Multi-family Mortgage Default Risk Associated with Energy Inefficiency: Fannie Mae Securitized Loans

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Abstract

This report presents the empirical results of fitting proportional hazard prepayment and default models to the termination performance of Fannie Mae multifamily mortgages. Our empirical specification accounts both for proxies related to traditional option exercise factors, such as the likelihood of monthly variation in negative equity, proxied by the end-of-month loan-to-value ratio, and the differential between the contract rate on the mortgage and the current 10-year Treasury rate. We also introduce co-incident factors, double triggers, that are associated with shocks to electricity costs and an energy efficiency measure that is associated with shocks to net cash. We find that both the option exercise channel and the double trigger channels are importantly associated with both prepayment and default. These results provide a novel extension to the current literature on "double trigger" controls for default, by showing that the effect of shocks to energy factors on net cash is directly related to the 60-day distress of the Fannie Mae multifamily mortgages in our sample and energy related factors also affect prepayment.

Key words: Mortgages, Energy risk.

JEL codes: G21

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1 Introduction

Prior studies find mortgage defaults to be related to energy use and volatility (see, for example, Issler, Mathew, Sun, and Wallace, 2017; Jaffee, Issler, Stanton, and Wallace, 2017) and also show that energy ratings and use affect commercial building values (see, for example, Eichholtz, Kok, and Quigley, 2010; Jaffee, Stanton, and Wallace, 2018). The motivation for the study described in this report is to assess the impact of energy use on the default risk of multi-family mortgage securitized by Fannie Mae between 2002 and 2020.

An important feature of the Fannie Mae multifamily mortgage data is the dominance of prepayment in the observed termination behavior of these mortgages. For that reason, even though the focus of our analysis is default, we follow standard methodologies to estimate reduced-form mortgage termination models (see, for example, Ciochetti, Deng, Lee, Shilling, and Yao, 2003; Clapp, An, and Deng, 2006; Deng, Quigley, and Van Order, 2000; Schwartz and Torous, 1989; Stanton and Wallace, 2018; Titman and Torous, 1989) that account for both prepayment and default. We include two measures related to energy consumption and energy efficiency: i) a dynamic measure of the cumulative differential between the realized and the pro forma electricity cost of the building which we call the electricity price gap; ii) a static measure of property specific energy efficiency defined as the ratio of the mean utility cost of the building divided by the mean of net cash flows. These new energy related metrics are consistent with "double trigger" models of commercial default in which it is not just the degree of expected negative equity of the borrower's debt position (i.e. the relative value of the asset to the mortgage value) that triggers default but also shocks associated with loss of cash flow due either to loss of tenants, increases in operating costs, or both that stress the borrowers ability, or willingness, to make the debt service payments (see, for example, An, Fisher, and Anthony, 2015; An and Sanders, 2010; Capone and Golding, 2002; Riddiough and Thompson, 1993).

One of the challenges of empirical models of prepayment and default includes the difficulty of obtaining time varying information for the key determinants of these terminations events. Traditionally, reduced form models include time-varying factors that proxy for the embedded values of the prepayment and default options and the likelihood that these options will be exercised. The two primary time varying proxies are i) the difference between the contract rate on the mortgage and the current likely refinancing rate (usually assumed to be the 10 year Treasury rate) and ii) a proxy for negative equity, measured by a time-varying loan-to-value ratio. Empirically, prepayment option exercise is consistently associated with elevated levels of the coupon differential (see, for example, Deng et al., 2000; Schwartz and Torous, 1989; Stanton and Wallace, 2018; Titman and Torous, 1989) whereas negative equity has been found empirically to acts as a friction, or cost, on exercising the prepayment option (see, for example, Clapp et al., 2006; Deng et al., 2000; Stanton and Wallace, 2018; Titman and Torous, 1989). Symmetrically, exercise of the default option has been found to be positively determined by proxies for negative equity as well as the level of coupon differential (see, for example, Clapp et al., 2006; Deng et al., 2000; Stanton and Wallace, 2018; Titman and Torous, 1989; Tu and Eppli, 2003). The "double trigger" default literature attributes default incidence to the joint incidence of negative equity and other adverse shocks to net operating income (example, An et al., 2015; An and Sanders, 2010; Capone and Golding, 2002; Foote and Willen, 2017; Riddiough and Thompson, 1993). For commmercial real estate, the focus of the adverse shocks has been on net operating income which was also an important focus of (An et al., 2015) who focused on the dynamics of NOI for the Fannie Mae portfolio before 2000. Interestingly on average, utilities including water, natural gas, and electricity account for 17.5% (standard deviation of 7.7%) of total operating expenses and the average operating expense ratio (total operating expenses/Gross potential income) is 47.5% (standard deviation of 13.2%) for our sample of Fannie Mae multifamily loans originated between 2002 through 2019. The focus of this paper is to control for both the option exercise related proxies and the triggering effect of cash flow shocks associated with electricity costs and energy efficiency on the default risk of our sample of 26,500 Fannie Mae multifamily loans.

This paper is organized as follows. We discuss the new Fannie Mae data in Section 2. The measurement of the electricity price gap is presented in Section 3 and measurement of the property-specific energy efficiency is present in Section 4. The time-varying loan-to-value measurement is discussed Section 5. Section 6 presents the summary statistics for the constructed Fannie Mae data set. The setup for the estimation of the proportional hazard models of prepayment and default is presented in Section 7 and Section 8 concludes.

2 Fannie Mae multifamily data

Data for this analysis was obtained from Fannie Mae's (FNMA) Delegated Underwriting and Servicing (DUS) website. The program provides publicly available historical data containing information related to loan origination, loan performance, property characteristics, and securitization for commercial real estate mortgages. Fannie Mae's DUS program is the largest government-sponsored initiative for providing financing for multifamily properties, and the data collected for this study represents a significant portion of the U.S. market. Appendix A presents more details and references for Fannie Mae's DUS program.

