortgage performance?, Bank of England working papers 852, Bank of England.

Kaplan, E. L., Meier, P. (1958), Nonparametric estimation from incomplete observations, *Journal of the American Statistical Association*, 53(282), 457–481.

Kaza, N., Quercia, R. G., Tian, C. Y. (2014), Home energy efficiency and mortgage risks, *Cityscape*, 16(1), 279–298.

Metz, C. E. (1978), Basic principles of roc analysis, *Seminars in Nuclear Medicine*, 8(4), 283–298.

Qi, M., Scheule, H., Zhang, Y. (2020), Positive payment shocks, liquidity and refinance constraints and default risk of home equity lines of credit at end of draw, *The Journal of Real Estate Finance and Economics*, pp. 1–32.

Zweig, M. H., Campbell, G. (1993), Receiver-operating characteristic (roc) plots: a fundamental evaluation tool in clinical medicine., *Clinical chemistry*, 39 4, 561–77.

A An alternative definition of Energy Efficiency

In this section, we follow Billio *et al.* (2021) and extend the concept of energy efficiency to B-rated buildings. The model specifications are the same as in the main analysis and the estimation results for the logit and Cox regressions are reported in Tables 7 and 8, respectively. As can be seen, EE is still negatively related to the probability of default, but the results are weaker and the model coefficient is not significantly different from zero for several specifications. There are several reasons for this. First, the vast majority of loans for A-/B-rated properties were approved recently, so the observation period may not be sufficient to identify many defaults. Model (4) in Table 7 shows that the presence of fixed effects for the year of loan origination reduces the statistical significance of the EE variable in the logit estimates. Moreover, credit score is a good predictor of default in all model constellations. This suggests that the control variables used may be missing some important household characteristics that could help separate the EE effect from other household-specific aspects. For instance, environmentally conscious households with higher incomes are more likely to purchase or build an energy efficient dwelling because they can both afford it and benefit from it. Analyses of this type are reserved for future research, as data granularity and availability remain the major obstacles.

Table 7: Logit regression results to assess the relationship between buildings' energy efficiency and the default risk of the borrowers. The dependent variable is binary indicating whether a mortgage is in default (e.g., at least three months in arrears) or not. The dummy variable EE equals one if the energy efficiency of a building is A- or B-rated, and zero otherwise. Mortgage controls are borrower's credit score, loan-to-value, and loan term (in years). Dwelling control is building age at loan origination. Borrower control is borrower's age at loan origination. Market controls are monthly Italian inflation rate (change in the consume price index to previous year's value in the same month), quarterly unemployment rate at regional level, quarterly house price index growth at regional level. Origination year and NUTS1-region fixed effects (FE) are included where indicated. Standard errors (reported in square brackets) are robust. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level, respectively.

Dependent variable: Default dummy

	(1)	(2)	(3)	(4)	(5)	(6)
EE (A/B rating)	-0.2492**	-0.2318*	-0.2374**	-0.1880	-0.1713	-0.1664
	[0.1129]	[0.1191]	[0.1189]	[0.1181]	[0.1184]	[0.1183]
Credit score	-0.0159***	-0.0159***	-0.0157***	-0.0151***	-0.0151***	-0.0152***
	[0.0004]	[0.0004]	[0.0004]	[0.0004]	[0.0004]	[0.0004]
Loan-to-Value	0.3378*	0.3384*	0.3897*	0.9995***	0.9810***	0.9746***
	[0.1997]	[0.1995]	[0.1997]	[0.2129]	[0.2148]	[0.2149]
Loan term	0.0344***	0.0344***	0.0410***	0.0425***	0.0407***	0.0409***
	[0.0058]	[0.0058]	[0.0060]	[0.0060]	[0.0061]	[0.0061]
Building age		0.0006	0.0003	0.0027**	0.0025*	0.0024*
		[0.0013]	[0.0013]	[0.0013]	[0.0013]	[0.0013]
Borrower age			0.0124***	0.0139***	0.0134***	0.0133***
			[0.0037]	[0.0037]	[0.0037]	[0.0037]
Inflation						13.5078
						[11.1017]
Unemployment						4.2891
						[2.6441]
HPI growth						-2.8819
						[3.8299]
Observations	70,666	70,666	70,666	70,666	70,666	70,666
Dwelling controls	No	Yes	Yes	Yes	Yes	Yes
Household controls	No	No	Yes	Yes	Yes	Yes
Market controls	No	No	No	No	No	Yes
Mortgage controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	No	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
SE	Rob.	Rob.	Rob.	Rob.	Rob.	Rob.
Pseudo R-squared	0.114	0.114	0.115	0.159	0.162	0.162

Table 8: Cox regression results to assess the relationship between buildings' energy efficiency and the default risk of the borrowers. The dependent variable is binary indicating whether a mortgage is in default (e.g., at least three months in arrears) or not. The dummy variable EE equals one if the energy efficiency of a building is A- or B-rated, and zero otherwise. Mortgage controls are borrower's credit score, loan-to-value, and loan term (in years). Dwelling control is building age at loan origination. Borrower control is borrower's age at loan origination. Market controls are monthly Italian inflation rate (change in the consume price index to previous year's value in the same month), quarterly unemployment rate at regional level, quarterly house price index growth at regional level. Origination year and NUTS1-region fixed effects (FE) are included where indicated. Standard errors (reported in square brackets) are robust. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level, respectively.

Dependent variable: Default dummy

	(1)	(2)	(3)	(4)	(5)	(6)
EE (A/B rating)	-0.2399**	-0.1502	-0.1534	-0.1565	-0.1392	-0.1353
	[0.1109]	[0.1162]	[0.1158]	[0.1160]	[0.1164]	[0.1163]
Credit score	-0.0143***	-0.0143***	-0.0140***	-0.0140***	-0.0140***	-0.0141***
	[0.0004]	[0.0004]	[0.0004]	[0.0004]	[0.0004]	[0.0004]
Loan-to-Value	0.8612***	0.8717***	0.9268***	0.8864***	0.8573***	0.8481***
	[0.2064]	[0.2059]	[0.2051]	[0.2072]	[0.2092]	[0.2092]
Loan term	0.0323***	0.0327***	0.0398***	0.0399***	0.0378***	0.0381***
	[0.0055]	[0.0055]	[0.0058]	[0.0058]	[0.0059]	[0.0059]
Building age		0.0029**	0.0026**	0.0025*	0.0022*	0.0022*
		[0.0013]	[0.0013]	[0.0013]	[0.0013]	[0.0013]
Borrower age			0.0136***	0.0135***	0.0129***	0.0128***
			[0.0036]	[0.0036]	[0.0036]	[0.0036]
Inflation						7.7273
						[11.0224]
Unemployment						3.6253
						[2.5980]
HPI growth						2.0206
						[3.8231]
Observations	70,642	70,642	70,642	70,642	70,642	70,642
Dwelling controls	No	Yes	Yes	Yes	Yes	Yes
Household controls	No	No	Yes	Yes	Yes	Yes
Market controls	No	No	No	No	No	Yes
Mortgage controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	No	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
SE	Rob.	Rob.	Rob.	Rob.	Rob.	Rob.
Pseudo R-squared	0.0560	0.0562	0.0570	0.0574	0.0586	0.0587

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