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A MULTI-FACTOR PROBIT ANALYSIS OF NON-PERFORMING COMMERCIAL

MORTGAGE-BACKED SECURITY LOANS

BY

PHILIP ANTHONY SEAGRAVES

Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

of

Doctor of Philosophy

in the Robinson College of Business

of

Georgia State University

GEORGIA STATE UNIVERSITY

ROBINSON COLLEGE OF BUSINESS

2012

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ACCEPTANCE

This dissertation was prepared under the direction of Philip Anthony Seagraves' Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the College of Business Administration of Georgia State University.

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ABSTRACT

A MULTI-FACTOR PROBIT ANALYSIS OF NON-PERFORMING
COMMERCIAL MORTGAGE-BACKED SECURITY LOANS

By

Philip Anthony Seagraves

July 10, 2012

Committee Chair: Dr. Jonathan A. Wiley

Major Academic Unit: Real Estate

Commercial mortgage underwriters have traditionally relied upon a standard set of criteria for approving and pricing loans. The increased level of commercial mortgage loan defaults from 1%

at the start of 2009 to 9.32% by the end of 2011[1] provides motivation for questioning underwriting standards which previously served the lending industry well. This dissertation investigates factors that affect the probability of Non-performance among commercial mortgage-backed security (CMBS) loans, proposes conditions under which the standard ratios may not apply, and tests additional criteria which may prove useful during economic periods previously not experienced by commercial mortgage underwriters. In this dissertation, Cap Rate Spread, the difference between the cap rate of a property and the Coupon Rate of the associated loan, is introduced to test whether the probability of Non-performance can be better predicted than by relying on traditional commercial mortgage underwriting criteria such as Loan to Value (LTV) and Debt Service Coverage Ratio (DSCR). Testing the research hypotheses with a probit model using a database of 47,883 U.S. CMBS loans from 1993 to 2011, Cap Rate Spread is found to have a significantly negative relationship with loan Non-performance. That is, as the Cap Rate Spread falls, the probability of Non-performance rises appreciably.

A numerical model suggests that among loans which would have passed the standard ratio tests requiring loans to have values of LTV less than .8 and DSCR greater than 1.25, a Cap Rate Spread criteria requiring loans to have a value greater than 1% would have prevented the origination of an additional 1,798 CMBS loans reducing the rate of Non-performance from 14.9% with only the LTV and DSCR criteria to just 11.6% by adding the Cap Rate Spread

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[1] Moody's Investor Service: U.S. CMBS loan delinquencies rise to 9.32%, Global Credit Research, New York, January 20, 2012.

criteria. Of course, adding additional criteria will also lead to errors of rejecting loans which would have performed well. Back testing with the same sample of CMBS loans, this Type I error rate rises from 19% with only the LTV and DSCR criteria to 34% with the addition of the Cap Rate Spread.

Ultimately, CMBS loan underwriters must individually determine an acceptable level of Non-performance appropriate to their business model and tolerance for risk. Using intuition, experience, tools, and rules, each underwriter must choose a balance between the competing risks of rejecting potentially profitable loans and accepting loans which will fail. This research result is important because it helps deepen our understanding of the relationships between property income and loan performance and provides an additional tool that underwriters may employ in assessing CMBS loan risk.

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Background

Standard underwriting models for commercial loans rely upon classic measures such as the size of the loan relative to the value of the property (Loan to Value Ratio, LTV) and the ratio of net income from the property to the size of the annual debt payments (Debt Service Coverage Ratio, DSCR) for approving and pricing debt. LTV and DSCR are presented in equations (1) and (2) respectively.

$$Loan\ to\ Value\ (LTV) = \frac{Original\ Loan\ Balance\ (LOAN)}{Project\ Value\ (VALUE)} \tag{1}$$

$$\mathrm{DebtServiceCoverageRatio(DSCR)} = \frac{\mathrm{NetOperatingIncome(NOI)}}{\mathrm{DebtService(DS)}} \tag{2}$$

LTV is a widely used measure of loan risk and one of the most commonly cited features, along with interest rates, used to describe individual deals and the general debt environment. As the loan amount approaches or surpasses the value of the underlying asset, the default risk increases. This risk is also a function of other factors such as the experience of the borrower, the type of project, geography, the state of the economy, and competition.

DSCR is also an important criterion used by loan underwriters to determine the riskiness of a loan. This measure provides a simple indicator of a borrower's ability to continue making their debt payments in the face of reduced rental income or increased expenses. As the DSCR rises, the borrower has a greater cushion against rent pressures, tenant turnover, unexpected expenses, or the effects of natural disasters for maintaining their debt service obligations. As with LTV, the ability of DSCR to provide a valuable risk screening function may be related to other economic factors such as market interest rates.

From 2009 to 2011, the rate of default for commercial mortgages rose significantly. An indicator of future default rates, 17% of the CMBS loans in the Bloomberg database[2] on September 15, 2011, were classified as "non-performing" (See Table 1).

Table 1 ■ CMBS Loan Status as of 3rd Quarter 2011

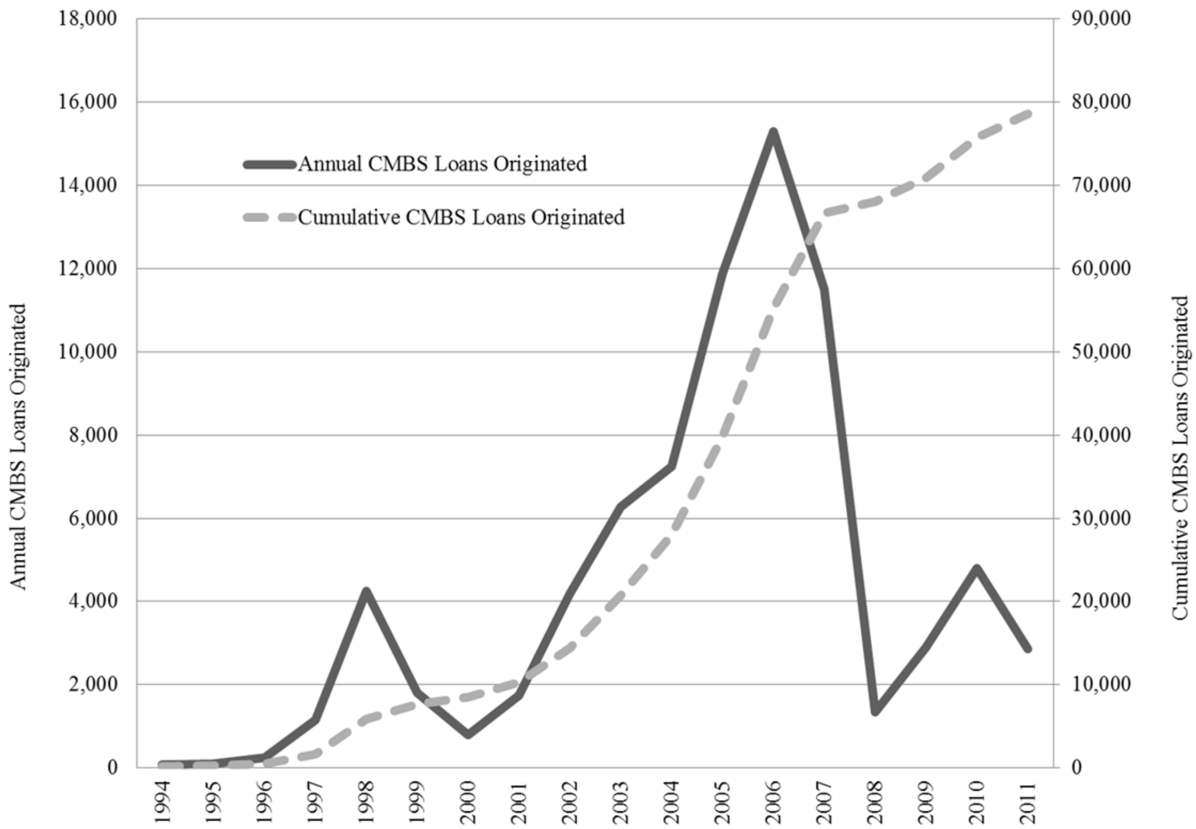
Loan Status	Observations	Percent
Performing	58,517	83.09%
Grace	4,988	7.08%
Late	1,708	2.43%
Delinquent, less than one year	2,020	2.87%
Delinquent, greater than one year	855	1.21%
Foreclosure	836	1.19%
REO	1,021	1.45%
Matured, non-performing	482	0.68%

Notes: Source Bloomberg CMBS Data Service. Excludes loans classified as defeased, special, matured, and mixed.