For our study, we downloaded three distinct data sets [1]:

- Combined loan origination, property characteristics, and securitization (deal/pool information) - this data set was constructed by downloading information from each individual deal from January 2000 to December 2019 using the 'Advanced Search' feature provided by the website. It contains data for about 86,000 loans and properties.
- Loan Performance - this data set provides monthly performance data for individual loans from January 2000 to December 2019. It contains historical information about loan balances, as well as delinquency status. At the time of this study, the data set covers about 51,000 loans [2].
- Property Financial - this data set contains additional information for properties collateralizing the loans. It covers about 70,000 properties in the DUS website. For a subset of about 36,000 properties, it lists utility expenditures, net cash flow, operating expenses, and other relevant financial variables for the most recent years. As discussed in section 4 below, this data set contains the information for calculating our measure of energy efficiency, named as Scaled Utility Cost Index (Scaled UCI), computed as the ratio of average yearly utility costs to the average yearly net cash flows for the property.

We constructed the data for our analyses by merging these three data sources and filtered for loans collateralizing multifamily property types originated on or after January 2002. This yielded a sample of 26,500 loans.

Tables 5 in Appendix B shows geographic and year of origination distributions for the merged and filtered data sets. The geographic location of properties covers all U.S. states and the District of Columbia, but only 6 states account for about 50% of the loans. There is also concentration on the distribution of year of origination, with the past 5 years accounting for about 50% of the loans.

3 Measurement of the electricity price gap

In this study we construct the electricity price gap using the same approach as described in Wallace, Issler, Mathew, and Sun (2017). This variable measures building-specific risk

[1] One must register to Fannie Mae's website for downloading the data set. https://mfdusdisclose.fanniemae.com/#/home. Accessed September 2020.

[2] Fannie Mae. Multifamily Loan Performance Data. https://capmrkt.fanniemae.com/portal/funding-the-market/credit-risk/multifamily/loan-performance-data.html. Accessed September 2020.

exposure driven by the volatile of electricity prices, its direct impact on the building financial performance, and consequently property owner's ability to serve the underlying mortgage.

The variable is constructed as the difference between the forecasted and actual electricity prices of a building over the mortgage holding period. The electricity price gap is computed by summing the deviations of the realized monthly energy prices from the "expected" monthly prices anticipated by the borrower, and/or lender, at the time of mortgage origination. It captures the fact that during the term of the mortgage a high positive cumulative price difference, or the electricity price gap, signals higher than expected total energy expenditures since mortgage inception. This creates a cumulative deficit in NOI, which in turn increases the likelihood of default.

Differing from Wallace et al. (2017), instead of using wholesale locational marginal prices (LMP) for the property's electricity Independent System Operator (ISO) zone, we build our historical price data set using the commercial sector retail electricity prices as reported by the U.S. Energy Information Administration (EIA) for the property's state [3].

Formally, the time t electricity price gap for a commercial mortgage within a state k and originated at a month/year t_0 is expressed as

$$pgap_k(t_0, t) = \sum_{s=t_1}^{s=t} S_k(s) - (H_k(t_0))_{month(s)}, \tag{1}$$

where t and s represent month/year cash flows for the loan, $S_k(s)$ is the realized retail electricity price for the commercial sector, measured in cents per kilowatt-hour, for state k on month/year s. The second term accounts for the seasonality of electricity. In particular, the term $H_k(t_0)$ is a twelve-element vector containing historical electricity retail prices for the preceding year of the loan origination date t_0. The function $month(s)$ is used to index the vector $H_k(t_0)$ for the corresponding month of year of s. More formally, $month(s) \in \{1, 2, ..., 12\}$. This indexing approach means that for each realized month/year price, we are subtracting the anticipated *pro forma* expected price for the same month of the year, and thus comparing the appropriate seasonal prices to each other (i.e. comparing *pro forma* March prices to realized March prices and so on through the seasons). The full history for the electricity price gap is computed by iterating t in Equation 1 from the month of loan origination t_0 to the month of loan termination T.

[3]EIA Electricity Data Browser. Average retail price of electricity to customer by end-use sector, and state. https://www.eia.gov/electricity/data/browser/#/topic/7?agg=0,1&geo=vvvvvvvvvvvvo&linechart=ELEC.PRICE.TX-ALL.M~ELEC.PRICE.TX-RES.M~ELEC.PRICE.TX-COM.M~ELEC.PRICE.TX-IND.M&columnchart=ELEC.PRICE.TX-ALL.M~ELEC.PRICE.TX-RES.M~ELEC.PRICE.TX-COM.M~ELEC.PRICE.TX-IND.M&map=ELEC.PRICE.US-ALL.M&freq=M&start=200101&end=202004&ctype=linechart&ltype=pin&rtype=s&maptype=0&rse=0&pin=&endsec=vg . Accessed September 2020.

4 Measurement of the property-specific energy efficiency

Previous studies of commercial mortgage defaults, such as Wallace et al. (2017), employ Source Energy Use Intensity (Source EUI) as the building measure of energy efficiency. Source EUI accounts for the total amount of raw fuel that is required to operate the building per square foot including all transmission, delivery and production losses. Mathew, Wallace, and Issler (2020) use Scaled Source EUI, a measure of Source EUI that is scaled to the the Net Operating Income (NOI) of the property per square foot, as the primary measure of energy efficiency. Their motivation for scaling Source EUI by NOI per square foot is that this new variable is better able to capture the magnitude of the contribution of energy costs to the borrower's ability to serve the property mortgage. The higher the EUI (energy use per square foot) the higher the energy costs per square foot, as compared to other more efficient buildings. And, the higher the energy costs relative to NOI (both scaled by square foot), the lower the ability for the borrower to pay its mortgage dues.

