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Testing the Double-Trigger Hypothesis Using Loan-Level Annual Financial Statement Data from an FHA-Insured Multifamily Program[1]

By

Albert J. Lee
Summit Consulting, LLC
email: albert.lee@summitllc.us

Yvon H. Pho
Deloitte & Touche, LLP
email: vpho@deloitte.com

Colin A. Cushman
Generation Mortgage
email: colin.cushman@generationmortgage.com

Abstract

The multifamily (MF) mortgage default literature has focused on the importance of equity (as quantified by loan-to-value) and cash flow (as quantified by debt service coverage) as predictors of loan default. This paper sheds new light on this old topic by using property-level financial data collected by HUD for its Section 221(d)(4) portfolio of MF properties insured by the Federal Housing Administration (FHA). In particular, three hypotheses are evaluated in this paper. The first is the double-trigger hypothesis advanced by Capone and Goldberg (2002). Their seminal research found evidence to suggest that both negative cash flow and negative equity jointly increase a MF property's default propensity. We confirmed that this influence holds true for the FHA Section 221(d)(4) portfolio. Second, we tested the importance of other liquidity metrics in the default decision. The third is whether, and to what extent, rental market conditions influence a MF property's default propensity, holding fixed the property's financial conditions. We find that liquidity metrics, and rental market conditions play a significant role in the MF mortgage default decision.

I. Introduction

[1] This paper reflects the views of the authors and does not reflect the views of the U.S. Department of Housing and Urban Development.

Determining the drivers of multifamily (MF) loan defaults is of interest to many industry analysts and researchers; and a variety of default modeling techniques has been developed. Data limitations, however, have hindered continued progress in this area of research. In particular, property-level financial data are lacking, and thus market-level proxies are used as proxies for financial performance of individual MF properties. This paper sheds new light on this topic by using a property-level financial database collected by the U.S. Department of Housing and Urban Development (HUD) for its portfolio of FHA-insured MF properties under the Section 221(d)(4) program.

Since 1998, HUD has collected electronic property-level annual financial statement (AFS) data for its insured MF portfolio. These financial data comprise over 500 financial accounts that provide a detailed picture of a property's financial operations. Since financial reporting is compulsory and collected annually, the data panel records the history of a property's financial performance and, more importantly, the progression leading up to a default.

The richness of the data allows us to examine a number of hypotheses tested only indirectly in the literature. In particular, three hypotheses are evaluated in this paper. The first hypothesis was originally advanced by Goldberg and Capone (2002).[2] Their seminal research found evidence to suggest that both negative cash flow and negative equity jointly increase a MF property's default propensity. These two conditions increase the propensity of a default to occur, and the authors refer to these two conditions as the double-trigger of MF defaults.[3] The data allow us to thoroughly examine the double-trigger hypothesis. The second hypothesis examined in this paper is whether, and to what extent, other property-level financial ratios matter. AFS provides a number of liquidity metrics that measure a property's ability to meet short-term financial obligations beyond mortgage payments. The third hypothesis is about rental market conditions, and their influence on a MF property's propensity to default.

Substantiated by the data and detailed in the text, this article finds evidence supporting the double-trigger hypothesis. The analysis also concludes that other property-level liquidity metrics significantly influence a MF mortgage loan's propensity to default. Specifically, low cash reserves and other short-term liquidity metrics increase default risk. High market vacancy rates also increase the propensity to default, even after controlling for property-specific occupancy. Collectively, these results reinforce the importance of the double-trigger condition in predicting MF mortgage loan default. However, they also provide fresh insight into other relevant predictors such as liquidity constraints and rental market conditions as important drivers.[4]

The rest of the paper is organized as follows:

II. Brief description of the FHA Section 221(d)(4) program;

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[2] Goldberg, Lawrence & Capone, Charles A. "A dynamic double-trigger model of multifamily mortgage default." *Real Estate Economics* 2002: 30(1), 85-113.

[3] While the presence of both negative equity and negative cash flow jointly increases the propensity of mortgage default for MF loans, the same is not true for residential mortgages. As found by Foote, Gerardi & Willen (2009), residential mortgage borrowers under conditions of negative cash flow will prefer to sell their homes rather than default.

[4] Lee and Baerenklau (2010) presents a dynamic programming analysis on the optimality of commercial mortgage defaults with a cash-in-advance constraint, showing that in the presence of a high level of cash reserve, commercial mortgage loan defaults occur only when LTV and DSCR are both severely negative.

III. Review of commercial default literature;
IV. Definition of outcome variable;
V. Modeling framework;
VI. Description of the data;
VII. Model estimation results; and
VIII. Conclusion and summary.

II. Brief Description of the FHA Section 221(d)(4) program

FHA's Section 221(d)(4) program, established by the National Housing Act of 1959, authorized HUD to insure mortgages made by private lending institutions to help finance the construction or substantial rehabilitation of MF rental or cooperative housing for moderate-income or displaced families. The program combines new construction loans with substantial rehabilitation loans; and in the FHA loan data, there is no clear distinction between the two different types. Projects consist of five or more units, and may include detached, semi-detached, row, walk-up, or elevator structures. Under this program, HUD may insure up to 90 percent of a project's replacement cost. The program allows for long-term fixed rate mortgages that can be financed with Government National Mortgage Association (GNMA) mortgage backed securities. The mortgage terms for FHA Section 221(d)(4) multifamily loans are a maximum of 40 years or three-quarters of the property's remaining economic life, and generally have no prepayment restrictions.[5]

There are two distinctive features of the Section 221(d)(4) program that are uncommon in the conventional commercial loan market. First, no balloon payments are required prior to mortgage full-term maturation. Second, financing is provided during the construction phase. These features of the Section 221(d)(4) program have made it FHA's largest MF apartment loan product.[6]

III. Review of Commercial Default Literature

This research further extends the default risk literature, and draws upon the work of many who have laid the foundation and pioneered the research in mortgage default predictive modeling. Broadly speaking, the literature has advanced in three primary ways: 1) identifying and isolating relevant default predictors; 2) improving the measurement of relevant default predictors; and 3) advancing estimation techniques. The literature explores commercial and residential mortgages separately, although several of the factors influence both. While the data limit our analysis to a subset of commercial properties, notably multifamily properties, the literature review more broadly encompasses other commercial property types including office, retail, hotels, and industrial.

Identifying and Isolating Relevant Default Predictors

Determining the factors influencing mortgage default has been investigated at length, and many property, loan, and borrower characteristics have been considered. Bogdon and Follain (1996) and Galster et al. (1999) studied commercial mortgages and examined interest rate, cash flow,

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[5] For more information, please see http://portal.hud.gov/hudportal/documents/huddoc?id=Chapter_3_Eligible_Multi.pdf or http://portal.hud.gov/hudportal/documents/huddoc?id=DOC_35303.pdf.

[6] For more information, please see http://portal.hud.gov/hudportal/HUD?src=/program_offices/housing/mfh/progdesc/rentcoophsg221d3n4.

loan-to-value (LTV), debt service coverage ratio (DSCR), rent-to-value, net operating income-to-value, and vacancy loss ratios. Throughout the literature, the three most common factors found to influence default are DSCR (a measure of short term cash flow), LTV (a measure of equity position), and vacancy rate (a measure of market economic conditions).

Vandell et al. (1993) and Yildirim (2008) examined commercial loans and concluded that LTV is highly significant in explaining default. Archer et al. (2002) examined 9,639 adjustable-rate and fixed rate multifamily mortgages securitized by the Resolution Trust Corporation (RTC) and Federal Deposit Insurance Corporation (FDIC) between 1991 and 1996, and concluded that the strongest predictors of commercial default were DSCR in addition to select property characteristics such as location and number of units. They also considered origination LTV, and found the effect of origination LTV to be inconsistent, namely it is statistically significant for adjustable-rate mortgages but not for fixed-rate mortgages. The authors conclude that LTV is endogenous to the loan origination process with lenders calibrating LTV to mitigate risk. Ciochetti et al. (2002) identify DSCR and LTV as statistically significant using data from 2,589 commercial loans originated between 1974 and 1990 from a life insurance company. Chen and Deng's (2003) commercial default analysis revealed LTV, cash flow, and vacancy rates to be strong predictors of default. Modeling servicer and borrower behaviors throughout the default process from initial delinquency to default, the authors analyzed 493 special serviced commercial mortgage loans. They concluded that a borrower's default hazard increases with LTV, and decreases with cash flow, and market-level vacancy rates. Yildirim (2008) found DSCR to be statistically significant for commercial loans.

With rare exception, the literature consistently found LTV and DSCR to influence default, and these two factors were eventually referred to as the "double trigger." Goldberg and Capone (1998) first propose the "double trigger" concept in their study of the root causes of the "great real estate selloff" of multifamily properties in the early 1990s. The authors develop a theoretical model showing that borrowers will default if the underlying project has both negative equity and negative cash flow. A mortgage default model was estimated for 7,564 loans acquired by Fannie Mae and Freddie Mac between 1983 and 1995 and simulations were performed to help explain why default rates rose in the 1980s and 1990s. The results of their estimation model show that the double trigger effect is real in that LTV and DSCR are strong predictors of multifamily mortgage default. Furthermore, there is a slightly stronger effect of LTV on default relative to DSCR. Ciochetti et al. (2006) evaluated the significance of DSCR, a cash flow variable, on default and concluded that borrowers with negative equity will not default if the income generated from the commercial property is sufficient to cover mortgage payments. This is one of the several studies performed that provides supporting evidence for the "double trigger" effect. Foote et al. (2008), Elul et al. (2010), and Bhutta et al. (2010) also find evidence for the "double trigger" effect, but focus on the single-family residential mortgage market.