Figure 1 presents annual CMBS loan originations from 1994 through late 2011. During the high-growth period for CMBS in the mid-2000s through the subsequent market crash, underwriters continued to rely upon LTV and DSCR to determine the risk of loans.

[2] Database including some observations subsequently eliminated for final analysis due to missing data. Final sample size after cleaning includes 47,883 observations.

Figure 1 ■ CMBS Loan Originations per Year



LTV and DSCR provide useful but limited help in determining the risks of CMBS loans. Perhaps other measures can aid in the analysis. Another important consideration may be the yield of real estate projects relative to their loan value or total project value. While LTV and DSCR measures are value/value or cash flow/cash flow measures respectively, a debt or Cap Rate measure provides a cash flow/value view which may be sensitive to economic conditions such as interest rates. If the overall yield of a project on either the debt or total cost is high, it is likely be that loans experience less stress through a range of economic conditions. In this dissertation, three alternative measures are considered, including the Debt Yield, Cap Rate, and the Cap Rate Spread, presented below in equations (3), (4) and (5) respectively.

$$\textit{Debt Yield (DYLD)} = \frac{\textit{Net Operating Income (NOI)}}{\textit{Original Loan Balance (LOAN)}} \tag{3}$$

$$\textit{Cap Rate (CAPRT)} = \frac{\textit{Net Operating Income (NOI)}}{\textit{Project Value (VALUE)}} \tag{4}$$

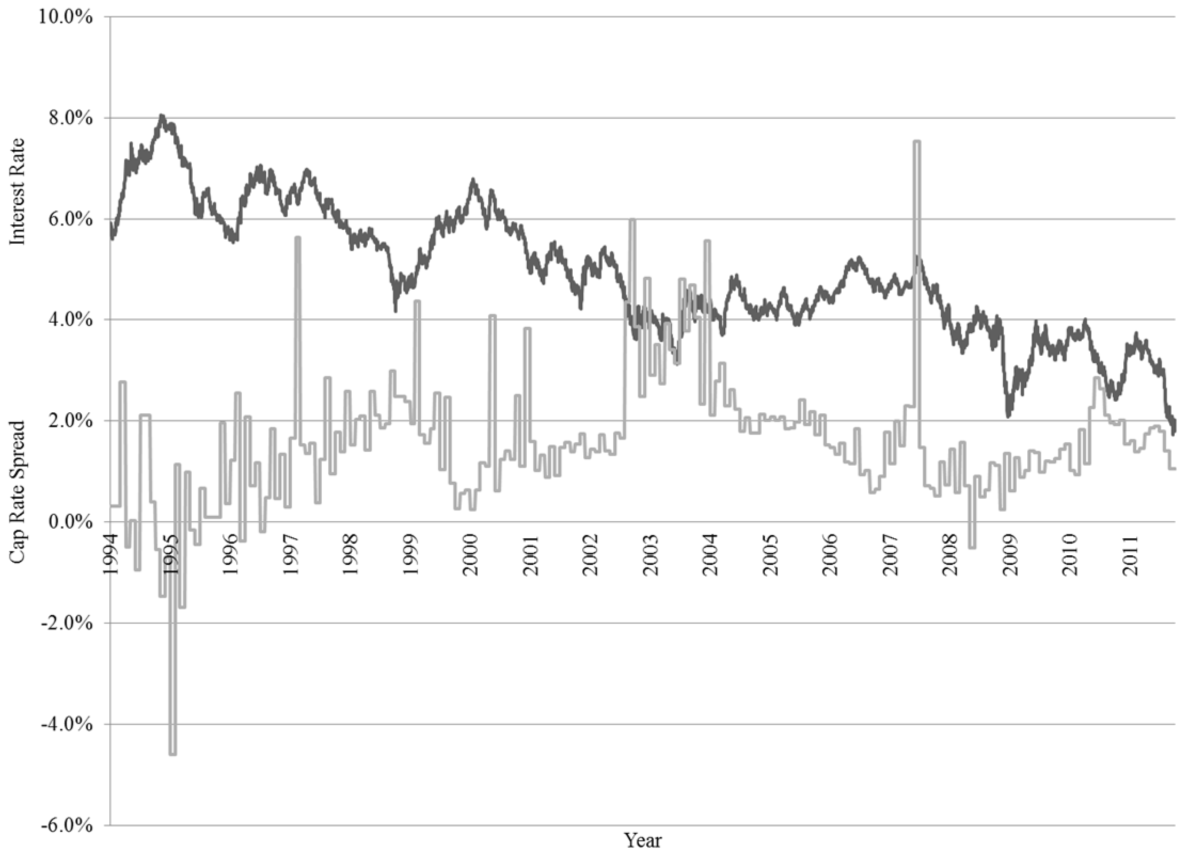
$$\textit{Cap Rate Spread (SPREAD)} = \textit{CAPRT} - \textit{Coupon}, \tag{5}$$

where Coupon is the net coupon rate on the loan. If LTV and DSCR were limited in their ability to predict loan default leading up to the recent market crash, perhaps their usefulness declined as interest rates fell. If so, other measures such as Debt Yield, Cap Rate, and the Cap Rate Spread may have emerged as important criteria in assessing risk and should be used to complement other methods and improve overall default prediction reliability. It can be shown that Debt Yield, as defined above, is simply the Cap Rate divided by the LTV at origination for the loan. A simple example makes the connection quite clear: a project valued at 100 with a loan of 70 will have a LTV of .7 and, if the NOI is 10, the Cap Rate will be .1 and the Debt Yield .14 calculated as either 10/70 or .1/.7. Acknowledging that both Debt Yield and Cap Rate may provide further insights into the factors related to CMBS loan performance, I focus on the measure Cap Rate Spread for the remainder of this dissertation.

During the critical phase of CMBS history beginning in the mid-1990s through today, interest rates have experienced periods of both falling and rising and have dropped to less than half of what they were at the beginning of this time period. Figure 2 shows that in the mid-1990s, rates on 10-Year Treasuries were around 7% and eventually fell below 2% in the fourth quarter of 2011. The second series on Figure 2 (the lighter line) shows the Cap Rate Spread over the course of the sample period. This series is expected to move in the opposite direction of interest trends as the Cap Rate Spread is constructed using the coupon rate on the loan.