Our analyses use a more direct approach than Scaled Source EUI for measuring the fraction of energy expenditures to NOI. As described in Appendix A, Fannie Mae's DUS data set provides information on the utility costs and net cash flows for the underlying property in the *Property Financial* part of the data set. Though utility costs may include other expenditures not related to energy, it represents for most cases a good approximation for the total energy expenditures of the building. Also, net cash flow is a good approximation of NOI. The ratio of these two variables, named Scaled Utility Cost Index (Scaled UCI), is our variable of interest.

For a given property, the *Property Financial* section of the DUS data set reports utility costs and net cash flows for multiple years [4]. We construct our variable of interest by taking the ratio of mean utility costs to the mean of net cash flows. Formally,

$$Scaled\ UCI = \frac{Mean(UtilityCosts)}{Mean(NetCashFlows)}. \tag{2}$$

Similarly to Scaled Source EUI, this variable captures both, the energy efficiency of the building and the energy cost contribution for NOI.

[4] Reported years may not necessarily coincide with the year of loan origination.

5 Measurement of the loan-to-value ratio

Similarly to the electricity price gap and coupon gap, loan to value ratio (LTV) is a dynamic (time varying) variable in our model. We estimate it for each month of the loan performance data set by first deriving the property value at the time of loan origination using both, the reported origination LTV and loan amount provided by Fannie Mae's DUS performance data. Formally,

$$Property\ Value(t_0) = LTV(t_0)Balance(t_0), \tag{3}$$

where t_0 is the year and month of loan origination. We then estimate the property value for each subsequent period t by multiplying the property price at origination by the gross rate of return of the Core Sector Green Street Advisors' Commercial Property Price Index (CPPI) [5]. Dynamic LTV is derived, for each month, as simply the ratio of the loan remaining principal balance, also reported on Fannie Mae's performance data, to the to the estimated property value,

$$LTV(t) = \frac{Balance(t)}{Property\ Value(t_0) \times CPPI(t)/CPPI(t_0)}. \tag{4}$$

6 Fannie Mae summary statistics

Table 1 below tabulates the mean and standard deviations for the key variables of our study computed the month the loan enters into, or maintains, one of the following situations: 1) defaulted, characterized by a 60 days or more of delinquency, or a more severe event, 2) prepaid, signaled by a prepayment or an early refinancing event, and 3) current, defined by non-defaulted loans that are still outstanding or matured. Out of the 26,500 observations, only 165 loans entered into a defaulted state. This small fraction can be explained, in part, by the large number of loans that are still outstanding (current) in the data set. The latter group shows a comparable mean loan age to those that defaulted and a lower age to those on the prepaid group. This implies that there is a good chance that, in the future, some of the non-matured current loans will be 60-plus days delinquent and ending up being added to the statistics of the defaulted group.

Consistent with our intuition, these summary statistics show that defaulted loans have a higher mean LTV than loans that are prepaid and current. They also show a lower mean age when compared to loans that are prepaid. Mechanically, months to balloon payment

[5] Green Street's Commercial Property Price Index (CPPI) https://www.greenstreetadvisors.com/insights/CPPI. Accessed September 2020

displays an opposite behaviour. As expected, the mean coupon gap is lowest for the prepaid group, indicating that borrowers are taking advantage of low mortgage rates for refinancing their loans.

It is interesting to note the counterintuitive mean for the electricity price gap for the distressed group. Section 7 below discusses the results of the proportional hazard model calibration. In particular, Table 4 shows that the coefficient for this explanatory variable is higher for the defaulted loans than the prepaid loans. This indicates that after one introduces additional controls, the conditional mean of the electricity price gap would display a behaviour matching our intuition.

Table 1: Mean and Standard Deviation of Loans at Termination

	Defaulted	Prepaid	Current	Total
Loan Age (months)	51	77	50	57
	(42)	(37)	(38)	(39)
Electricity Price Gap (Cents/KWh)	5	50	26	32
	(80)	(101)	(78)	(85)
Loan to Value Ratio (LTV)	72.5	66.9	66.3	66.5
	(8.2)	(12)	(12.1)	(12)
Coupon Gap (%)	2.6	2.2	2.8	2.6
	(1.1)	(1.2)	(0.8)	(0.9)
Months to Balloon Payment	77	41	89	76
	(66)	(39)	(60)	(59)
Observations	165	6,763	19,572	26,500

Table 2 shows, for the same groups of loans, the mean and standard deviation of key variables at the time of loan origination. Property value was derived as the ratio of the loan amount to LTV. Similarly, NOI was derived as the product of DSCR to the annual debt service, which is calculated as a function of interest rate, loan amount, and the amortization term. The defaulted group shows a lower mean loan amount, property value, and NOI than the means of other groups, implying that defaulted loans are more concentrated in smaller size properties in the data set. Note also that defaulted loans have a higher mean LTV at origination when compared to other groups. This is in accordance with our intuition that lenders would require a higher mean coupon rate for underwriting such loans.

Table 2: Mean and Standard Deviation of Loans at Origination

	Defaulted	Prepaid	Current	Total
Origination UPB ($000)	6,678	9,314	13,104	12,097
	(10,055)	(12,734)	(19,440)	(18,000)
Origination Property Value ($000)	9,112	14,134	20,249	14,134
	(13,349)	(20,944)	(32,495)	(20,944)
Origination NOI ($000)	675	998	1,210	1,152
	(1,044)	(1,447)	(1,740)	(1,669)
Origination LTV	72	67	66	66
	(8)	(12)	(12)	(12)
Origination DSCR	1.69	1.75	1.68	1.69
	(0.59)	(0.69)	(0.54)	(0.59)
Origination Coupon Rate (%)	5.39	4.79	4.51	4.58
	(1.21)	(1.14)	(0.79)	(0.90)
Months to Balloon	128	118	138	133
	(54)	(43)	(55)	(53)
Amortization Term (months)	357	336	312	319
	(30)	(86)	(120)	(112)
Observations	165	6,763	19,572	26,500

Table 3 shows that our measure of energy efficiency shows a much higher mean for the distressed group than all other groups of loans. This suggests that less efficient buildings are more prone to have their loans defaulted that those for more energy efficient buildings.