Improving the Measurement of Relevant Default Predictors

The relative predictive power of LTV and DSCR depends on when and how they are measured. Generally, LTV and DSCR could be measured as static variables as origination or time-varying variables in time series. This distinction is important for two reasons. First, the former presents a one-time measure of anticipated, future performance whereas the latter records multiple observations based on historical performance. Second, this distinction is especially important between new construction and substantial rehabilitation loans. New construction loans have no performance history, thus only origination data are available. In contrast, substantial rehabilitation loans have actual performance history, including actual rents at full occupancy. Consequently, the literature has evolved to examine both origination and contemporaneous values for LTV and DSCR.

Vandell et al. (1993) examined both variables and found contemporaneous LTV to have high explanatory power but not DSCR at origination. The Goldberg and Capone (1998) study mentioned previously used contemporaneous values of LTV and DSCR. Ciochetti et al. (2002) examine contemporaneous values of DSCR and LTV in addition to values at origination, and find that contemporaneous variables are more predictive than static variables in modeling default risk. Ciochetti et al. (2003) estimate contemporaneous values for LTV and DSCR, and find that, although statistically significant, contemporaneous LTV is less important than contemporaneous DSCR in predicting default. Ciochetti et al. (2006) evaluate both original and contemporaneous DSCR and conclude that original DSCR is statistically insignificant to mortgage default once contemporaneous DSCR is added as a control. Kau, Keenan, and Yildirim (2009) use commercial loan data from a risk management software firm and apply a structural model to estimate and update LTV over time using Real Estate Investment Trust property-type indices rather than relying on LTV at origination. They found LTV to be statistically significant in predicting default with over-predictions occurring in populations with low LTV values among its loans. Seslen and Wheaton (2010) use Trepp, LLC and Torto Wheaton Research commercial mortgage data to estimate a contemporaneous measure of LTV and DSCR. Both covariates were statistically significant when included independently in their model. However, when the authors combine both covariates to test the existence of a "double trigger" effect, the LTV ratio is no longer statistically significant. The authors explain this result to be due to the strong correlation between the two covariates.

Ambrose and Sanders presented contrasting views in a series of papers. In their 2002 article, the authors calculated monthly estimates for property value using the National Association of Real Estate Investment Trusts (NAREIT) index to update LTV. The authors employ a competing risks model for prepayment and default on 4,257 commercial loans from 33 CMBS deals, and conclude that neither negative equity nor LTV influences default. In 2003, they examined commercial mortgages and CMBS loans, and find no statistically significant effect of LTV at origination. Similar to Archer et al. (2002), the authors argue that this may be due to endogeneity, that riskier loans were underwritten with a stringent LTV requirement.

Advancing Estimation Techniques

While logit models have been used for modeling mortgage default (e.g., Goldberg and Capone (1998), Archer et al. (2002), Ambrose and Sanders (2003), Elul et al. (2010), Bhutta et al. (2010), and Seslen and Wheaton (2010)), the Cox proportional hazard model has become the more popular estimation technique. One of the primary benefits of the proportional hazard model over the logit model is its simpler set of assumptions that do not greatly affect the interpretation of the model results. There are additional benefits, however. Zhou (2000) explains that Cox proportional hazard models naturally handle right-censored data through the use of partial likelihood equations while logistic regression, as noted by Hardy and Bryman (2009), are not appropriate in time to event data where the data observed exhibits right-censoring. In addition to Zhou's explanation of the preference of Cox proportional hazards models in the presence of right-censored data, Allison (1982) brings up that proportional hazards models allow for the explanatory variables to change over time using partial likelihood estimation techniques. While this is also possible in logit regression, Beck, Katz, and Tucker (1998) notes that the logit modification uses dummy variables which can be complicated by left-censoring and variables that are fixed across units. Many studies apply the Cox proportional hazard model including Green and Shoven (1986), Schwartz and Torous (1989), Deng, Quigley and Van Order (2000), Ciochetti et al. (2002), Ciochetti et al. (2003), Chen and Deng (2003), Deng et al. (2005), Vandell (1992), and Yildirim (2008) and we will follow this methodology.

The residential mortgage default literature has long acknowledged the competing nature between defaults and prepayments. Deng (1997) used a proportional hazards framework to develop a competing risks model for prepayment and default in residential mortgages. Deng, Quigley, and Van Order (2000) also apply a proportional hazard model with competing risks to model prepayment and default in single family mortgage loans issued between 1976 and 1983 that were purchased by Freddie Mac. They consider original LTV in their analysis, and find a positive correlation between LTV at origination and default risk, suggesting that the initial LTV ratio may reflect investor preferences for risk. Stated differently, riskier borrowers are associated with high LTV loans.

Similar acknowledgement has been made in the commercial mortgage default literature. Ambrose and Sanders (2003) is an example applying a competing risks model to commercial mortgages and CMBS loans. Ciochetti et al. (2003) estimate two proportional hazards models with competing risks for commercial mortgage default. The first model includes the standard predictors for mortgage default such as loan and property characteristics, borrower information, economic conditions, whereas the second model expands upon the first by explicitly correcting for originator bias by applying weights to individual loans based upon how representative the loan is to the population. Their data consists of 2,043 loans originated by a single lender between 1974 and 1995. Ciochetti et al. (2006), mentioned earlier, developed a competing risks hazard model for prepayment and default using commercial loan-level data of 2,589 loans between 1974 and 1990 from a multi-line insurance company. Seslen and Wheaton (2010) model the competing risks of prepayment and default using a panel multinomial logit with loan age fixed effects to test the statistical significance of contemporaneous loan stress, as measured by LTV and DSCR, on loan termination.

This article advances the literature and draws from the lessons learned by other scholars in three distinct ways. First, we re-examine the double-trigger hypothesis in the presence of other contemporaneous property-level liquidity measures. Prepayment is censored in this analysis due to the double trigger hypothesis not directly affecting prepayment. Second, we build a proportional hazard model and apply it to FHA MF loan data. This allows us to test the double-trigger hypothesis and determine whether other liquidity measures influence default. The FHA data provide a unique and rich data source for analysis by providing loan information not only at origination but also throughout the life of the loan. The event history nature of the data lends itself to a multitude of different loan analyses. Additionally, unlike the commercial loan data used in previous research studies that come from one originator, these loans come from a diversified mix of FHA-approved originators. Third, the FHA data enable us to derive contemporaneous measures for several factors, notably LTV, DSCR and other property-level liquidity metrics. The FHA data contain annual financial statement information that is electronically updated by property owners. This feature allows time-relevant financial data to be incorporated into the analysis.

IV. Definition of Outcome Variable

The modeling framework hypothesizes a rational property-owner who evaluates whether it is in her financial interest to default on an FHA-insured MF mortgage loan given property-level financials and rental market conditions. In this context, a default on a mortgage loan is equivalent to the owner exercising her put option to sell the property back to the mortgage issuer at the current loan balance of the property. Therefore, the default decision under consideration is distinct from a delinquent mortgage payment that is subsequently reinstated by a late payment.[7]

To reinforce the distinction that these defaults are uncured by reinstatements, the event of interest is an *uncured default*, i.e., failure of a mortgage payment immediately preceding a regular financial claim of the FHA insurance fund. Specifically, an uncured default lies at the intersection of three conditions:

1. The financial state necessary to trigger a default for which the borrower has no intention to cure;
2. The financial state that would motivate the lender of the defaulted mortgage to assign the loan to FHA; and
3. The institutional conditions that facilitate FHA to accept the defaulted mortgage as a claim.

Therefore, in its most complex state, an uncured default could be a three-way decision involving a borrower, a mortgage lender, and FHA. This paper assumes that the second and third conditions necessarily follow the first.

V. Modeling Framework

A Cox proportional hazard (CPH) estimation technique is used in this analysis. The dependent variable is a *hazard rate* for an uncured default.[8] Formally, *hazard rate* (h_t) is the probability that an uncured default will occur at time t – defined as the number of days from endorsement – for a particular loan, given that the loan has survived (without an uncured default) up to time t.[9] The CPH model hypothesizes that the hazard rate is a product of two distinct components: the

[7] Operationally, the definition of a delinquent loan follows a well prescribed set of rules. A loan is considered delinquent if non-payment extends beyond the 15-day grace period that FHA allows a borrower. The delinquency state continues for 15 days; and on the 30th day from the payment due date, also referred to as the default date, the loan transitions into fiscal default. On the 60th day, the lender is required to alert HUD of the default. The lender should be communicating with the borrower throughout this nonpayment period in order to both identify the reason for delinquency and/or default and explore reinstatement workout options. By the 75th day from the default date, the lender must elect to either assign the loan to HUD or request an extension. The extension period is granted by local HUD offices, typically in 30-day increments, contingent upon proof from the lender that a valid and viable plan exists to reinstate the loan. Extensions are approved at the discretion of the local HUD office and can be granted continuously.