Prior to 2003, the negative relationship appears clear in both direction and magnitude of the rate swings. However, the period after 2003 appears to have changed somewhat with a period of relatively stable interest rates coupled with Cap Rate Spreads which fell from 4% in 2003 to 1% in 2007. Even more noticeable beginning in 2007, the relationship seems to have become positive with successive periods during which both rates appear to fall or rise together. This seeming change provides a backdrop and further motivation for this study and may explain an increased role for Cap Rate Spread in predicting loan Non-performance in the more recent periods. The relationship between market interest rates and Cap Rate Spread may have changed during this period and merits further investigation confirming the change and testing hypothetical causes, if any.

Figure 2 ■ Cap Rate Spread and Market Yield on 10-Year Treasuries



Commercial loans written during different interest rate environments could start with the same DSCR yet have very different underlying cash flows. A future shock to the cash flows of these different projects could lead one to default while the other project would be able to remain current with debt service. Loans on projects with low overall returns, particularly those which also have low spreads between the project's Cap Rate and the rate of interest on the debt, may be at an increased risk of Non-performance and default. Introducing Cap Rate Spread into loan origination decision models may aid in identifying loans with an increased likelihood of experiencing future difficulty.

The main source for data used in this dissertation is the Bloomberg CMBS loan database, with originations dating from 1967 through 2011. The full database of both domestic and foreign loans includes 78,546 loans, as well as the 107,747 individual buildings and properties financed with the funds. In addition to property level information, the records include limited information about the current (recent) leases, or lack thereof, on these properties. Although the Bloomberg CMBS database also includes international loans starting in 1967, this dissertation will focus on U.S. loans during the period 1993-2011, during which the CMBS market grew rapidly.

This 1993-2011 period selected as the sample for this dissertation also coincides with changing economic conditions that include periods of both rising and falling interest rates, such as the period that began with 10-Year Treasury yields of 7% in late 1994 that dropped to 3.5% by April 2003. The shorter time period, the focus on U.S.-only loans, missing data, and outlier elimination results in a sample size of 47,883 loans. More than half of these loans fall into just one sizable group which combine a Rate Type of Fixed and an Amortization Type of Balloon. This group of loans that represents a typical CMBS loan during the significant growth of the industry is selected for more detailed investigation and analysis.

The loan data include the original loan balance, the balance as of securitization, the loan to value at origination, the amortization type, bond type, debt service coverage ratio, NOI, current and recent loan status, maturity and loan type, protection features, rate type, occupancy, and the recent value of the property. The property records include location, square footage, Cap Rate, NOI, and Net Cash Flow. The lease records (not used in this dissertation) include the tenant name, expiration date, square footage, lease exposure in dollars, and the proportion of overall square footage that each lease represents of the overall property total.

Objectives of the Dissertation

The overall objective for this dissertation is to extend the body of knowledge regarding an important aspect of the real estate debt market—the performance of loans underwritten for the CMBS market. The specific questions of interest addressed in this dissertation are as follows:

1. Can measures other than LTV and DSCR, such as Cap Rate Spread, provide additional information useful in predicting default of CMBS loans?
2. How do the typical Fixed Rate Balloon loans differ from other loans in their relationships between Non-performance and underwriting ratios such as LTV, DSCR and Cap Rate Spread?
3. During the recent financial crisis, could reliance on Cap Rate Spread have provided additional protection against future loan Non-performance?

To answer these questions, the relationships between the probability of Non-performance and the variables of interest, LTV, DSCR, and Cap Rate Spread are estimated with probit models. In addition to these variables of interest, the models also include variables which control for interest rates, recent stock market performance, loan interest rate, recent origination activity, loan size, and indicators for categorical variables such as rate type, amortization type, originating firm and property type. To test for sensitivity to the endogeneity between loan coupon rates and the ratios LTV and DSCR, I estimate the Non-performance relationships with a two-stage model which first estimates a predicted coupon rate. This predicted coupon rate is used to construct the Cap Rate Spread variable in the second stage of the model.

Sensitivity to the distribution assumption is tested by substituting a logistic model, with a logistic distribution, for the probit approach, which relies upon a cumulative normal distribution. Using typical screening criteria for LTV and DSCR, the analysis is performed with a sample of loans which would meet conservative underwriting standards to determine how Cap Rate Spread would perform among these presumably safe loans. Finally, a numerical analysis is undertaken to estimate the quantity of CMBS loans which would have been avoided following the conservative LTV/DSCR criteria and the additional loans which would have been avoided by adding a Cap Rate Spread floor. As a part of this numerical analysis, a limited type I error rate-like approach suggests the quantity of currently performing loans which would have never been originated had a Cap Rate Spread floor been utilized. One must be cautious in this regard as it may be that many of these loans predicted by Cap Rate Spread to be in a non-performing state have simply not entered this state… yet. Understanding the full extent of the Type II error, loans that are still performing but ultimately doomed to fail, is necessarily a matter of time.

Contribution of the Dissertation

This dissertation extends the real estate finance literature by proposing and testing new hypotheses about factors important in estimating the risks of commercial mortgages. Industry practice and the academic literature regard the traditional measures of LTV and DSCR as the primary criteria in underwriting commercial mortgages. This dissertation builds upon this foundation by taking into account additional considerations which may aid in predicting the performance of CMBS loans.

This dissertation takes a fresh approach to modeling the probability of CMBS loan default. The methodology incorporates variables described by past research, such as LTV, DSCR, and property type, but extends the scope of past work by adding factors such as Cap Rate Spread and exploring both the theoretical and practical implications of relying upon a Cap Rate Spread underwriting rule for CMBS loans. Using both single- and two-stage probit regression and numerical analysis, the expanded set of explanatory variables is incorporated into a model to estimate the probability of CMBS loan default and provides a hypothetical view of the consequences of relying on an additional underwriting rule based on the results.

To provide a background and theoretical foundation for the effects of regulatory and market events, this dissertation also documents and presents a historical perspective on the outside forces influencing origination decisions and how these decisions may have played a role in subsequent loan defaults in the CMBS pools. By extending the literature on CMBS loan default with factors such as recent loan origination activity, Cap Rate Spread, and introducing the potential effects on originator behavior induced by a changing regulatory environment, this dissertation adds to the collective knowledge of real estate finance and related disciplines.

Organization of the Dissertation

The balance of this dissertation is organized as follows: Chapter Two presents a background of past and current literature and the hypotheses tested in this dissertation; Chapter Three describes the data and methodologies employed in this dissertation; Chapters Four, Five, and Six present the results, a numerical analysis, and conclusions, respectively. The dissertation concludes with a list of references.

CHAPTER TWO – LITERATURE REVIEW

This chapter begins with a brief background of the CMBS market and a review of the academic research findings relating LTV and DSCR to CMBS loan performance and default. The literature on LTV and DSCR helps establish a foundation for this research by providing guidance on empirical methods, control variables and robustness measures. The next section discusses research findings which suggest additional factors related to default, alternative methodologies, related theories, and a broader look at loan default where the intersection between performance and default theory and methodology overlap with the CMBS market.

CMBS Background

Although the earliest CMBS loans recorded in the Bloomberg database date to the 1960s, the early-1990s saw an increasing acceptance of residential and commercial mortgage-backed securities with the mid- to late 1990s marked by the introduction of CMBS holding loans specifically originated for ultimate securitization. The Financial Institutes Reform, Recovery and Enforcement Act (FIRREA), and the resulting Resolution Trust Corporation (RTC) provided the impetus for CMBS growth through their efforts to liquidate the enormous real estate portfolios of the failed thrifts. The sample period under study also includes a myriad of legislative initiatives and changes such as SEC Regulation AB, Basel, the Volcker Rule, FDIC Safe Harbor, and Dodd-Frank, which may impact the incentives and resulting behavior of CMBS loan underwriters now and into the future.