Table 3: Mean and Standard Deviation of Scaled UCI

	Defaulted	Prepaid	Current	Total
Scaled UCI	0.383	0.193	0.170	0.177
	(0.612)	(0.405)	(0.148)	(0.246)
Observations	165	6,763	19,572	26,500

7 Prepayment and default hazard estimation

As shown in Table 1, the dominant termination outcome in the Fannie Mae multifamily data is prepayment with an unconditional loan-level average prepayment rate of 25%. In contrast, default which we define as 60 day delinquent is significantly more rare with an unconditional loan-level average default rate of .2% over the period from 2002 through May of 2020. Another unfortunate feature of the data is that, although not evident in Table 1 the actual overall default rate in the data was closer to 1%, however, many of the defaulted observations did not report their energy expenditures and were therefore not included in the estimation data set of 26,500 multifamily loans. The prepaid loans did not exhibit similar patterns of missing data. Obviously, the severe imbalances in the incidence of prepayment and default in the data, raises questions concerning sample selection bias that will have to be addressed in subsequent work. The imbalances also limited the application of a full competing risk model with controls for the cross correlations of the residuals between prepayment and default, or the sub-distribution hazards. Instead, we estimate time varying proportional hazard models for prepayment and default. However, since our goal is just to predict the hazard rates, we assume that default and prepayment are independent and model them without controls for the sub-distribution hazards.

We use a method called episode splitting to estimate the prepayment and default model.[6] For a each monthly interval, we account for characteristics of the economy during that month, such as the current interest rate, and characteristics of the loan during that month, such as its loan-to-value ratio. We include monthly measures of whether the loan either prepaid or defaulted in that monthly interval. Due to the data limitations discussed above, our proxy variable for energy efficiency, *Scaled UCI*, is an average for each loan and does not time vary across months.

As shown, in Appendix C, although we are assuming that the loan-level covariates, $\nu_{t_{k-1}}$, vary over time, in our case they vary monthly, they are invariant between t_{k-1} and t_k (i.e. within a month). Since our ultimate interest is to use the hazard estimates[7] as part of a valuation exercise, we follow (Schwartz and Torous, 1989; Titman and Torous, 1989) and assume that the baseline hazards, $\lambda_{0pre,def}(t)$, differ for prepayment and default but they are both log-logistic. This functional form is consistent with the observation that all other things equal, conditional terminations are typically low in the early years of a commercial mortgage, then gradually rise over time, hit a maximum, and then gradually fall with seasoning. Given these assumptions, the conditional survivor function for prepayment or default be written as,[8]

$$\begin{aligned} S_{pre,def}(t_k|t_{k-1}) &= exp\left(-\int_{t_{k-1}}^{t_k} \lambda_{0pre,def}(u)exp(\beta_{pre,def}\nu(u))du\right) \\ &= exp\left(-exp(\beta_{pre,def}\nu_{t_{k-1}})\int_{t_{k-1}}^{t_k} \frac{\gamma_{pre,def}p_{pre,def}(\gamma_{pre,def}u)^{p_{pre,def}-1}}{1+(\gamma_{pre,def}u)^{p}_{pre,def}}du\right), \end{aligned}$$

[6]Episode splitting is a method to reorganize the loan-level data into a set of n monthly time observations for each loan (e.g. For a loan, that survives for 10 months that loan id would be measured as 10 separate time observations with the same id but with time t dependent characteristics

[7]The hazard is the probability that the loan defaults on that month given that it has survived up to that month, t.

[8]The survivor function is the probability that a mortgage "survives," or has not defaulted up to time t.

where ν_t, are observed over time from the origination date on the mortgage until termination due to a default event, defined as a 60 day delinquency, or prepayment event, or until the end of the observation period May, 2020, if the loan is still extant on that date.

The time-varying covariate vector, ν_t, for prepayment and default includes monthly measures the end-of-month values for the electricity price gap, the loan-to-value ratio, the coupon gap which is the differential between the interest rate on the mortgage and the observed 10-year rate, and a measure of the time in months until the full balance on the loan is due in full, the balloon date. We also include a non-time varying proxy for the property's energy efficiency as discussed in Section 4 and fixed effects for the year of origination and state in which the loan is located to control for other sources of heterogeneity such as national and regional business cycle effects.

We report the estimation results for prepayment hazards in the upper part of Table 4. As shown in the table, all of the covariates are statistically significant and have the expected sign. The higher the loan-to-value ratio, the lower the hazard of refinancing, whereas the higher the difference between the contract rate on the loan rate and the current 10-year Treasury rate, the lower the prepayment hazard. The two important energy related cost and efficiency measures, the electricity price gap and Scaled UCI, also have a positive effect on prepayment suggesting that building owners are motivated to reduce their cost of debt by refinancing, or perhaps by refinancing to extract some equity, when their energy related variable costs are high. As expected, prepayment is lower the closer the loan is to its maturity date, or the the balloon payment date, since the shorter interval of time before the full balance is due the lower the potential savings that could be achieved from refinancing into a lower interest rate.