[8] The outcome of interest for this analysis is uncured default. Therefore, other loan terminations, such as prepayments become censored at the time of the termination event. These loans remain in the data set and are used in model estimation during the period the loan is active.

[9] A loan becomes endorsed once FHA insures the mortgage, which typically occurs soon after loan origination.

baseline hazard, which is a function only of survival time, and the *relative hazard*.[10] The model is shown as:

$$h_t(x) = h_0(t)\exp(x\beta),$$

where $h_0(t)$ is the baseline hazard and $\exp(x\beta)$ is the relative hazard.

By construction, the CPH model hypothesizes that the deviation from the baseline hazard due to a unit change in any covariate is the same irrespective of analysis time *t*.

VI. Description of the Data

Four primary data sources are used in this study to examine the factors influencing a property owner's default decision. These include:

1. FHA — detailed loan information including on program, terms, performance, and annual financial statement data submitted by MF property owners[11];
2. Historical series of annual interest rates on constant-maturity 10-year Treasury Bonds from the St. Louis Federal Reserve Bank website;[12]
3. REIS, Inc. — market data on changes in market rents and vacancies at the metropolitan level; and
4. Cap rate series from the National Council of Real Estate Investment Fiduciaries (NCREIF), and RBS Greenwich Capital.

The eight factors – six property-level financial covariates constructed using FHA data and two market condition variables from REIS – are described in Table 1 below.

Table 1: Definition of Covariates

Covariate	Description
1. Debt Service Coverage Ratio (DSCR)	DSCR is the ratio of monthly income to monthly debt payment. It is the most widely used benchmark of an income-producing property's ability to generate sufficient revenue to pay for its monthly expenses. A property with a DSCR of less than one indicates that the incoming revenue is insufficient to cover mortgage payments and operating expenses, i.e., the property generates negative cash flow. Generally, the higher the ratio the better the financial performance of the property. DSCR is a measure lenders use to identify a property's investment risk.
2. Quick Ratio (QR)	QR is the ratio of current assets to current liabilities. It

[10] See Page 16, "Event History Analysis: Regression for Longitudinal Event Data," Paul Allison, Sage Publications (1984). Another standard reference is "Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence" by Judith D. Singer and John B. Willett, Oxford University Press (2003).
[11] Only audited or owner-certified (when audited is unavailable) financial statements are used in the analysis.
[12] http://www.federalreserve.gov/releases/h15/data/Annual/H15_TCMNOM_Y10.txt

Covariate	Description
	is an indicator of a property's ability to meet its short-term obligations with its most liquid assets.[13] A property with a QR greater than one implies that liquid assets are sufficient to cover current liabilities. Whereas the DSCR measures a property's overall cash flow, the QR measures a property's ability to pay back all forms of a company's current liabilities. Electronically collected since 2002.
3. Occupancy Rate (OR)	OR is the ratio of net rental revenue (rent revenue less vacancies) to total potential rent revenue. It measures a property's economic occupancy. Electronically collected since 2002.
4. Reserves per Unit (RPU)	RPU is the ratio of total cash reserves to the number of units. It measures the level of replacement reserve and residual receipts reserve available for each property. It is calculated on a per unit basis.
5. Loan-to-Value (LTV)	LTV is a ratio of a mortgage's unpaid principal balance (UPB) to the value of the underlying property. UPB is approximated by an amortization schedule based on an FHA-insured mortgage's initial amount, its coupon rate, and its loan term.[14] Property value is based on an estimated annual net operating income (NOI), which is based on potential market rents, divided by a proxy of a capitalization ratio. NOIs and capitalization ratios are updated annually.
6. Double-Trigger Indicator	Double-Trigger is a binary indicator signifying the presence of two conditions[15]: negative cash flow coupled with negative equity. Operationally, DSCR less than 1 signifies negative cash flow, and LTV greater than 0.9 signifies negative equity.[16] The double-trigger indicator takes on one when both of these conditions are met and zero otherwise.
7. Rental Vacancy Rate	This is the percentage of all available units vacant or unoccupied at a particular time. Provided quarterly by REIS for most major metropolitan statistical areas (MSAs) in the continental U.S.[17]
8. Net Absorption Rate	This is the rate at which unoccupied units at the beginning of a period become occupied at the end of a period while taking into consideration space vacated during the period. Provided quarterly by REIS.

[13] Examples of liquid assets for MF properties include cash balances, reserves, stocks, certificates of deposit, treasuries, or securities.

[14] This calculation assumes that payments are on time and in full unless a default occurs.

[15] The Capone and Goldberg definition of the double-trigger hypothesis was a probabilistic measure. Here, an indicator variable is used as a deterministic measure which does not measure "in-the-monieness" magnitude. The DSCR value is still reported and the value is calculated based on cash flow and other financial fundamentals.

[16] The calculation of value is based on a property's maximum potential. The actual management and physical condition of a property may fail to achieve its maximum market potential. Consequently the actual value and its market potential could diverge. Acknowledging this divergence, the 0.9 LTV threshold level was set after an extensive data analysis of the distribution of defaults in the FHA portfolio.

[17] REIS metropolitan statistical areas, referred to as metro and submarkets, while geographically comprehensive do not directly correspond to MSAs defined by the Office of Management and Budget.

With the exception of LTV and the Double-Trigger Indicator, all covariates are obtained directly from the AFS and REIS data. The actual calculation of LTV for this paper is complex, and we refer interested readers to the Appendix where we explain how Goldberg and Capone (1998) was adopted and modified to construct contemporaneous LTV. Market vacancy rate, rent prices, interest rates and portfolio-average measures of rents and expense ratios influence our LTV calculation.[18]

AFS data from property owners were made electronically available in 1998. While REIS data are electronically available for several years prior to this, the analysis period for this study is restricted to 1998 to 2008 due to AFS data availability. REIS provides external market data and generates reports on individual metropolitan areas and property types. These reports present key supply, demand, and rental statistics on the local market, summarize economic and demographic influences, and review major new construction projects. Data are provided for geographic areas smaller than an MSA, referred to as *submarkets*.[19] A submarket may be generally described as a neighborhood, and is defined by REIS as an area where property prices tend to move in conjunction. We used REIS data because the data focus specifically on the MF housing market and provide the most detailed geographic coverage on a large sample size.[20] Moreover, REIS is the only data source that provides information by property class, which enables luxury apartments to be excluded from vacancy rate calculations.[21]

Recall that HUD began collecting electronic annual financial statements in 1998. We define the study period from the inception of electronic data collection (January 1998) to the date of data extraction, April 29, 2008. Each mortgage loan must have at least one AFS on file to be included in the estimation database. The final data set contains 4,953 FHA-insured Section 221(d)(4) mortgage loans, of which 170 defaulted.[22] Although electronic data collection started relatively recently, the median endorsement date for these mortgage loans is January 1988, about

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[18] REIS provided changes in market rents and vacancies at metro, submarket and MSA levels, and the lowest level of granularity by geographic area was used. The AFS data quantify property-level potential rents, and the F47 data specify mortgage loan amortization schedules. Historical series of annual interest rates on constant-maturity10-year Treasury Bonds from the Federal Reserve Bank of St. Louis website serve as an interest rate proxy.

[19] REIS defines submarkets geographically through a proprietary definition based on natural and economic boundaries, but not on any political or Census-based geography.

[20] However, REIS excludes from its sample rent-stabilized, subsidized, or income-restricted apartments. This analysis is restricted to properties in FHA's Section 221(d)(4) program which excludes properties with project-based subsidies (http://portal.hud.gov/hudportal/HUD?src=/program_offices/housing/mfh/progdesc/rentcoophsg221d3n4), and is the most analogous to properties captured by REIS. The REIS data are compiled from quarterly visits to 40 percent of properties in each submarket.

[21] REIS core markets are further separated into property classes (i.e., Class A, Class B/C) and submarkets. Class A properties are based on one of two criteria. First, a very high rent ranking among other properties in either the metro or the submarket coupled with an adequate ranking in both the metro and submarket. Second, Class A buildings must be equipped with first class amenities. Based upon this description, the authors used REIS vacancy rates for Class B/C apartments rather than Class A to represent MF properties in the FHA-insured portfolio. If Class B/C vacancy rates were not available, aggregate rates for all property classes were used. For more information, please see http://www.reis.com/subscriptions/help/subsc_help_index.cfm?report=SubmarketClassCutTrends.

[22] A choice-based sampling frame was considered due to the small number of defaults, but the vast majority of observations are non-events. Survival analysis takes care of censoring and therefore it was deemed unnecessary to do choice-based sampling, which would be considered for a logit or probit model.

10 years prior to AFS collection.[23] By the time loans entered the study period, many mortgage loans were relatively mature.

Figure 1 below presents the distribution of loans by loan amount at time of endorsement in 2013 dollars. While the large majority of loans are $40 million or less, there are a small number of loans exceeding this threshold up to $201 million. The long right tail of the distribution pulls the average loan size to $8 million, which is greater than the median value of $5.7 million.