The emergence of another securitization option in the mid2000s, collateralized debt obligations (CDOs), may also have influenced the origination standards of CMBS originators. In an environment with fewer restrictions on borrowers, the CDO alternative may have provided a more attractive option for those wishing to access a capital market hungry for yield and willing to invest heavily in commercial real estate. This competition for loans may have lead CMBS underwriters to relax their standards by offering higher LTVs and lower DSCRs to stave off an erosion of market share in a blossoming CDO market that typically provided floating rate terms and less onerous prepayment limitations.

Commercial mortgage default, which had a significant impact on insurance companies and pension funds throughout the 1980s, received a great deal of attention in the academic community. Since then, subjects such as the factors contributing to default, models of default probability, the valuation of prepayment and default options, and pricing have regularly appeared in prominent real estate, finance, and economics journals (Kau, Keenan, Muller III, and Epperson 1987; Vandell 1984; Vandell 1992). Research as early as the pioneering study by Vandell (1984) points out that using the models designed for residential default are inadequate because of the income-producing nature of commercial real estate and the differing economic sensitivities inherent in these distinct debt instruments. Vandell (1984) also suggests that the simple ratio tests in use at the time, such as LTV and DSCR, would not provide the intended information to help keep default risk below some predetermined level. The author contends that default prediction models should include information about the property such as location.

Vandell (1984) further posits that economic conditions such as interest rates, which change over time, are also important factors that affect the performance of commercial mortgages. In a detailed evaluation of the traditional ratio measures, the author also suggests that these ratios are woefully inadequate because they fail to make the connection between cash flows and the equity in a framework where cash flows and equity are volatile over time and may exhibit varying volatility between borrowers. This observation provides an important motivation for the investigation in this dissertation of Cap Rate Spread which makes the connection between cash flows and equity.

In one of the first works on the growing field of CMBS, Kau, Keenan, Muller, and Epperson (1987) identify two default scenarios: the first is when the value of the collateral is less than the outstanding balance of the loan; the second, when the collateral is worth more than the balance of the loan. The authors point out that for the second type of default to occur, there must be a large spread between market and contract interest rates during the prepayment lockout period. If not for the lockout period, prepayment rather than default would be the result when the property value is greater than the loan balance. This insight suggests that newer loans, which are more likely to be within the lockout period, are more prone to default with falling interest rates than loans which are older and more likely to be past the lockout date. Loans originated later in the sample period, thus more likely to be in the lockout period, and also faced with falling interest rates may be particularly susceptible to entering a state of Non-performance or default. This condition, along with the use of interest rate control variables, further motivates the study of Non-performance and the relationship between interest rate spread measures such as Cap Rate Spread.

The Kau, Keenan, Muller, and Epperson (1987) model assumed borrowers would exhibit what they termed "ruthless default," which means that borrowers would default as soon as their equity value fell below the mortgage value. Their model also assumed no transaction costs for default. Vandell (1992) challenged these assumption by testing an alternative theoretical model of rational default in the presence of transaction costs and found that surprisingly few borrowers defaulted even when LTV exceeded 1.1, a state in which borrowers are significantly "under water". Allowing for the possibility that some loans with high LTV were restructured, 75-85% of loans in this high-LTV category were retained by both borrower and lender, presumably to avoid the high costs of default.

Although the Vandell (1992) study—which uses quarterly data to relate the incidence of default to contemporaneous measures of LTV—focuses on contemporaneous measures influencing the probability of default, several features of the research provide guidance for this dissertation. Focusing on regions such as the South and the manner in which current interest rates affect the market value of the loans, the study points out the importance of both geography and interest-rate trends in predicting commercial mortgage default. In an interesting extension, Vandell (1992) uses simulation to project, under varying scenarios, the future of mortgage defaults, suggesting that foreclosure rates would double by 1993.

Following the widespread collapse of savings and loans and the subsequent large-scale commercial real estate liquidation by the Resolution Trust Corporation, the subject of loan default moved to the forefront in the eyes of academic researchers in a wide range of business disciplines including finance, economics, and real estate. In an evaluation of apartment mortgages and the factors leading to default, Archer, Elmer, Harrison, and Ling (2002) found that LTV was not related to default. Their conclusion suggests that LTV is a primary factor in pricing loans with lower-risk borrowers who are offered higher LTV debt structures. As a result, loan pricing (interest rate) and LTV are jointly determined. This endogeneity hypothesis is supported by their results, which also found property characteristics such as location and cash flow at the time of origination (DSCR) to be the primary factors in predicting default in their sample of multifamily mortgages from 1991-1996. The sample of the Archer, Elmer, Harrison, and Ling (2002) study, comprising 495 loans securitized by the RTC and FDIC, covered only a brief period of CMBS history and a much smaller number of loans than this dissertation utilizes. With the benefit of an increased sample size and longer period of time covering a variety of economic conditions, this dissertation should better detect and interpret the factors related to loan defaults while carefully considering potential endogeneity issues.

Interest Rates

As the market for CMBS was blossoming, Gallo, Buttimer, Lockwood, and Rutherford (1997) studied the performance of mutual funds holding mortgage-backed securities (MBS) relative to a variety of market benchmarks. Using single- and multi-index models, they found that MBS mutual funds underperformed other mutual funds and provided evidence that this was attributable to fund expenses, MBS selection, and timing. Gallo, Buttimer, Lockwood, and Rutherford (1997) also found that the effects were sensitive to periods of rising and falling interest rates.

When interest rates were rising, the MBS mutual funds underperformed, while no such result was detected during periods of falling interest rates. The authors also found that performance was heavily influenced by outlier periods, with performance more than two standard deviations away from the mean monthly returns. This result suggests that influences on the performance of MBS may change over time and that a long time series may mask dynamic relationships.

Commercial mortgage default and prepayment may also be evaluated in a competing risks framework wherein the borrower may, in any period, take one of three actions: prepay, default, or remain current. Ambrose and Sanders (2003) model the prepayment option as a function of changing interest rates relative to the loan coupon rate while taking into account the effects of prepayment lockouts and yield maintenance provisions that may be a part of individual loan agreements. Recognizing that interest rate expectations may affect the prepayment outcome, the authors also incorporate a yield curve variable into their empirical method: the spread between 1-Year and 10-Year Treasury rates. Since their analysis views prepayment and default as options, a measure of volatility is required to appropriately value the option. For interest rates, Ambrose and Sanders (2003) include a rolling standard deviation of the prior 24 months of the 10-Year Treasury.

Ambrose and Sanders (2003) find a significant and positive relationship between interest rate spreads and the loan coupon rates. Significant relationships were also found between default and both the term spread and interest-rate volatility, with the former being negative and the latter positive. In contrast to other results described in this dissertation, the authors found no significant relationship between LTV at the time of origination and default, though they did find that these higher LTV mortgages were more likely to prepay.

Also using a proportional hazard with competing risks, Ciochetti, Deng, Lee, Shilling, and Yao (2003) test for factors contributing to default and prepayment. In addition to the typical ratios at the time of origination, the authors use an estimate of contemporaneous DSCR and LTV on a quarterly basis using changes in the NCREIF property appreciation and the NCREIF income yield to approximate what would have happened at a property level if the values and incomes were affected in the same way as the other properties represented by the NCREIF data. Reasoning that the effects may vary depending upon the size of the loan, the authors also incorporate dummy variables for small, medium, and large.