The estimation results for the default hazards are reported in lower part of Table 4. As expected, the loan-to-value ratio is positively and statistically significantly associated with the hazard of mortgage default. The coupon gap, the differential between the contract rate on the mortgage and the current 10 year Treasury rate is also statistically positively associated with higher default hazards. Similar to the prepayment result, the energy cost and efficiency measure are both statistically significant and positively associated with the default hazard. The proxy for average energy efficiency, scaled UCI, is shown to be a positive and statistically significant determinant of the default hazard meaning that as the energy expenditures per square foot increase the default probability rises. The electricity price gap is also shown to be a positive and statistically significant determinant of default meaning that the greater the cumulative gap between the loan's pro-forma electricity cost estimates and the realized marginal price of electricity the higher the hazard of default. Since most of these loans amortize over one horizon and are due in another, as shown, the number of months remaining before the full balance of the loan is due is also a statistically significant and negative factor in the hazard of default, meaning that the closer the loan is to it's balance due date (the balloon payment date) the higher the default probability.

Figure 1 presents the fitted log logistic baseline hazards for prepayment and default. The

Table 4: **Proportional hazard model estimates for the competing risk of prepayment and default.** This table presents the coefficient estimates for a competing risk proportional hazard model of prepayment and default for multifamily mortgages that were originated and securitized by Fannie Mae between 2002 and 2020.

	Prepayment	
	Coefficient Estimate	Standard Error
γ_{pre}	0.03510***	1.85E-07
p_{pre}	7.426467***	0.00005
Electricity price gap	1.49E-03***	1.53E-07
Loan-to-value ratio	-1.50E-02***	9.30E-07
Coupon gap	0.510562***	0.000013
Scaled UCI	0.060478***	0.000015
Time to balloon	2.99E-02***	5.36E-07
Year fixed effects	Yes	
State fixed effects	Yes	
Number of observations	26,500	
Negative Log Likelihood	35,298.97	
χ^2		
	Default	
	Coefficient Estimate	Standard Error
γ_{def}	0.012176***	0.000005
p_{def}	1.915758***	0.000075
Electricity price gap	2.10E-03***	1.91E-07
Loan-to-value ratio	0.029318***	0.000001
Coupon gap	0.023145***	0.000017
Scaled UCI	0.184623***	0.000008
Time to balloon	-2.11E-02***	4.85E-07
Year fixed effects	Yes	
State fixed effects	Yes	
Number of Observations	26,500	
Negative Log Likelihood	21,107.26	
χ^2		

$^{***}P < 0.01$

baseline hazard functions measure the probability of termination for either prepayment or default under homogenous conditions, $\nu = 0$. As shown in Figure 1, the baseline hazard for sixty day delinquency, which is our measure of default, reaches a maximum at month 78 with an 1.017% conditional probability of default. This maximum is about 27 months later than the unconditional average of 51 months that is reported in the summary statistics in Table 1, and it is higher than the average unconditional default rate of .62% reported in the table. The estimated baseline hazard for prepayment reaches a maximum at 37 months from origination. This compares with the unconditional average loan age at default of 77 months as reported in Table 1. The baseline hazard maximum for prepayment as a function of time to maturity is 17.6%, which is lower than the 25.5% average unconditional probability of prepayment reported in Table 1. Of course, these baselines are proportionally shifted by the coefficient estimates for the time varying covariates to obtain the monthly conditional probabilities of default and/or prepayment. The baseline hazards do appear to capture the order of magnitude difference in the prepayment and default rates in the Fannie Mae multifamily mortgages, the estimated average timing of the baseline option exercise is more rapid.

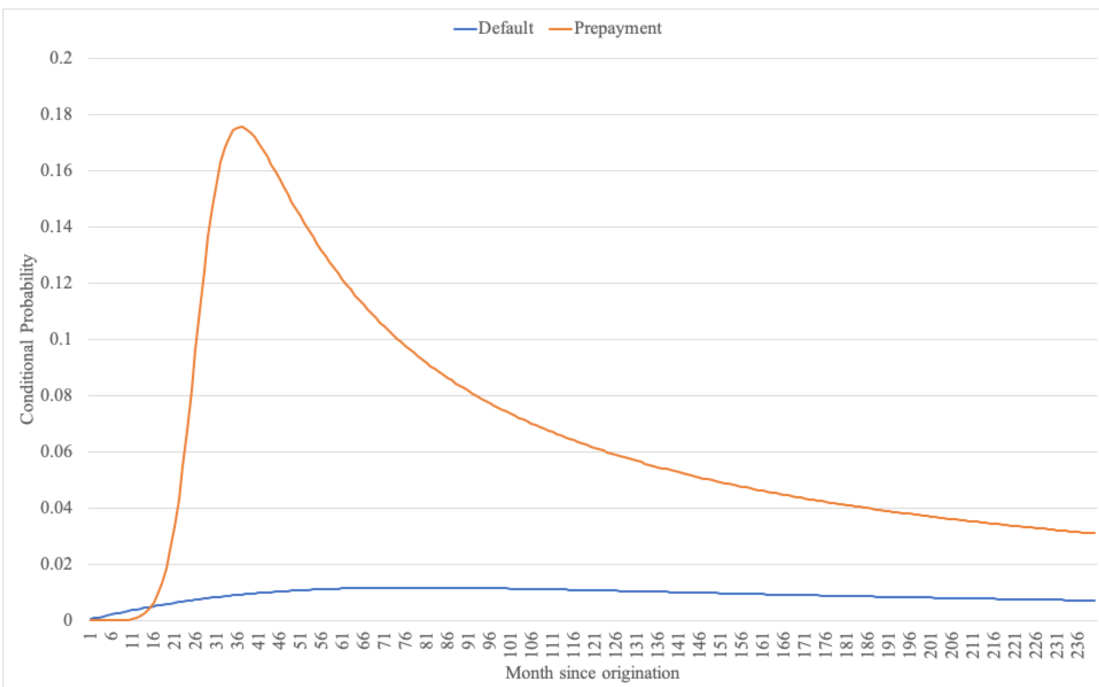

Figure 1: This figure presents estimates for the log logistic baseline hazards of prepayment and default for the Fannie Mae multifamily mortgages.