Figure 1: Loan Size Histogram (2013 dollars)

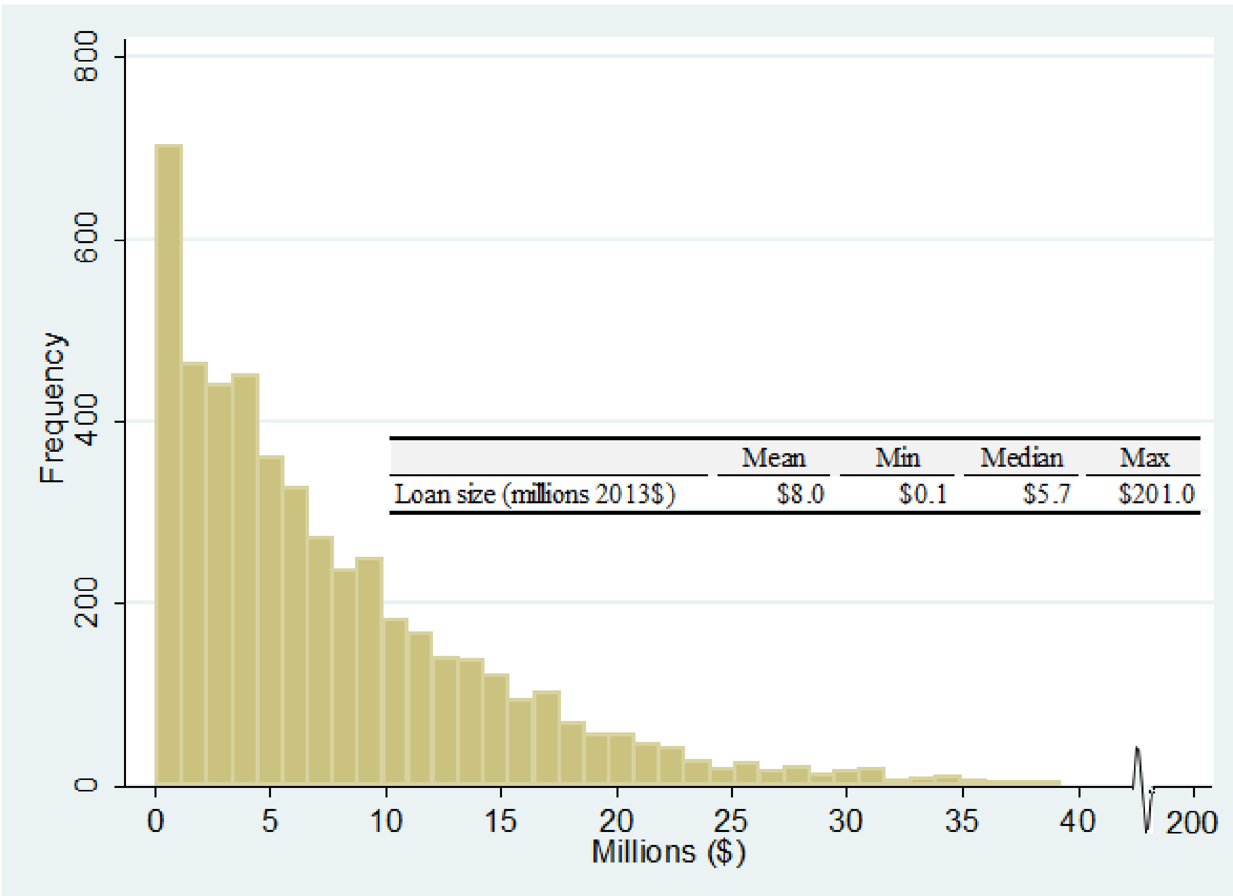

Figure 2 shows the share and average size of the loan by state. Texas, Ohio, and California have the greatest number of FHA loans, each with over 300 loans during the study period. However, Massachusetts and Nevada have the largest average loan size.

[23] These are based on the initial endorsement date.

Figure 2: Geographic Distribution of FHA Multifamily Loans

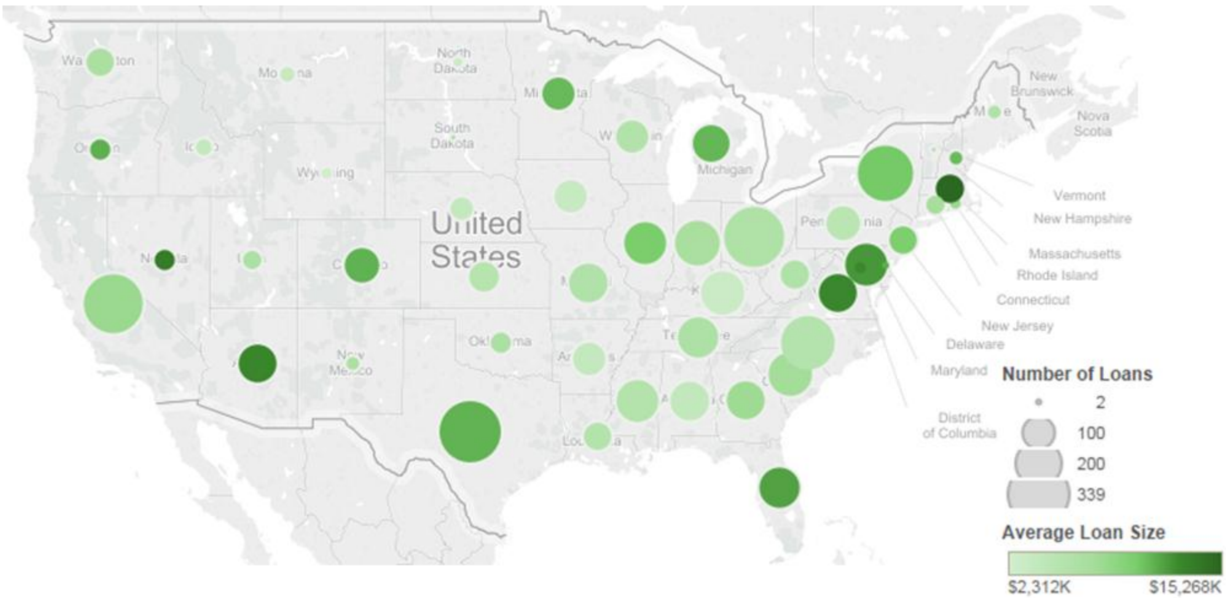

Table 2 below provides summary statistics of mortgage age in years when loans entered and exited the study period. On average, a loan has 33 observations (or events) in the event history, enters the data at 11 years of age, exits the data at 15 years of age, and is in the analysis data set for 4 years.[24] The default rate is 3.4 percent, indicating that 170 loans defaulted out of the total 4,953 loans.

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[24] Events may include endorsements, AFS and vacancy updates. For terminated loans, event may also include prepayment, uncured default and maturity, i.e., loans paid in full according to loan terms.

Table 2: Analysis Sample Duration Statistics

Analysis time _t: (event_date-origin)/365.25
Enter on or after: time mdy(1,1,1998)
Id: FHA Number

		Per Loan			
Category	Total	Mean	Min	Median	Max
No. of loans	4,953				
No. of records	163,610	33	1	29	95
(First) entry time		11	0	7	35
(Final) exit time		15	1	11	39
Time at risk	18,944	4	0	3	9
Failures	170	0.034	0	0	1

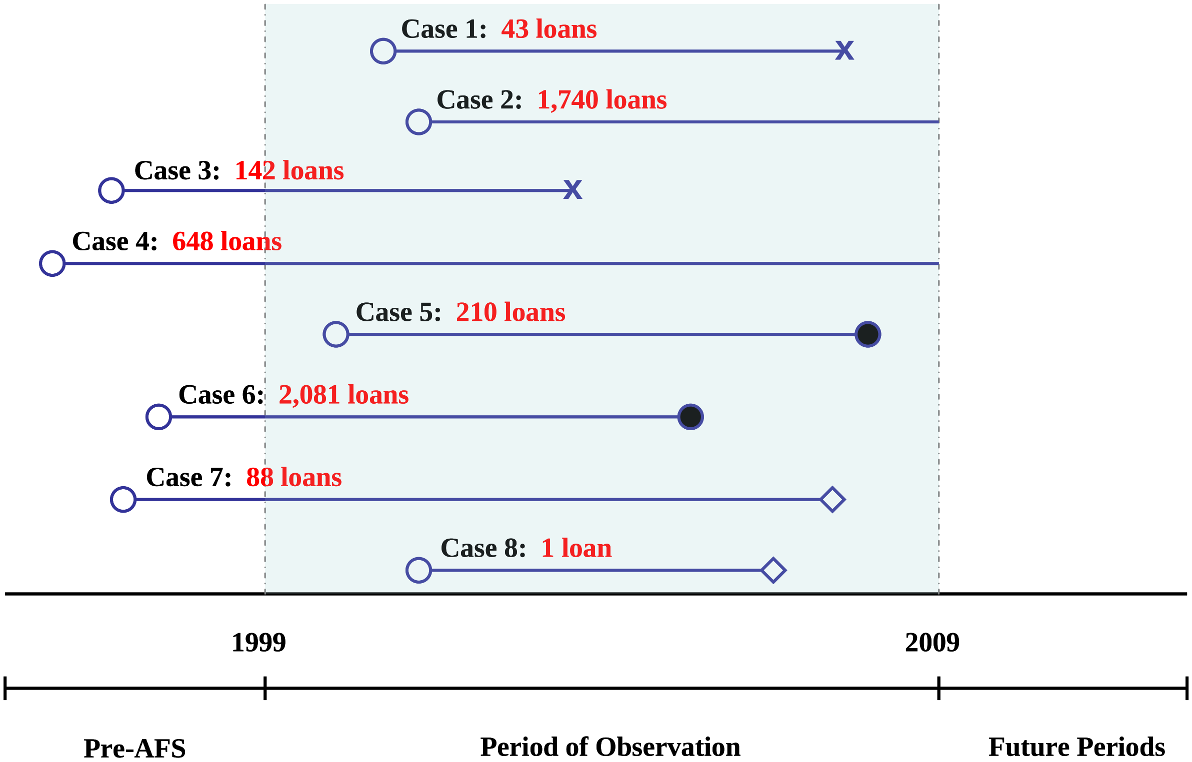
Source: FHA data.
Note: Figures reported in this table is subject to rounding. The unit of time is in years. The total time at risk is 18,944, which is the total number of years for the 4,953 loans exposed to uncured default risk. On average, each loan is exposed to about 3.8 years of uncured default risk.