Ciochetti and his colleagues found that the contemporaneous DSCR was significant and negatively related to the probability of default, while the DSCR at origination was insignificant. Similarly, the authors found that as contemporaneous LTV rose, so did the probability of default, though in a non-linear fashion. They also found significant increases in default probability among medium and large loans, balloon loans, and loans with a smaller spread between the coupon rate and 10-Year Treasury rates. The study used dummy variables for the different property types but found none to be significantly related to default probability or prepayment. To eliminate potential originator bias, this study used a weighting technique to make the smaller sample better fit the population.

The Ciochetti et al. (2003) study uses a sample of 2,043 commercial loans from one large insurance company with quarterly detail on default and prepayment. Their proportional hazard model with competing risks takes advantage of the quarterly data and provides a clear picture of how default and prepayment unfold over time but the larger sample of nearly 50,000 loans collected and analyzed for this dissertation spans a longer time period and provides additional insights into the relationships between loan features at origination and subsequent Non-performance.

In one of the early studies of the CMBS market, Childs, Ott, and Riddiough (1996) refer to CMBS as “a new and increasingly important class of structured debt.” Their work considers CMBS loan default risk in the context of CMBS tranche pricing. They employ a two-stage approach that first estimates the points at which borrowers in the pool will default and then uses Monte Carlo analysis to “follow” the loans through various paths while iterating interest rate and property price state variables. The findings for the senior tranche indicate that higher rates of default correlate with low rate outcomes. Finding positive correlation between interest rates and property values, the authors further suggest that the low rates would be associated with larger loans and higher probabilities of default. Their findings provide further motivation for evaluating the relationships between Non-performance and the level of interest rates, the size of loans, and the spread between Cap Rates and the interest rates on the loans, Cap Rate Spread.

Additional Considerations

Other factors and events such as geography, originators, property types, legislative changes, industry dynamics, and competition from new investment vehicles may affect performance of properties or the decision-making process at origination and lead to differences in the probability of Non-performance or default among commercial mortgages.

While the information available at the time of origination provides valuable insight into the probability of default of a commercial mortgage, it may also be the case that events that occur after origination affect the ultimate performance of a loan. A downturn in local economic conditions surrounding the properties funded by each loan may also put pressure on a borrower’s ability to repay the debt. Conversely, a strong local economy may provide some measure of protection against default even for highly leveraged commercial real estate projects. Using a regional analysis, Archer, Elmer, Harrison, and Ling (2002) incorporate home price appreciation, wage rates, per capita incomes, and employment levels, and found significant differences among several of the regions identified by the National Council of Real Estate Investment Fiduciaries (NCREIF).

Using only loan level data may ignore important information in estimating the probability of default. Characteristics of the property such as type, size, and number of tenants may also provide insight at origination as to the default probability of CMBS loans. Archer, Elmer, Harrison, and Ling (2002) incorporate multifamily property level information such as number of units, price per unit, year the building was completed, and whether the property is located in a judicial foreclosure state. They found that only the property age was significant in their logistic model.

When holding out the entire group of property level characteristics, tests for significance (change in Pseudo R^2, and Chi-Square) indicate that, as a group, the property level characteristics are more important than any other group of variables, including LTV, DSCR, financial institution, post-origination MSA factors, and location of the collateral. Though the property level factors dominate, property location significantly affects default probability. These results indicate that loan underwriters do not fully adjust their origination criteria to account for these property level and location risks. A sample with far more observations in each geographic cell may provide further insights into this dimension of loan default outcomes.

Following the Gallo, Buttimer, Lockwood, and Rutherford (1997) study of MBS mutual fund returns, Xu and Fung (2005) investigated the returns of an important residential MBS index. Estimating the relationships using a VAR model with data from 1988 through 2001, the authors found, among other factors, that index returns are related to interest rates, term structures, and new home sales. Their results were confirmed by using variance decomposition and impulse response techniques. The authors break their sample period into two periods to discern the effects of the introduction of the Office of Housing Enterprise Oversight (OFHEO) in 1992. They posit that the introduction of this governmental entity may have altered the risks inherent in the MBS market. By analyzing the sample during these two regimes, the authors found evidence of a structural change in the MBS market after which investors recognized that these securities may be exposed to greater risk than previously assumed. This study suggests that the introduction of regulatory and statutory events into a set of variables provides important insight into how the CMBS market has developed over the last twenty years.

Titman and Tsyplakov (2010) studied the characteristics of commercial mortgage originators and found that loans originated by recent stock price losers tended to default more often than loans of other firms. They also found that broad financial market performance was an important factor, with differences greater during significant market downturns. This result provides motivation for including broad market indicators, such as interest rates, in the new models, as these may also affect the probability of default for firms originating during these periods and may also affect individual originators differently.

The authors ascribe the effects to firms choosing short-term profits at the expense of their reputation. Firms earned short-term profits in the form of origination fees by lowering their underwriting standards and taking on riskier loans. This hypothesis is supported by evidence that ratings agencies tend to assign lower scores to pools that contain loans from underwriting firms whose stock price have seen recent declines, firms more likely to take on riskier underwriting behavior. See also Deng, Gabriel, and Sanders (2011) and Furfine (2011).

Grovenstein, Harding, Sirmans, Thebpanya, and Turnbull (2005) tackle the seeming inconsistency between the options theoretic prediction of LTV's impact on default and what is borne out in other studies by building on the notion that LTV, along with DSCR, is endogenous to loan pricing. Expanding on the work of Archer, Elmer, Harrison, and Ling (2002), they posit that, unlike most residential mortgage underwriters, commercial mortgage underwriters simultaneously adjust LTV and DSCR along with other contract terms of the loans, such as the interest rate. If, as the authors suggest, these influences are jointly determined, then seemingly inexplicable relationships between default probability and the standard underwriting ratios make perfect sense.

Grovenstein et al. (2005) employ a much larger sample of loans (10,547) than prior studies and predict that there should be no unpriced LTV risk of default in commercial mortgage loans. With the exception of the multifamily and hospitality sectors, the results support their hypothesis, finding that LTV at origination is largely insignificant in predicting default. The authors offer possible reasons for the multifamily and hospitality results, including investor preference for GSE-backed multifamily properties and the 9/11 terrorist attacks.

In another recent study, Black, Chu, Cohen, and Nichols (2011) found significant differences between types of originators and suggested that the differences arose from incentive distortions that vary among different groups of originators, including conduit lenders and balance sheet lenders such as insurance companies, finance companies, and commercial banks. They found a greater likelihood of default among conduit lenders that originated all their loans for subsequent sale to other parties. Although the authors expected adverse selection to dominate, they found that balance sheet lenders underwrote higher-quality loans. They attributed this to higher-quality underwriting systems and more experienced underwriters because of the quantity of other loans originated for their own balance sheets.

Using a technique similar to estimating the volatility of a security when the price and option value are known, Downing, Stanton, and Wallace (2008) use the Titman and Torous (1989) mortgage-pricing model to arrive at an implied volatility of CMBS loans. Their approach uses a large sample (more than 14,000 loans originated from 1996-2005) to also simulate the default rates on CMBS loans and ultimately model the subordination levels required to prevent defaults on the various tranches, such as BBB securities. The Downing, Stanton, and Wallace (2008) study provides an early warning of things to come as defaults on CMBS securities began to balloon. The authors point out that while volatilities remained constant, subordination levels of securities steadily declined, suggesting a much higher default probability than their credit ratings indicated.

Additional sources for CMBS and commercial mortgage default research include Christopoulos, Jarrow and Yildirim (2008), Yildirim (2008), De Leonardis and Rocci (2008), Kau, Keenan, and Yildirim (2009), Corcoran (2009), Chen and Deng (2010), An, Deng, and Sanders (2010), An and Sanders (2010), and Seslen and Wheaton (2010).