We find that the magnitude of the coefficient for energy efficiency is also significant. Various studies have shown that building energy use can vary considerably from year to year just due to operational factors such as occupancy, building facilities management and year-to-year weather changes. Month-to-month variations can be even higher. A recent study of 1500 commissioning projects showed median savings ranging from 5-14%, just from simple non-capital energy savings measures such as equipment scheduling and thermostat settings (Crowe, Mills, Poeling, Curtin, Bjørnskov, Fischer, and Granderson, 2020). The elasticity of the probability of default on or before the balloon date is derived in Appendix D. Our model shows that a 10% increase in the utility costs translates into a 12 bps shock in the probability of default on or before the balloon date. This result suggests that utility costs are economically significant considering that the sample default rate is 62 bps.

Overall, the estimated proportional hazard model results do suggest that the greater the cumulative gap between the loan's pro forma electricity cost estimates and the realized cost of electricity the higher the hazard of default. In addition, we find that the effect of higher energy costs per dollar of net cash flows, our proxy for energy efficiency, also significantly affects the survival rates of the Fannie Mae multifamily mortgages. Both of these channels would directly affect the debt-service-coverage ratios, which is a measure also found to be important in double trigger default models. Given the statistically and economically significant coefficients on the energy efficiency measure, Scaled UCI, and the electricity price gap as well as the proxies for option exercise these results do support the arguments underlying the double trigger specifications for commercial mortgage default. The novelty of our results is that the triggered shocks to net cash flow are associated with measured energy factors.

8 Conclusions

This report presents the empirical results of fitting proportional hazard prepayment and default models to the termination performance of Fannie Mae multifamily mortgages. Our empirical specification accounts both for proxies related to traditional option exercise factors, such as the likelihood of monthly variation in negative equity, proxied by the end-of-month loan-to-value ratio, and the differential between the contract rate on the mortgage and the current 10-year Treasury rate. We also introduce co-incident factors, double triggers, that are associated with shocks to electricity costs and an energy efficiency measure that is associated with shocks to net cash. We find that both the option exercise channel and the double trigger channels are importantly associated with both prepayment and default. These results provide a novel extension to the current literature on "double trigger" controls for default, by showing that the effect of shocks to energy factors on net cash is directly related to the 60-day distress of the Fannie Mae multifamily mortgages in our sample and energy related factors also affect prepayment.

9 Acknowledgment

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A Fannie Mae DUS Program Data Set

Initiated in 1988, Fannie Mae's (FNMA) Delegated Underwriting and Servicing (DUS) program is designed to provide affordable multifamily housing by providing financing for acquisition or refinance of commercial real estate properties. FNMA has partnered with multiple lenders coordinating their activities for underwriting, funding, and servicing loans for multifamily properties. Through these lenders, FNMA either finances or guarantees the financing of different types of multifamily properties including apartment buildings, manufactured housing communities, seniors housing, etc. Eligible multifamily properties must be income-producing multifamily rental properties or cooperatives with a minimum of five individual units. DUS loan size ranges from $1 million to $50 million and are generally non-recourse. Loans are pooled and securitized as single class CMBSs and carry Fannie Mae's guaranty of timely payment of principal and interest.

For a loan to be eligible to the DUS program, it must satisfy specific requirements for their loan-to-value and debt-service-coverage ratios. In addition each property underlying the multifamily loan is subject to three assessments: 1) a property appraisal conforming to Uniform Standards of Professional Appraisal Practice (USPAP) standards, 2) an environmental assessment or an American Society for Testing and Materials (ASTM) screen, and 3) a physical needs assessment performed by qualified personnel designated by the DUS. More information about the DUS Program can be found at https://capmrkt.fanniemae.com/resources/file/mbs/pdf/mbsenger-0819.pdf.

B Loan State and Year of Origination Distributions

Table 5: State and Year of Origination Distributions

State	Loan Count	%	Cumulative %
California	4,764	18.0%	18.0%
Texas	3,890	14.7%	32.7%
Florida	1,366	5.2%	37.8%
New York	1,158	4.4%	42.2%
Washington	1,018	3.8%	46.0%
Georgia	986	3.7%	49.7%
Illinois	925	3.5%	53.2%
North Carolina	915	3.5%	56.7%
Virginia	675	2.5%	59.2%
Maryland	644	2.4%	61.7%
Ohio	642	2.4%	64.1%
Arizona	599	2.3%	66.3%
Colorado	571	2.2%	68.5%
Oregon	559	2.1%	70.6%
Pennsylvania	517	2.0%	72.6%
Michigan	477	1.8%	74.4%
Tennessee	466	1.8%	76.1%
South Carolina	456	1.7%	77.8%
Minnesota	430	1.6%	79.5%
Massachusetts	388	1.5%	80.9%
Missouri	357	1.3%	82.3%
Indiana	318	1.2%	83.5%
Alabama	317	1.2%	84.7%
Louisiana	314	1.2%	85.9%
Utah	309	1.2%	87.0%
Nevada	297	1.1%	88.1%
Wisconsin	285	1.1%	89.2%
Oklahoma	279	1.1%	90.3%
New Jersey	263	1.0%	91.3%
Connecticut	253	1.0%	92.2%
Arkansas	242	0.9%	93.1%
Kentucky	227	0.9%	94.0%
Kansas	217	0.8%	94.8%
Mississippi	182	0.7%	95.5%
District of Columbia	167	0.6%	96.1%
New Mexico	159	0.6%	96.7%
Iowa	136	0.5%	97.2%
Idaho	132	0.5%	97.7%
Nebraska	109	0.4%	98.1%
New Hampshire	86	0.3%	98.5%
Delaware	72	0.3%	98.7%
Rhode Island	64	0.2%	99.0%
Montana	53	0.2%	99.2%
South Dakota	44	0.2%	99.4%
West Virginia	36	0.1%	99.5%
North Dakota	35	0.1%	99.6%
Maine	29	0.1%	99.7%
Alaska	28	0.1%	99.8%
Hawaii	25	0.1%	99.9%
Wyoming	17	0.1%	100.0%
Vermont	2	0.0%	100.0%
Total	26,500	100.0%	