One important note is the late average entrance time of loans in the data. Esaki and Goldman (2005) provide insight into the relationship between commercial mortgage defaults and time of loan origination for 18,000 loans and found that the peak in defaults were between years 3 and 7 of loan origination for investment grade commercial mortgages, resulting in a set of commercial mortgages with a default rate of 15.2 percent. However, their data differs from the coverage of the data set used in this paper by including loans with balloon payments and non-MF type commercial loans, which can result in a higher default rate. Half of the loans in this study enter within the first seven years of its origination.

Censoring Patterns

Figure 4 below illustrates all data patterns found in the final data set. As shown, the data exhibit left censoring and right censoring and, for 648 loans, both left and right censoring simultaneously. The majority of the loans, or 2,959, were endorsed prior to 1999 (left censored) and 2,388 loans were still active beyond the study period (right censored). The fact that the majority of cases enter the data set prior to 1999 explains the relatively high average loan age of 11 shown in Table 1. Cases 1, 5, and 8 do not exhibit censoring since the entire life of the loan is observed during the study period. The left censored observations are not back-filled with financial statement data; however, vacancy rate data are incorporated into the loan record for the entire study period regardless of whether financial data are available.

Figure 3: Data Patterns



Source: FHA data.
Note: Crosses ('X') refer to uncured default; empty circles refer to endorsement; solid circles refer to terminations due to prepayments; diamonds refer to terminations other than uncured default or prepayment. One example of a termination type other than uncured default or prepayment is maturity. Not all of these observations are used in the final regression due to missing data and other outlier issues.

Summary Statistics

Table 3 below presents annual summary statistics of a loan's payment status by default status for the entire study period. Any loan that defaulted during our study period is included in the "Default Loans" category, and the table presents select statistics for all years prior to default, at which point the loan is no longer observed. Since the data from the annual financial statements are submitted at the property owner's fiscal year end, they are inherently backward looking and reflect the prior year's financial performance. Stated differently, financial performance data for defaulted loans are only recorded for the years preceding default, and not captured once the loans default. These statistics foreshadow what to expect from the CPH regression, and signal that there are distinct characteristics between default loans and non-default loans. Improved understanding of these characteristic differences could provide early identification for loans on the path to default.

Without exception, non-default observations exhibit uniformly stronger property-level financials in terms of average DSCR, QR, OR, and RPU. The average DSCR and QR are consistently above one for non-default loans whereas the same is not true for default loans. Additionally, in many instances RPU for non-default loans is twice as large as those for default loans. Average LTV is also lower for non-default loans and, consequently, are much less likely to trip the double-trigger threshold than the default loans. In terms of market condition measures by REIS, non-default observations exhibit neither a substantially lower average vacancy rate nor higher net absorption rate. This surprising result suggests that market conditions may not be as relevant as property management for loan performance, which will be tested empirically in the model. From these statistics, we expect that strong property-level financials and equity position suppress default. To a varying extent, rental market conditions also influence a mortgage loan's default propensity.

Table 3: Summary Statistics by Default Status, Average unless Otherwise Indicated

	Non-default Loans									
Description	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
N	57	134	2,713	2,819	2,769	2,651	2,656	2,591	2,576	2,366
DSCR	1.23	1.16**	1.28**	1.25**	1.18**	1.12**	1.12**	1.10**	1.14**	1.14
Quick Ratio	1.85	1.55*	1.84**	1.75**	1.52**	1.41**	1.33**	1.27**	1.31**	1.31
Occupancy Rate	95.56	95.30	95.47**	95.24**	94.28**	93.39**	93.22**	93.10**	93.43*	93.54
Reserves per Unit	$1,511.63	$1,289.80**	$1,293.51**	$1,359.49**	$1,479.25**	$1,673.15**	$1,957.06**	$2,077.68**	$2,223.34**	$2,264.16
REIS Vacancy Rate	4.07	3.52	4.25	5.77	6.83	7.29**	6.86	6.29	6.49	6.75
Minimum	1.70	1.00	0.50	0.90	1.28	1.17	1.33	1.65	1.24	1.30
Maximum	9.30	8.23	14.83	19.50	20.85	20.00	16.69	14.02	14.18	14.40
Loan-to-Value	0.77	1.15	0.69**	0.59**	0.59**	0.60**	0.59**	0.59**	0.56	0.54
Minimum	0.27	0.18	0.01	(1.75)	(1.38)	(1.57)	(1.77)	(1.54)	(1.66)	(1.63)
Maximum	2.38	12.35	39.95	14.43	68.88	132.63	131.95	33.07	122.16	121.23
Double trigger indicator	0.22	0.30**	0.09**	0.07**	0.06**	0.10**	0.11**	0.16**	0.13	0.12
REIS Net Absorption Rate	2.07	2.67*	1.13	(0.06)	(0.03)	0.12**	0.09**	(0.05)	0.20	0.69

	Default Loans									
Description	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
N	8	25	128	121	105	89	60	25	12	-
Remaining Years to Default	5	4	3	2	1	1	1	0	-	-
DSCR	1.10	0.89**	0.90**	0.87**	0.79**	0.73**	0.76**	0.79**	0.75**	-
Quick Ratio	2.01	0.86*	0.37**	0.53**	0.49**	0.42**	0.32**	0.33**	0.17**	-
Occupancy Rate	94.98	93.35	90.71**	89.73**	88.30**	86.43**	87.52**	86.13**	85.01**	-
Reserves per Unit	$1,116.97	$742.51**	$778.54**	$842.34**	$711.13**	$807.30**	$795.53**	$958.42**	$793.87**	$ -
REIS Vacancy Rate	3.36	3.32	4.46	6.04	7.15	7.96**	7.11	6.55	7.50	-
Minimum	2.00	1.27	1.04	1.67	1.82	1.17	1.34	1.60	4.78	-
Maximum	5.40	6.70	14.83	19.50	20.90	20.00	15.04	14.04	12.70	-
Loan-to-Value	0.88	1.26	1.16**	0.88**	0.87**	0.99**	1.28**	1.19**	7.38	-
Minimum	0.46	0.29	0.25	0.12	(0.62)	0.32	0.27	0.45	0.57	-
Maximum	1.35	4.77	14.32	3.67	4.95	5.05	14.40	4.86	78.30	-
Double trigger indicator	0.38	0.72**	0.33**	0.29**	0.27**	0.36**	0.35**	0.40**	0.25	-
REIS Net Absorption Rate	1.48	2.03*	1.15	(0.03)	(0.07)	(0.03)**	0.29**	0.02	(0.11)	-

Source: FHA data.
Note: Unit of observation, *N*, is a MF mortgage loan. No Section 221(d)(4) loans in our sample defaulted in 2008. Outliers—values exceeding the 1^{st}- and the 99^{th}-percentiles—are excluded.
**, * Represents that the indicator is statistically different at the 1 percent and 5 percent levels, respectively.

Correlation Statistics

Since many of these property-level financial measures are derived from the same accounting identities, it is instructive to examine the correlations among these covariates to understand their internal consistencies. Table 4 presents pair-wise correlation coefficients among the covariates. The DSCR and QR pair exhibits the strongest correlation at 0.5. This is not surprising given the number of common accounts shared by these financial ratios. The second highest correlation is between the Double-Trigger Indicator and the property occupancy rate. This, too, is not surprising since occupancy rate affects net operating income, which, in turn, affects both DSCR and LTV, the two components of the Double-Trigger Indicator. Between the two REIS rental market condition measures, rental market vacancy rate exhibits a much stronger influence on property-level financial ratios. As expected, rental market vacancy rate exhibits the strongest negative correlation with property-level occupancy rate. In summary, while these variables are correlated in a direction that is consistent with economic intuition, their magnitudes do not warrant concerns regarding multicollinearity in the CPH regression model.