Alternative Approaches

The majority of research in the commercial mortgage default domain focuses either on equity (through LTV), or cash flow (through the DSCR of a loan, either at origination or over time as the loan seasons). Goldberg and Capone (1998; 2002) advanced a theory that these equity and cash flow measures, if used alone, would provide biased estimates of the probability of default on commercial mortgages. They posited that relying on LTV alone would tend to overestimate the probability of default for commercial mortgages while reliance on DSCR would tend to underestimate the probability of default.

Goldberg and Capone (1998; 2002) suggested that their double-trigger model would better estimate the probability of default than other approaches because the combination of negative equity and negative cash flow would push borrowers to default even though borrowers facing only one of these conditions may be unlikely to default. The results of this research combining equity and cash flows into loan performance predictors in the multifamily sector from 1983-1995 provide motivation to build upon this work with other equity/cash flow measures in a more extensive sample of commercial mortgages.

Summary

The real estate literature provides ample evidence that LTV and DSCR are important factors in measuring risk among commercial real estate loans. Beginning with theoretical research into the default that use hazard models to predict future outcomes, and including more recent studies that leverage increasing years of historical data, the research has largely been silent regarding yield measures such as Cap Rate Spread. The recent growth in the CMBS market, the rise in default rates, and falling interest rates provides motivation to investigate an alternate measure, Cap Rate Spread, which may help us better understand CMBS loan default risk.

Hypotheses

Motivated by empirical results of prior CMBS research, limitations of prior models to predict CMBS performance in some circumstances, and observations of the increased level of CMBS loan default in the wake of the recent financial crisis, the following hypotheses are tested in this dissertation:

H1: There is a significant and negative relationship between the Cap Rate Spread of a CMBS loan at origination and the probability of Non-performance.

While the empirical evidence is mixed on the adequacy of ratio tests at origination to predict the likelihood of default, it is reasonable to expect that a hybrid of the typical ratio tests, one that compares project cash flows to project value would provide additional information that would be useful in estimating default probability. The subsequent hypotheses are tightly related to Hypothesis 1.

H2: Among a homogenous sample of typical CMBS loans, Cap Rate Spread will have a negative and significant relationship with Non-performance.

Hypothesis 2 recognizes that the relationship between Cap Rate Spread and Non-performance, if any, may vary among loans with differing combinations of rate and amortization type. Due to the wide range of loan types and borrower characteristics, the expected relationships may not be detected in the empirical tests for Hypothesis 1. In order to test the theoretical relationship with a relatively homogenous group of loans, fixed rate balloon loans are selected for a closer investigation. A negative and even more significant relationship between Cap Rate Spread and CMBS loan Non-performance CMBS is expected among this group.

H3: Among loans which would satisfy typical underwriting ratio tests for LTV and DSCR, Cap Rate Spread will have a negative and significant relationship with Non-performance.

Hypothesis 3 considers the expected outcome of policies which extend the traditional underwriting standards to include Cap Rate Spread. In order for an additional CMBS underwriting ratio test to be of practical value, it must provide information beyond that of the well-known and accepted standards for LTV and DSCR. It is expected that, when a sample of loans which would have been considered "safe" by LTV and DSCR standards is employed to estimate the relationship between Cap Rate Spreads, the coefficient estimates for Cap Rate Spread will be negative and significant.

H4: A Cap Rate Spread floor underwriting standard would have considerably lowered the level of CMBS loan Non-performance during the recent financial crisis.

The theory tested under Hypothesis 4 arises from the goal of offering some practical utility as an outcome of this research. Of course, Hypothesis 4 may be proven by simply choosing a very high Cap Rate Spread that would eliminate all loans. Therefore, the results of tests for Hypothesis 4 should be viewed as hypothetical and merely designed to demonstrate the results of one choice for a Cap Rate Spread floor. Although the numerical analysis used to "test" Hypothesis 4 does not provide statistical evidence in the traditional sense, it should offer some guidance to participants in the CMBS market seeking alternative or additional underwriting criteria.

CHAPTER THREE – DATA AND METHODOLOGY

Data

This dissertation uses detailed information about loans held in CMBS from the Bloomberg CMBS Loan database. This data source provides loan-level information from the time of origination, the most recent period, and a record of recent status indicators. A subset of the full CMBS loans database selected for this research consists of loan records for 47,883 U.S. loans beginning on 1/1/1993 and ending on 9/15/2011. The second source of data, also from the Bloomberg CMBS system, is a detailed listing of the CMBS collateral backing up the loans. These data include the locations, area, and other property-level details. Table 2 describes select data from the Bloomberg loans and property series. Constant maturity yields of U.S. Treasury bond rates are provided by the U.S. Department of the Treasury. Using methods similar to Archer, Elmer, Harrison, and Ling (2002), outliers and extreme cases in ratios such as LTV and DSCR are eliminated.

In addition to the fields directly gathered from the sources listed above, several variables, including many key variables of interest, were calculated as described in the introduction of this dissertation. These variables include Cap Rate Spread, recent S&P returns, recent CMBS Origination activity, and predicted Coupon Rate used in the first stage of the two-stage models.

Although, the Bloomberg database included CMBS loans beginning in 1967, this dissertation focuses on the period of great CMBS expansion through the mid-1990s, beginning with 1993.

The starting sample of 78,546 loans is reduced by 55 to 78,491 by eliminating loans prior to 1993.

Table 2 ■ Variables from the Bloomberg CMBS Loan Database and other sources.

Name	Variable	Description
Amortization Type	*AMORT*	Indicator variables for the type of ammortization such as Interest Only
Coupon Rate	*NETCPN*	The original loan coupon rate
Coupon Spread	*CPNSPRD*	The difference between the coupon rate and the U.S. 10 Year Treasury Note
DSCR	*DSCR*	Debt service coverage ratio as of the date of securitization
10 Yr Treasury	*INT*	The constant maturity yield on the 10 year U.S. Treasury Note
Loan Balance	*LnSIZE*	Loan balance as of the date of securitization (natural log)
LTV	*LTV*	Loan to value ratio as of the date of securitization
NOI	*NOI*	Net operating incomeas of the date of securitization
Non Performing	*NONP*	Indicator variable: 1 if Non-Performing, 0 otherwise
Origination Dt	*ORIG_DT*	Calendar date of loan origination
Origination Volume	*DEALS*	The number of originations in the 12 months prior to the origination of the observation
Originator	*ORIG*	Indicator variables for loan originator such as Morgan Stanley
Property Type	*PTYPE*	Indicator variables for the type of property such as Hospitality or Office
Rate Type	*RATE*	Indicator variables for loan rate type such as Fixed or LIBOR
S&P Returns	*SPY*	The 12 month return on the S&P index prior to the origination of the observation
State	*STATE*	Indicator variables for state such as California or New York

Notes: Variables from the Bloomberg loans database, property database, the U.S. Treasury for T note history, and Yahoo Finance for S&P index historical values.

Because the focus of this research is on CMBS loans in the U.S. market, the final sample includes only those loans originated for U.S. properties. Removing properties in Canada, Mexico, Great Britain, France, Italy, Czechoslovakia, and other countries further eliminated 5,295 loans from the sample, leaving a U.S.-only sample of 73,196 loans. Because the variables of interest and the calculated items required for the regression are not present in all observations, some of the loans are eliminated from the sample due to missing data. Screening for observations with a valid NOI, required for the computation of Cap Rate and Cap Rate Spread, reduced the database to 51,251 loans. Requiring loans to have original balances greater than 0 eliminated 69 loans, bringing the total to 51,182.