Year of Origination	Loan Count	%
2002	35	0.1%
2003	102	0.4%
2004	117	0.4%
2005	167	0.6%
2006	241	0.9%
2007	343	1.3%
2008	705	2.7%
2009	984	3.7%
2010	1,258	4.7%
2011	1,578	6.0%
2012	2,238	8.4%
2013	2,161	8.2%
2014	1,828	6.9%
2015	2,340	8.8%
2016	2,698	10.2%
2017	2,962	11.2%
2018	3,129	11.8%
2019	3,614	13.6%

C The maximum likelihood estimator for time varying covariates

To obtain the maximum likelihood function, we first redefine the survivor function in terms of conditional probabilities as,

$$S(t_k|t_{k-1}) = \frac{S(t_k)}{S(t_{k-1})} = \exp\left(-\int_{t_{k-1}}^{t_k} \lambda(u)du\right).$$

From Bayes Theorem, the survivor function is thus

$$S(t) = \prod_{k=1}^{N} S(t_k|t_{k-1}),$$

and the log-likelihood with episode splitting for each hazard is

$$\ln L(\theta) = \sum_{i \in unc.} \ln \lambda(t_i) + \sum_{j \in all} \sum_{k=1}^{N_j} \ln S(t_k|t_{k-1}).$$

Under the standard assumption that the covariates $\nu_{t_{k-1}}$ are invariant between t_{k-1} and t_k, assuring so that the integral in the pseudo-survivor function has a closed form solution, and the standard assumption in mortgage termination models that the baseline hazard is log-logistic (Schwartz and Torous, 1989)), then as shown in the text, the conditional survivor function can be written as,

$$\begin{aligned} S(t_k|t_{k-1}) &= exp\left(-\int_{t_{k-1}}^{t_k} \lambda_0(u)exp(\beta\nu(u))du\right) \\ &= exp\left(-exp(\beta\nu_{t_{k-1}})\int_{t_{k-1}}^{t_k} \frac{\gamma p(\gamma u)^{p-1}}{1+(\gamma u)^p}du\right) \end{aligned}$$

the log of the conditional survivor function with episode splitting is thus,

$$\begin{aligned} \ln S(t_k|t_{k-1}) &= -\int_{t_{k-1}}^{t_k} \frac{p\gamma(\gamma t)^{p-1}}{1+(\gamma t)^p} e^{\beta\nu_{t_{k-1}}} dt \\ &= -e^{\beta\nu_{t_{k-1}}}\left[\ln(1+(\gamma t_k)^p) - \ln(1+(\gamma t_{k-1})^p)\right]. \end{aligned}$$

The log-likelihood function for a given independent risk, either prepayment or default, is

$$
\begin{aligned}
\ln L(\theta) &= \sum_{i \in unc.} \ln(p\gamma) + (p-1)\ln(\gamma t_i) - \ln(1+(\gamma t_i)^p) + \beta \nu_{t_i} \\
&- \sum_{j \in all} \sum_{k=1}^{N_i} e^{\beta \nu_{t_{jk-1}}} \left[\ln(1+(\gamma t_{jk})^p) - \ln(1+(\gamma t_{jk-1})^p) \right],
\end{aligned}
$$

and the gradient of log-likelihood function is,

$$
\begin{aligned}
\frac{\partial \ln L}{\partial \gamma} &= \sum_{i \in unc.} \left(\frac{p}{\gamma} - \frac{t_i^p p \gamma^{p-1}}{1+(\gamma t_i)^p} \right) - \sum_{j \in all} \sum_{k=1}^{N_j} e^{\beta \nu_{t_{jk-1}}} \left[\frac{t_{jk}^p p \gamma^{p-1}}{1+(\gamma t_{jk})^p} - \frac{t_{jk-1}^p p \gamma^{p-1}}{1+(\gamma t_{jk-1})^p} \right] \\
\frac{\partial \ln L}{\partial p} &= \sum_{i \in unc.} \left(\frac{1}{p} + \ln(\gamma t_i) - \frac{(\gamma t_i)^p \ln(\gamma t_i)}{1+(\gamma t_i)^p} \right) \\
&- \sum_{j \in all} \sum_{k=1}^{N_j} e^{\beta \nu_{t_{jk-1}}} \left[\frac{(\gamma t_{jk})^p \ln(\gamma t_{jk})}{1+(\gamma t_{jk})^p} - \frac{(\gamma t_{jk-1})^p \ln(\gamma t_{jk-1})}{1+(\gamma t_{jk-1})^p} \right] \\
\frac{\partial \ln L}{\partial \beta_i} &= \sum_{k \in unc.} \nu_{it_k} - \sum_{j \in all} \sum_{k=1}^{N_j} e^{\beta \nu_{t_{jk-1}}} \left[\ln(1+(\gamma t_{jk})^p) - \ln(1+(\gamma t_{jk-1})^p) \right] \nu_{it_{jk-1}}.
\end{aligned}
$$

.