Table 4: Pairwise Correlation of Covariates

Covariate	DSCR	Quick Ratio	Occupancy Rate	Reserves per Unit	REIS Vacancy Rate	Loan-to-Value	Double trigger Indicator
DSCR	1						
Quick Ratio	0.500 *	1					
Occupancy Rate	0.317 *	0.213 *	1				
Reserves per Unit	0.023 *	0.013	0.233 *	1			
REIS Vacancy Rate	-0.167 *	-0.152 *	-0.233 *	-0.125 *	1		
Loan-to-Value	-0.158 *	-0.066 *	-0.158 *	-0.062 *	0.023 *	1	
Double trigger indicator	-0.384 *	-0.206 *	-0.423 *	-0.140 *	0.083 *	0.238 *	1
REIS Net Absorption Rate	-0.012	-0.023 *	-0.044 *	-0.024 *	0.057 *	0.009	0.052 *

Source: FHA data.
* Denotes statistical significance at the 5 percent level.

VII. Model Estimation Results

To examine the relative influence of these covariates on the default hazard rate, we specified a CPH model in which the financial ratios, REIS rental market measure, and LTV enter linearly. By construction, the Double-Trigger Indicator is a binary variable. Although it would not affect the size and the statistical significance of the regression coefficient, it helps to interpret a baseline hazard if selected covariates are centered at values that reflect a hypothetical "baseline" mortgage. A baseline mortgage is defined as having the following characteristics:

1. Debt Service Coverage Ratio = 1.00
2. Quick ratio = 1.00
3. Occupancy Rate (in percent) = 90
4. Reserves per Unit (in dollars) = $1,000
5. LTV = 0.5
6. REIS Vacancy Rate (in percent) = 10
7. REIS Net Absorption Rate (in percent)[25] = 24

Since centering does not alter the regression coefficients, these baseline values are chosen to illustrate a representative loan, and to assist in interpreting the baseline hazards. Based on theory and sample statistics by default status, Table 5 summarizes our expectations of the direction and statistical significance of the covariates.

Table 5: Expected Relationships between Covariates and Uncured Default

Covariate	Expected Sign	Remarks
Debt Service Coverage Ratio	Negative	Default propensity decreases as the ability to meet debt obligations increases
Quick Ratio	Negative	Default propensity decreases as liquidity increases
Occupancy Rate	Negative	Default propensity decreases as more units are rented resulting in

[25] Set at the sample average.

Covariate	Expected Sign	Remarks
		more cash flow
Reserves per Unit	Negative	Default propensity decreases as the level of reserves increases to weather economic downturns
Loan to Value	Positive	Default propensity increases as the ratio of loan to value increases.[26]
Double-Trigger Indicator	Positive	Default propensity increases with increasing negative cash flow and negative equity.
REIS Vacancy Rate	Positive	Even after controlling for property-level financials, default propensity increases with increasing market vacancy rate.
REIS Net Absorption Rate	Negative	Even after controlling for property-level financials, default propensity decreases as the absorption rate for newly available rental units increases.

Shown in Table 6, four models were estimated to quantify separately and jointly the influence of the Double-Trigger Indicator, property-level financials, and rental market conditions. The dependent variable in all four models is the hazard of an uncured default. Model 1 includes only the double-trigger indicator and its individual components to investigate whether LTV or DSCR can be attributed as the primary driver of influence. Model 2 tests whether, and to what extent, property-level financial ratios alone explain the uncured default propensity. Model 3 examines the predictive power of external rental market conditions. Finally, Model 4 is the full model containing all covariates.

The data suggest that DSCR, negative cash flow, the double trigger indicator, property-level financials, and external rental market vacancy rates are, individually and collectively, strong predictors of default with relationships consistent with the expected signs shown in Table 5. Model 4 confirms the robustness of the results when additional controls are included, as the direction of influence for the covariates remains unchanged. The magnitude of the hazard differs, however, leading some covariates to have reduced impact and statistical significance. In particular, the effects of the negative cash flow dummy and the double-trigger indicator in the full model are reduced by nearly half and two-thirds, respectively. Generally, the external vacancy rate and property-level financial hazard ratios remain largely unchanged and statistically significant at the one or five percent levels.

[26] According to the double-trigger hypothesis, LTV has a non-linear effect on default. Its effect is strongest when equity is negative.

Table 6: Regression Results (in Hazard Ratios)

Covariate	Model 1	Model 2	Model 3	Model 4
(a)	(b)	(c)	(d)	(e)
Loan-to-value	1.00	1.00		1.00
DSCR	0.98 ***	0.98 ***		0.98 ***
Dummy variables:				
Negative cash flow binary indicator	4.01 ***			2.21 **
Negative equity binary indicator	2.57			1.43
Double-Trigger binary indicator	6.88 ***			2.60 **
Quick Ratio		0.99 ***		0.99 ***
Occupancy Rate		0.96 ***		0.97 ***
Reserves per Unit		0.96 ***		0.96 ***
REIS Vacancy Rate			1.19 ***	1.08 **
REIS Net Absorption Rate			1.00	1.00
N	162,223	162,223	162,223	162,223
BIC	2,010.82	1,929.95	2,232.97	1,974.97
LL	-975.42	-934.98	-1,104.49	-927.50

Note: *, **, *** denotes statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

From the regression results, we conclude that the double-trigger contributes to the default process. In fact, the data suggest that the combination of negative equity and negative cash flow increases the default hazard by 160 percent. The double-trigger indicator takes on a value of one when both of these conditions are met and zero otherwise. Thus, the true impact of the double-trigger being turned on is really the combination of three effects: negative cash flow; negative equity; and negative cash flow coupled with negative equity. Although the double-trigger indicator provides the greatest influence, it is not the only contributor as property-level financial ratios and external rental market vacancy rates also impart substantial influence on the default decision. In particular, improvements in DSCR, QR, OR, and RPU reduce the default hazard between one and four percent.

Average marginal effects are other metrics to quantify the impact of these covariates.[27] Table 7 presents the average unit change of the relative hazards due to a unit change of the covariates. A unit is defined as one percentage point (i.e., 0.01) for DSCR, QR and REIS Net Absorption Rate, whereas it is one percentage point (i.e., 1.00) for occupancy rate and REIS Vacancy Rate. For reserves per unit, a unit is measured in increments of $100. The average marginal effects are based on the full model, or Model 4.

[27] Paraphrasing Williams (2012), “the marginal effects for categorical variables show how” relative hazard “changes as the categorical variable changes from 0 to 1, after controlling…for the other variables in the model”. To calculate the average marginal effects, we treated the other variable values *as observed*. In other words, we computed relative hazard “for each case with the fixed and observed values of variables, and then we average the predicted values.”

Table 7: Average Marginal Effects for the Covariates from the Full CPH Model

Covariate	dy/dx	Std. err.	z	P>|z|	[95% Conf.	Interval]
(a)	(b)	(c)	(d)	(e)	(f)	(g)
Loan-to-Value	0.00	0.00	-0.61	0.54	0.00	0.00
DSCR	-0.05	0.02	-3.34	0.00	-0.08	-0.02
Negative equity (LTV>0.9) dummy	0.50	0.66	0.76	0.45	-0.79	1.78
Negative cash flow (DSCR < 1) dummy	1.51	1.11	1.37	0.17	-0.66	3.68
Double-trigger indicator	2.02	1.10	1.84	0.07	-0.13	4.17
Quick ratio	-0.02	0.01	-2.27	0.02	-0.04	0.00
Occupancy rate	-0.10	0.04	-2.76	0.01	-0.17	-0.03
Reserve per unit	-0.11	0.05	-2.47	0.01	-0.20	-0.02
REIS vacancy rate	0.21	0.09	2.31	0.02	0.03	0.38
REIS net absorption rate	0.00	0.00	-1.27	0.20	0.00	0.00

Note: dy/dx for categorical data is the discrete change in relative hazard. For example, the average marginal effects for the double trigger indicator is defined as the difference in adjusted relative hazards between cases in which double triggers are present (negative equity and negative cash flow indicators are 1) and cases in which cash flow and equity are both positive (negative equity and negative cash flow indicators are 0). The *z*-score (z) is based on the null hypothesis that the average marginal effect is zero.