To eliminate outliers, Archer, Elmer, Harrison, and Ling (2002) set cutoff criteria that required the contract rate to be between 5%-20% and higher than the 10-year constant maturity risk-free rate, an original LTV of less than 100%, and a DSCR between .9-5. The sample period for this research includes years during which rates below 5% were not uncommon, with 4,706 U.S. loans (6.2% of the total) carrying coupon rates below 5%. Allowing for the influence of these lower-rate loans, a cutoff level of 3% is used, which eliminated only 5 loans. Following the 20% cutoff point for the maximum rate eliminated no loans from the database, as the highest rate in the sample is 15%.

Further screening for database errors and outliers eliminated all observations with a LTV below 0 or above 1, further reducing the database by 200 to 52,086. Additional observations are removed from the database by eliminating those with a DSCR below .9 and above 5, further reducing the sample by 1,054 to 49,923. Finally, loans with a status of Defeased, Mixed, Matured, or Special are removed, reducing the sample by 2,040 to 47,883. Table 3 presents the waterfall of data screening and the resulting sample size.

Table 3 ■ Database Waterfall

Level / Restriction	Lost Observations	Remaining Observations
All Loans		78,546
After 2003	55	78,491
US Only	5,295	73,196
Valid NOI	21,945	51,251
Original Loan Balance > 0	69	51,182
3% + Coupon	5	51,177
LTV between 0 and 1	200	50,977
DSCR between .9 and 5	1,054	49,923
Valid Status	2,040	47,883

Notes: Each level represents the additional observations eliminated due to loans failing to meet the restriction listed. The Bloomberg database includes loans with international collateral, only those with US collateral only are used. Only observations which included net operating income, necessary for computing Cap Rate, are included. Observations with a loan balance of zero or a negative amount are eliminated. Loans with coupon rates below 3% are eliminated. Loans with LTV below 0 and above 1 are eliminated. Loans with DSCR below .9 or above 5 are eliminated. Loans with status of Defeased, Matured, Mixed or Special are eliminated.

Methodology

This dissertation uses a probit model to estimate the probability of Non-performance among loans within CMBS portfolios. The probit methodology estimates the parameters when a dichotomous dependent variable is regressed on one or more continuous or categorical variables. The resulting parameter estimates indicate the change in the probability of the dependent variable taking on the value of 1. The probit methodology was introduced by Chester Bliss (Bliss 1935; Greenberg 1980; Holford and White 2005) in collaboration with R.A. Fisher and is further developed by Finney and Stevens (1948) and Finney (1952). Either the probit or logit approach may be used in estimating the parameters in such a scenario.

The selection of a particular model, once influenced by computing power, is now typically a matter of preference (Vincent 2008). Hahn and Sawyer (2005), however, showed that with large sample sizes and random effects, the probit link function may provide superior results in a multivariate model than the logit approach, while in the presence of fixed effects or in situations with extreme values, there may either be no difference or the logit approach may provide better deviance results. An important assumption in selecting the probit methodology is that the relationship between the number of CMBS loans defaulting and LTV, DSCR, Debt Yield, and Cap Rate are normally distributed. To monitor the results for sensitivity to selection of probit over logit, select tests are also conducted using the logit approach.

The probit methodology was first used for applications such as mortality rates at various concentrations of drugs in medical studies where a base "mortality correction" must be made if the mortality in the control group is greater than 10%. For the CMBS loans under study here, no corollary exists for a no-treatment group, as all loans would have some level of LTV, DSCR, Debt Yield, and Cap Rate as opposed to a control group in a medical study that may have received a placebo and thus there would be zero concentration of the drug in question. With this in mind, there is no need in this study to adjust the base level of mortality (default) as suggested by Schneider-Orelli (1947).

The probit model takes following form:

$$Pr\ (Y = 1 \mid X) = \Phi(X'\beta), \qquad (6)$$

where Pr is the probability and Φ is the cumulative distribution function of the standard normal distribution. The parameters, denoted by β, are estimated with SAS© 9.2 using the PROBIT function, which relies on the maximum likelihood procedure.

In the biological sciences, the term LD50 refers to the medial lethal dose of a chemical or a toxic substance. If one were to consider financial ratios as potentially lethal substances for a CMBS loan, a certain level of one of these ratios may correspond to a median level of loan default, controlling for other factors. For example, if the LTV approaches a certain level, one might expect to see defaults in half of all CMBS loans. Similarly, as the DSCR falls, one would expect to reach a point where half of all loans default with insufficient cash flow to cover the mortgages. Centered in the distribution, the formula for LD50, the point at which a financial ratio could be said to "kill" half of all loans, is the same for both probit and logit models[3] (UCLA-ATS 2011). The formula for LD50 follows the form:

$$LD50 = -\ constant/coefficient. \tag{7}$$

As one moves, however, into the tails of the standard normal and logistic distributions, the probit and logit values diverge slightly due to differences in the normal and log functions. Substituting p for the level of the substance (ratio) in question, finding the LD for a probit model requires the following calculation:

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[3] For further description of LD50 and LDp calculations with both probit and logit methodologies, see the UCLA Academic Technology Services website at http://www.ats.ucla.edu/stat/mult_pkg/faq/general/ld50.htm

Probit LDp = (invnormal (p) - constant)/coefficient. (8)

With the logistic distribution, a logit model uses a different formula to compute the LD levels with the following formula:

Logit LDp = (log (p/(1-p)) - constant)/coefficient. (9)

The toxic substance metaphor becomes more interesting when one considers medical drug interactions and how they may lead to increased probability of deadly side effects. Levels of a substance (ratio in the case of loans) that cause mild reactions among subjects may, when combined with low levels of another substance (ratio or interest rates), lead to high mortality rates (loan defaults). For this reason, the models are extended to include interaction terms among the various loan ratios, and between them and other loan and economic characteristics such as Cap Rate Spread.

In this research, a probit model measures the impact of the independent variables on the probability of a CMBS loan having a current status of “Non-performance” as indicated in the database by the variable “Status.” A new variable labeled “NONP” is created, with all observations other than those having a Status of Perform or Perform (w)—which indicates that the loan is performing but has been placed on the servicer’s watch list. Non-performing loans are assigned a value of 1; Perform and Perform (w) loans are assigned a value of 0.

The equation below provides an example of the approach followed in this dissertation. In this example, only one of the ratio measures (LTV or DSCR) is included in the model along with the natural log of loan size, recent S&P index returns, market interest rate, the spread between the market rate and the loan rate, the spread between the Cap Rate and the loan rate, as well as indicator variables for amortization type, interest rate type, state, loan originator, and property type. These variables are all described later in the Data and Methodology section. Other models will incorporate combinations of the ratio measures, as well as two-stage equations, and split samples with the goal of testing the robustness of the results.

$$NONP\begin{Bmatrix}1\\0\end{Bmatrix} = f\,(LTV \text{ or } DSCR,\ LnSIZE,\ SPY,\ INT,\ CPNSPRD,\ CAPSPRD,\ AMORT_i,\ RATE_i,\ STATE_i,\ ORIG_i,\ PTYPE_i) \qquad (10)$$

Hypothesis 1

Hypothesis 1 tests the theory that the spread between the rate of interest on the loan and the Cap Rate at the time of origination (Cap Rate Spread – *CAPSPRD*) is negatively related to Non-performance. This theory would predict that as the cushion between the loan interest rate and the Cap Rate on the property increases, the incidence of Non-performance would drop. Conversely, the theory would predict that loans underwritten with a very low margin between the loan interest rate and the return on the property are at greater risk of Non-performance and ultimately of default. In testing Hypothesis 1, probit model parameters are estimated with the equation:

$$Pr\ (NONP = 1 \mid X) = \Phi(X'\beta), \qquad (11)$$

where X' is a vector of one of several combinations of the following covariates:

Loan to Value—this variable (*LTV*) is the ratio of the original loan balance to the value of the property. Lenders typically require between .75-.85 for project approval, though it was not uncommon during the mid-2000s for LTVs to be much higher, often approaching 1.0 and sometimes moving beyond.