D Derivation for the elasticity of default probability

From standard probability results (Johnson and Kotz, 1969; Kalbfleisch and Prentice, 1980, see,), the function

$$
F(t) = Pr(T \leq t) = 1 - exp\left(- \int_0^t e^{\beta \nu(u)} \lambda_0(u) du \right) \tag{5}
$$

expresses the unconditional probability of a mortgage defaulting at time T on or before an arbitrary time t, where β is a vector of coefficients for the proportional hazard model, ν is a vector of time-varying explanatory variables, and λ_0 is the modeled baseline hazard function. As described in Appendix C, our study employs the log-logistic function for the baseline hazard, which is defined as

$$
\lambda_0(u) = \frac{\gamma p (\gamma u)^{p-1}}{1+(\gamma u)^p}. \tag{6}
$$

The elasticity of the probability of default with respect to the non time-varying variable Scaled UCI, denoted by ν_0, is defined as

$$
\mathcal{E}(F(t))_{\nu_0} = \frac{\partial F(t)}{\partial \nu_0} \frac{\nu_0}{F(t)}. \tag{7}
$$

From equation 5,

$$\begin{aligned}\frac{\partial F(t)}{\partial \nu_0} &= -exp\left(-\int_0^t e^{\beta\nu(u)}\lambda_0(u)du\right) \times \frac{\partial}{\partial \nu_0}\left[-\int_0^t e^{\beta\nu(u)}\lambda_0(u)du\right] \\ &= -(1-F(t)) \times \beta_0\left[-\int_0^t e^{\beta\nu(u)}\lambda_0(u)du\right] \\ &= -\beta_0(1-F(t))\ln(1-F(t)),\end{aligned}$$

and the final expression for the elasticity in equation 7 becomes

$$\mathcal{E}(F(t))_{\nu_0} = -\beta_0\nu_0\frac{(1-F(t))\ln(1-F(t))}{F(t)}. \tag{8}$$

We use our Fannie Mae's loan performance data for estimating the function $F(t)$ in equation 5. We set $t = 120$ months as the typical time for balloon payment and estimate, for each time $u \in [1, 2, \ldots t]$, the average value of the the vector of explanatory variables $\nu(u)$ from the cross-sectional sample of loans in the data set. We then assess the numerical value of the integral by combining these results with the calibrated vector of coefficients β, and the values of the baseline function $\lambda_0(u)$ using the calibrated parameters γ and p.

References

An, Xudong, Jeffrey D. Fisher, and David Geltner Anthony, 2015, Cash flow performance of fannie mae multifamily real estate: Evidence from repeated noi and egi indices, Working paper, San Diego State University.

An, Xudong, and Anthony Sanders, 2010, Default of commercial mortgage loans during the financial crisis, Working paper, San Diego State University.

Capone, Charles A., and Lawrence Golding, 2002, A dynamic double trigger model of multifamily default, *Real Estate Economics* 20.

Ciochetti, Brian A., Yongheng Deng, Gail Lee, James D. Shilling, and Rui Yao, 2003, A proportional hazards model of commercial mortgage default with originator bias, *Journal of Real Estate Finance and Economics* 27, 5–23.

Clapp, John M., Xudong An, and Yongheng Deng, 2006, Unobserved heterogeneity in models of competing risks, *Real Estate Economics* 34.

Crowe, Eliot, Evan Mills, Tom Poeling, Claire Curtin, Diana Bjørnskov, Liz Fischer, and Jessica Granderson, 2020, Building commissioning costs and savings across three decades and 1500 north american buildings, *Energy and Buildings* 227, 110408.

Deng, Yongheng, John M. Quigley, and Robert Van Order, 2000, Mortgage terminations, heterogeneity and the exercise of mortgage options, *Econometrica* 68, 275–307.

Eichholtz, Piet, Nils Kok, and John Quigley, 2010, Doing well by doing good? Green office buildings, *American Economic Review* 100, 2492–2509.

Foote, Christopher L., and Paul S. Willen, 2017, Mortgage-default research and the recent foreclosure crisis, Working Paper 17-13, Federal Reserve Bank of Boston.

Issler, Paulo, Paul Mathew, Kaiyu Sun, and Nancy Wallace, 2017, Impact of energy factors on default risk in commercial mortgages, Working paper, Lawrence Berkeley National Laboratories.

Jaffee, Dwight, Paulo Issler, Richard Stanton, and Nancy Wallace, 2017, Energy efficiency and commercial-mortgage valuation, Working paper, U. C. Berkeley.

Jaffee, Dwight, Richard Stanton, and Nancy Wallace, 2018, Energy factors, leasing structure and the market price of office buildings in the U.S., *Journal of Real Estate Finance and Economics* (forthcoming), https://doi.org/10.1007/s11146-018-9676-x.

Johnson, Norman L., and Samuel Kotz, 1969, *Distributions in Statistics: Discrete Distributions* (John Wiley & Sons, New York).

Kalbfleisch, John D., and Ross L. Prentice, 1980, *The Statistical Analysis of Failure Time Data* (John Wiley, New York).

Mathew, Paul, Nancy Wallace, and Paulo Issler, 2020, The pricing risk of energy use intensity for office and multifamily mortgages .

Riddiough, Timothy J., and Howard E. Thompson, 1993, Commercial mortgage pricing with unobservable borrower default costs, *Real Estate Economics* 21, 265–19‘.

Schwartz, Eduardo S., and Walter N. Torous, 1989, Prepayment and the valuation of mortgage-backed securities, *Journal of Finance* 44, 375–392.

Stanton, Richard, and Nancy Wallace, 2018, CMBS subordination, ratings inflation, and regulatory-capital arbitrage, *Financial Management* 47, 175–201.

Titman, Sheridan, and Walter N. Torous, 1989, Valuing commercial mortgages: An empirical investigation of the contingent-claims approach to pricing risky debt, *Journal of Finance* 43, 345–374.

Tu, Charles C., and Mark Eppli, 2003, Term default, balloon risk, and credit risk in commercial mortgages, *journal of fixed income* 13.

Wallace, Nancy, Paulo Issler, Paul Mathew, and Kaiyu Sun, 2017, Impact of energy factors on default risk in commercial mortgages, *Berkeley Lab.(https://cbs. lbl. gov/sites/all/files/docs/Mortgage% 20Default% 20Risk% 20and% 20Energy% 20-Technical% 20Report% 205-12-17. pdf)* .