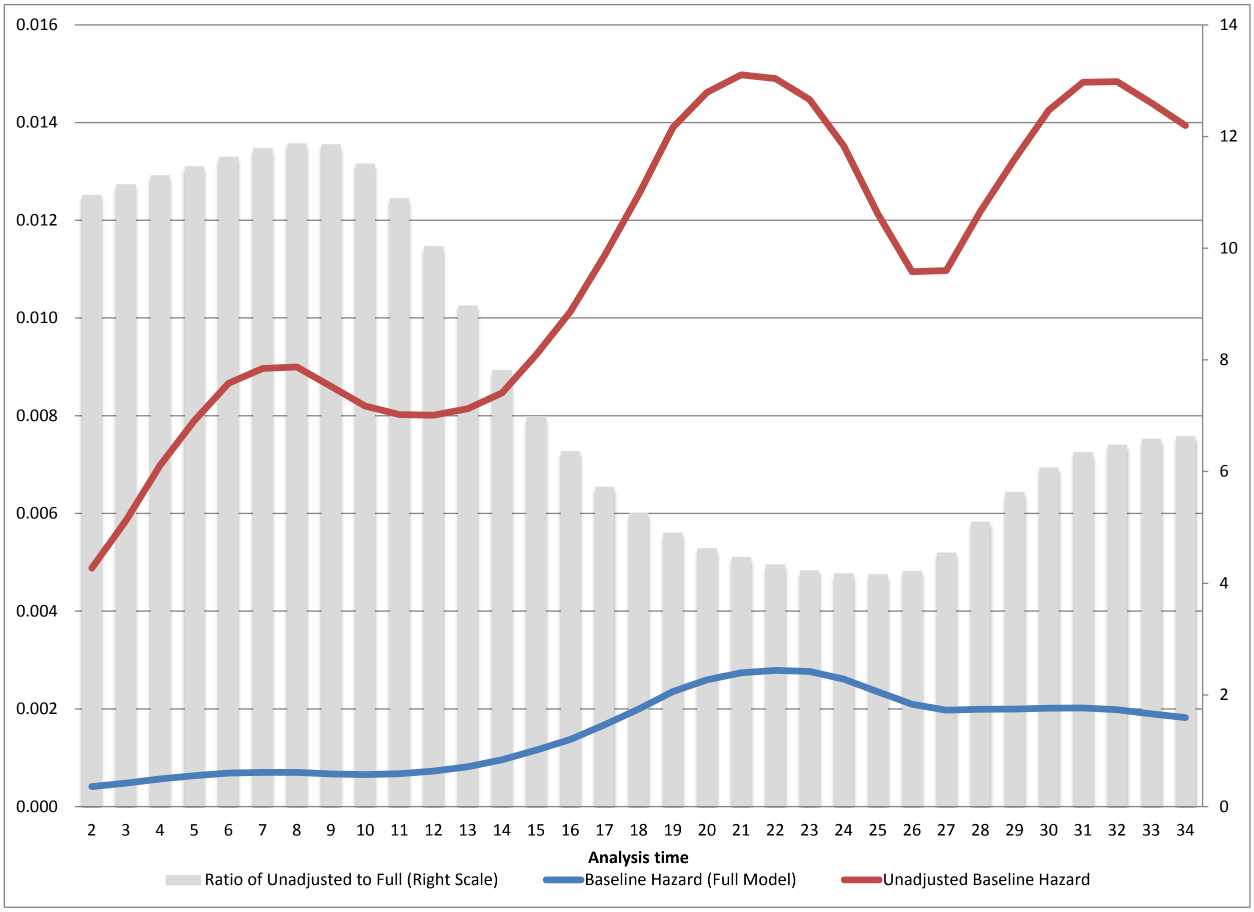
The data suggest that a $100 increase in reserve per unit reduces the relative hazard by 0.11. A percentage point change in occupancy rate reduces the relative hazard by 0.10. A one percent increase in DSCR and QR reduces the relative hazard by 0.05 percent and 0.02 percent, respectively. In contrast, a one percent increase in the REIS vacancy rate increases the relative hazard by 0.21. These changes are statistically significant at 5 percent. In the instance in which the double trigger is activated, the relative hazard is about 2.02. This effect is statistically significant at the 10 percent level.

On the other hand, LTV, the negative cash flow and negative equity dummies, and the REIS net absorption rate do not impart statistically significant average marginal effects to the relative hazard.

Finally, Figure 5 compares the *unadjusted* baseline hazard function from a null model to the baseline hazard function from Model 4 for a benchmark property with the following characteristics: DSCR=1.0; QR=1.0; OR=90 percent, RPU=$1,000, LTV=0.5, REIS vacancy rate=10 percent, and REIS net absorption rate=24 percent. The difference between the unadjusted baseline and the adjusted baseline hazard functions in the graph can be attributed to the impact of the covariates in Model 4. The bars in the graph illustrate the relationship between the unadjusted baseline hazard function and the adjusted baseline hazard function as a ratio. This ratio, which is the average predicted relative hazard, approximates the aggregate financial performance of FHA insured MF loans by loan age. The ratio is at its peak in the first ten years from loan endorsement before declining, signifying that younger loans on average have lower finance performance than loans that are ten year or older. At its peak, the ratio of the unadjusted baseline hazard to the baseline hazard is approximately 12. This shows that MF mortgage loans in their early years deviate from the benchmark characteristics significantly, which contribute to their default hazard.

We also note that the baseline hazard increases beginning in year 10, and plateaus at a higher hazard rate by year 27. Since financial performance is held constant in the baseline, this result may be due to physical deterioration as a property ages, which would increase the baseline hazard independently from a property's financial performance.

Figure 4: Baseline Hazard Functions



VIII. Conclusion and Summary

In summary, this paper seeks to model default risk in the Section 221(d)(4) FHA loan portfolio. In doing so, three hypotheses were tested. The first is the double-trigger hypothesis (negative cash flow and negative equity) advanced by Goldberg and Capone. The second is about the importance of property-level liquidity metrics. The third is whether external rental market conditions influence a loan's default propensity. Using a CPH regression model and controlling for a property's financial condition, we tested these hypotheses. Based on the estimated hazard ratios a loan in both a negative cash flow and negative equity financial position has a hazard rate that is 160 percent higher than equity loan when either one of these conditions is absence. MF mortgage loans in strong financial position, as evidenced by high liquidity, cash flow, occupancy, and reserves are less likely to reach uncured default. Finally, a one percentage-point increase in the REIS market vacancy rate increases a loan's default hazards by eight percent relative to a benchmark property, holding fixed property-level financial measures.

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Appendix: LTV Calculation

Loan-to-value (LTV) is the ratio of loan size to its asset value. Mortgage loan size is determined as the unpaid principal balance ("UPB") based on an amortization schedule. Asset values for properties are calculated based on Goldberg and Capone (1998), which estimates a market-based property value using a market-based NOI. Market-based NOI is updated using metropolitan-level data on changes in vacancies and rents over time.

Specifically, we follow these steps to calculate a contemporaneous LTV for each property in the sample:

1. Calculate an amortization schedule for each loan to determine its current loan balance.
2. Estimate an NOI for each property based on the difference between its gross potential rent and expenses. NOIs are updated according to changes in market rents and vacancy rates.
3. Estimate an initial capitalization rate (cap rate) for each property, and update cap rates to reflect changes in interest rates.
4. Contemporaneous asset values are a function of updated NOIs and cap rates.
5. Contemporaneous LTV is the ratio between the size of current loan balance to contemporaneous asset value.

An alternative to the aforementioned market-based approach is an estimation that relies on reported property-level NOI.[28] We favor the market-based approach because property-level NOI could be influenced by property management. For example, a poorly managed property could experience lower NOI as compared to an otherwise identical property under effective management. Therefore, a market-based NOI estimate reflects the *maximum* potential NOI of a property based on market conditions alone. In our view, a market-based valuation is appropriate because it reflects the maximum potential value that a property can fetch in the market irrespective of the quality of management.[29]

The asset value calculations derived in this paper are based on the methods developed by Goldberg and Capone (1998, 2002). They develop a market-based approach to determining asset values with the goal of developing an LTV proxy for use in a model that predicts mortgage default. The authors hypothesize that value estimates are a function of rental market conditions, which can either strengthen or weaken over time. In particular, in their model, LTV_0 is the starting point for equity default risk analysis and, over time, default probabilities are affected by

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[28] We also attempted to construct asset value using reported property-level NOI. This approach presents two problems, both conceptual and statistical. Because reported NOI can change significantly from year to year, this method of valuation could lead to wild variation of asset value from one year to the next, which we think is conceptually unreasonable. Because reported NOI is highly correlated with other reported property-level financial ratios (see, Ciochetti et al. (2003)), asset values based on reported NOI exhibit multicollinearity with other financial ratios, which imped the testing of our central hypothesis in a regression setting.

[29] Through a regression analysis, we also discovered that the physical condition of a property explains some of the variation between potential NOI and actual NOI. Specifically, we notice that properties in better physical condition exhibit NOI that is closer to their market potential.

changes in the net operating income (NOI) of the property. The authors further postulate that LTV is a function of *Value*, which is a function of annual NOI, which in turn is a function of vacancy rates and changes in rental prices. In other words,

$$LTV_t = \frac{Loan\ Balance_t}{Value_t} \text{ where,}$$
$$Value_t = f(NOI_t) \text{ and,}$$
$$NOI_t = f(Vacancy\ Rates_t, Rental\ Prices_t).$$

The authors then express current NOI_t as a function of previous NOI_0, market vacancy rates, current market rental price index, and a scale factor composed of expenses and vacancies. NOI in their model is expressed as an annual value. The derived expression for contemporaneous NOI_t is:

$$NOI_t = RPI_{m,t}\ NOI_0 - 2.15\ RPI_{m,t}\ NOI_0\ (VAC_{m,t} - VAC_{m,0})$$

Where:

$RPI_{m,t}$ = the index measure of the growth in rental prices measured at the MSA level
NOI_0 = the net operating income in the initial period
$(VAC_{m,t} - VAC_{m,0})$ = the change in vacancy rates from initial period to now, measured at the MSA level
2.15 = $1/(1 - k - v)$ = a scale factor where k and v are dollar expenses and vacancy losses both expressed as a percent of rental income in period t [30]

Rental income in the NOI variables is assumed to be at full occupancy. The above equation essentially states that current NOI at full occupancy equals NOI in the initial period, scaled by the change in rental prices, less any expenses and changes in vacancy rates.

Expense ratios and vacancy losses are assumed to be constant in the long-run, and,

$$NOI_t = RENT_t\,(1 - k - v)$$

The above equation states that NOI in any period can be determined by per-unit rent income at full-occupancy, long-term vacancy losses, and expense ratios. The authors state that specifying NOI_t in this fashion allows us to determine an initial period market-based NOI_t and to update it for each period.

The authors further argue that once NOI_t is determined, an expression for $Value$ can be determined by capitalizing the value using a capitalization rate (“cap rate”) formula. That is,

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[30] Goldberg and Capone (1998) use values for k and v that are based on data from annual national surveys of apartments in which the expense ratio averages to 47 percent, and the long-term vacancy rate is approximately 6.3 percent, or:

2.15 = 1/(1 – 0.47 - .063)

$$cap\ rate_t = \frac{NOI_t}{Asset\ Price_t}$$

A property value can now be specified as:

$$Asset\ Price_t \equiv Value_t = NOI_t / cap\ rate_t$$

Where:
$(1/\ cap\ rate_t)$ = capitalization rate multiplier ("*CRM*")

Furthermore, the authors state that since they have an expression that updates NOI over time, they also need to define an expression that updates CRM over time. Therefore, since cap-rate values are a function of current mortgage interest rates, a log-linear regression equation is specified to estimate the elasticity of interest rates on CRM over time, or,

$$ln\ CRM = \alpha + \beta\ ln\ r_t$$

Where:
r_t = interest rate at time *t*

CAP estimated values are then updated according to β, the coefficient in the above log-linear regression.

This results in the following specification for LTV_t:

$$LTV_T = \frac{L_t}{CAP_t * NOI_t}.$$

Where:
L_t = loan amount at time *t*

Methodology

The following steps generate contemporaneous LTV for the sample:

1. Calculated an amortization schedule for each loan to determine a quarterly loan amount.
2. Determined a quarterly value for each property using the following steps:
    a. Estimated and updated NOI by:
        i. Calculating a starting gross potential rent for each property from the property's first AFS submission;
        ii. Estimating the relationship between gross potential rent and NOI using portfolio-average expense ratios and vacancy rates; and
        iii. Generating a quarterly series of NOI values, based on the effect of changes in market rents and vacancies to NOI over time.
    b. Estimated and updated capitalization rates ("cap rates") by:
        i. Calculating an implied going-in cap rate for each property, based on starting loan terms, using the debt coverage ratio method; and

ii. Updating this going-in cap rate based on the estimated elasticity of cap rates to interest rates, estimated using portfolio data on new endorsements.

c. Estimated asset values by multiplying the annual cap rate by quarterly NOI to determine a market value for each insured property, for each quarter.

Determining the Loan Amount

The unpaid principal balance ("UPB") represents the amount outstanding on the mortgage, and is the "loan" amount, or the numerator in the LTV ratio. We estimated an amortization schedule for each loan, providing a UPB at each time of interest. This amortization schedule was based on the assumption that all FHA-insured loans are fully amortizing, and was computed based on the first payment date, loan term, and maturity date of the loan, as identified in F47.

Estimating Starting NOI

We started with the gross potential rent of the property as of the first AFS available for the property. Gross potential rent is defined as total rental income possible if every unit on the property has been rented. Gross potential rent includes gross rent, as well as any other rental payments received by the property, including, in the case of FHA-insured properties, assistance payments, commercial rent, and garage rent.

We adjusted the gross potential rent to develop a market value of NOI by netting out expenses and vacancies. To adjust for vacancies, Goldberg and Capone adjusted gross potential rent by a national structural vacancy rate (6.23 percent) and an estimate of a property's expense ratio. An *expense ratio* is the percent of gross potential rent that is dedicated to expenses, and is based on an assumption, common in the real estate industry, that expenses generally make up a fixed proportion of rent. Expense ratios are often calculated for different types of properties, or different regions.[31] There are several estimations of overall expense ratios available for all MF properties. For example, Capone and Goldberg used an expense ratio of 47 percent, based on data from a nationwide survey of property managers.[32]

However, rather than use national indices for average expense ratios and vacancy rates, we calculated expense ratios and vacancy rates from FHA data directly.

Using the results above, an initial (NOI_0) was computed that was set equal to the product of gross potential rents, vacancy losses as a percent of rent, and expenses as a percent of rent, or,

$$NOI_0 = RENT_0(1 - k - v)$$

Where:

$RENT_0$= gross potential rent
k= expense ratio
v= vacancy rate

[31] REIS provides submarket-level expense ratios as part of its Rent Comparable reporting tool.
[32] This survey was conducted by the Institute for Real Estate Management (IREM).

Updating NOI based on Rental Market Changes

The next step is to determine how this initial NOI is affected by quarterly changes in vacancy rates and rent growth. Data on vacancy rates and rent growth was downloaded from REIS, Inc, a commercial data provider. REIS provides MF market data at a regional, metropolitan, and submarket (neighborhood) level. We matched properties to market data at either a metropolitan level, or, for properties outside of a metropolitan area analyzed by REIS, to one of five REIS regional markets. Approximately 57 percent of properties were matched to data at the metropolitan level, while the remaining 43 percent of properties were matched to data at the regional level.

Initial NOI was then adjusted over time, using the rental price indices and changes in vacancy rates shown above. The following equation describes how NOI_0 is adjusted over time, using the above market data:

$$NOI_t = (1 - \frac{1}{1-k-v}(VAC_t - VAC_0))RPI_t NOI_0$$

Where:

- k= expense ratio
- v= vacancy rate
- RPI= metropolitan or regional rental price index[33]
- VAC_t-VAC_0=change in metropolitan or regional vacancy rate over time

Capitalization Rates

The next step is to convert the quarterly NOI series into a series of values using a capitalization rate ("cap rate"). In real estate, a cap rate represents the projected return on investment on a property for one year if the property were bought with cash. The projected NOI divided by the cap rate provides a property value. The higher the cap rate, the lower the property value.

Appraisers typically use several different methods to provide a set of cap rate values that range from pessimistic to optimistic estimates. A sampling of these methods includes the Ellwood method of calculated rates, the Band of Investment Method, and the Debt Coverage Ratio (DCR) Method. The Ellwood method involves making assumptions about future expectations in income, property value growth, and equity yield rates. The Band of Investment method sets the cap rate equal to a weighted average of the returns required to service the mortgage payment and the equity. The DCR method, also known as the "going-in" cap rate method, is used to estimate the cushion of net operating income above debt service. Cap rates are then estimated by multiplying the DSCR, mortgage interest rate, and the LTV ratio that would be required for a borrower to qualify for a mortgage on the property.[34] We chose to use the DCR method to determine cap rate estimates due to data availability and lower estimation error since this method produces more conservative cap rate estimates than other methods.

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[33] Calculated as 1+ the percent change in Asking Market Rent over the previous quarter (provided by REIS). In markets for which quarterly growth was not available, annual growth was divided by four and assumed to be constant over each quarter.

[34] The starting position for LTV is not available from the data. Consequently, the authors assume a starting position for LTV as the highest LTV limit available under the Section 221(d)(4) program.

$$Cap\ Rate = Required\ DSCR * Required\ LTV\ ratio * Mortgage\ Constant$$

Using the required loan terms for each program, a going-in cap rate was calculated for each property at the time of endorsement. [35] Adopting a methodology used by Capone and Goldberg, this cap rate was then adjusted over time based on an estimated elasticity of the annual cap rate to the interest rate on the 10-year Treasury rate, generally accepted to represent a risk-free interest rate.

This elasticity of the annual cap rate with respect to interest rates was estimated using portfolio data on endorsements on properties occurring during the analysis period, using the following log-linear relationship:

$$\ln\left(\frac{1}{CAPRATE_t}\right) = \alpha + \beta \ln(IntRate_t)$$

Results are of this regression are provided the following table:

Regression Results: Elasticity of Cap Rates with respect to Interest Rate

	Coefficient	t	P>/t/
ln(Interest Rate)	-0.35	-26.33	0.00
Constant	1.54	37.17	0.00
No. of Observations	7,184		
F	693		
Prob>F	0.00		
Adj R2	8.88%		

Source: MF-FASS data systems.

Consistent with Capone and Goldberg, we did not use the entire equation to predict a cap rate at each time period, but instead ignored the constant term, and only used the coefficient on the logged interest rate variable to estimate the elasticity of cap rates with respect to interest rates. This elasticity was used to update the going-in cap rate for each property, based on annual interest rates in the analysis period. Using this methodology, we calculated the average cap rates for properties each year in the study period.

Property Values

As was stated earlier, in order to determine an asset value for each property, for each quarter, each quarterly NOI estimate is divided by the annual cap rate. A property value can now be specified as:

[35] Information on FHA Loan terms were gathered from the DAP data system, as well as term sheets from lenders.

$$Asset\ Price_t \equiv Value_t = NOI_t\ /\ cap\ rate_t$$