Debt Service Coverage Ratio—this variable (*DSCR*) is the ratio of a borrower's (project's) annual net operating income to the annual debt service requirement including both principal and interest. Lenders generally require ratios between 1.1-1.25 for project approval.

Loan Size—the natural log of original loan balance in dollars (*LnSIZE*) for each observation. This variable is intended to capture loan performance risks and underwriting behavior differences related to the size of the project and loan amount originated.

Equity Market Returns—the yield on the S&P Index for the prior 3-month period. This variable is intended to capture the effects of the broad U.S. stock market on CMBS loan underwriting behavior. Recent gains or losses in the stock markets may differentially affect the underwriting decisions due to changed demand for CMBS products, return expectations, and sentiment. S&P Yield (*SPY*) measures the change in percent of the S&P Index for the three month period preceding the origination of the observation.

Interest Rate—the rate of the 10-Year constant maturity Treasury at the time of loan origination. This data series is retrieved from the U.S. Treasury website and is matched with the Bloomberg loan data using the date of origination for the loan and the date provided in the daily rate file. Interest Rate (*INT*) measures the market yield in percent per year on 10-Year constant-maturity Treasury securities, quoted on investment basis.

Origination Volume—the number of CMBS loans originated in the 12 months prior to the origination of the observation. This variable is scaled by a factor of .01 in order to aid the presentation and interpretation of the coefficient estimates. Origination (*DEALS*) measures the number of CMBS loan originations in the last 12 months, divided by 100.

Coupon Spread (*CPNSPRD*) – the difference between the coupon interest rate on the loan at origination (*NETCPN*) and the market yield on 10-Year Treasuries on the date of loan origination (*INT*). In theory, a commercial loan coupon rate should represent the investor's required rate of return, i.e., the discount rate utilized in determining the present value of the loan's cash flows. The difference between the prevailing interest rates and the coupon rate on a commercial mortgage should represent the originator's assessment of default risk for the loan relative to alternative investments and may serve as a normalized measure of loan risk. As the LTV on a loan rises and the DSCR on a loan falls, one would expect the coupon spread (*CPNSPRD*) to rise accordingly. As a result, multicollinearity is to be expected among these variables. Assuming, however, that underwriters consider other, perhaps unmeasured, factors in addition to LTV and DSCR in making origination judgments, the net coupon rate may capture attempts to price these risks into the loan.

Cap Rate Spread—this variable (*CAPSPRD*) is the spread between the coupon rate of the loan and the Cap Rate, the ratio of the net operating income of the property serving as collateral for the total value of the project. Cap Rate, also called the overall capitalization rate, is used in evaluating commercial real estate and represents an unleveraged rate of return on the project.

State — The largest group of the CMBS loans were originated for property in the state of California (10,576) while Vermont saw only 68 loans originated during the sample period. Due to differing economic conditions, regulatory environments, and business cycles, controlling for geography is an important consideration when estimating the factors affecting CMBS loan performance. In order to control for these geographic conditions, indicator variables are created for each state plus Washington, DC. $STATE_i$ indicator variables represent the State where the loan collateral is located.

Rate Type — The CMBS loan underwriters shifted risks to the borrower in varying degrees by offering different fixed and adjustable rate types. Like the amortization, the type of rate may reflect a bank's assessment of the risk and would be an important factor in understanding and comparing the actual rate set on the loan. For example, a rate of 5% may be at the same time high for an adjustable loan and low for a fixed rate loan. Example rate types include fixed and those indexed to LIBOR, EURIBOR, prime, COFI, and U.S. Treasuries. $RATE_i$ indicator variables represent the rate type of the loan.

Amortization Type —All things being equal, the amortization type for a loan may reflect a bank's assessment of the risk and would be an important factor in understanding and comparing the actual rate set on the loan. Example amortization types include fully amortizing, interest only, balloon amortizing, partial interest only, and mixed. $AMORT_i$ indicator variables represent the amortization type of the loan.

Property Type—the building serving as collateral for each CMBS loan may be in one of several different property-type categories including office, retail, industrial, and multifamily. Because each of these property types may be subject to differing sensitivities to the variables of interest in this study, they are incorporated into the model to control for this possibility. Over the last twenty years, in addition to periods of increasing and decreasing interest rates, there have also been periods or cycles of greater CMBS loan activity in different commercial property types. During some periods, for example, there was a much larger proportion of loan originations in multifamily dwellings, while other periods saw more activity in office or other property types.

Different property types may be more or less sensitive to varying economic conditions and thus the loans underwritten to fund projects in different property categories may vary in their probability of default. Further, the likelihood that loans in different property types will default may vary according to the interest rate environment during which they were originated. One motivation for this extension is the observation that some periods had originations that were almost exclusively in one property type while other periods had mixtures of different property types. Ignoring this important variable may introduce a missing variable bias and lead to erroneous conclusions regarding other variables that tend to vary over time. $PTYPE_i$ indicator variables represent the predominant property type serving as collateral for the loan.

Originator—the financial institution responsible for underwriting and originating the loan. The institutions rely upon the various ratios, industry knowledge, proprietary information, and personal relationships to assess risk and price the loan terms. The real estate literature proposes other variables such as recent negative stock performance of loan originators, which may prompt more risky underwriting in order to generate fees. Additionally, the history of the CMBS market includes large swings in the economy and regulatory changes which may have altered the behavior of loan originators in ways that precipitated the troubles that followed.

Some CMBS loan underwriters, such as U.S. conduits and foreign entities, have experienced high levels of mortgage defaults while others, such as insurance companies, have fared better despite intense economic pressure on the industry as a whole during the recent financial crisis (Black, Chu, Cohen, and Nichols 2011). Though some firms take a more aggressive approach with respect to LTV and DSCR standards, their methods may also be influenced by such factors as firm culture, incentive structures, and governance characteristics. This conjecture provides motivation to test for originating firm variables that go beyond the traditional ratio tests in predicting CMBS loan default. Therefore, in this dissertation, the analysis is extended by incorporating indicator variables for each CMBS loan originator. $ORIG_i$ indicator variables represent the firm originating the CMBS loan.

With the full list of variables, the model tested under Hypothesis 1 may be presented as:

$$NONP\begin{Bmatrix}1\\0\end{Bmatrix} = f\,(LTV \text{ or } DSCR,\ LnSIZE,\ SPY,\ INT,\ DEALS,\ CPNSPRD,\ CAPSPRD,\ AMORT_i\,,\ RATE_i,\ STATE_i,\ ORIG_i,\ PTYPE_i) \qquad (12)$$

Hypothesis 2

In testing Hypothesis 2, estimates are calculated using the prior probit model parameters with the sample divided into two distinct groups: Fixed-Rate Balloon loans and all other loans. As with the prior model, the dependent variable is Non-performance and *X'* is a vector of a covariates, including Cap Rate Spread as the variable of interest. The remaining variables used in the model to test Hypothesis 2 remain unchanged from the prior model, resulting in the following full model for Fixed Rate Balloon Loans:

$$NONP\begin{Bmatrix}1\\0\end{Bmatrix} = f\,(LTV \text{ or } DSCR,\ LnSIZE,\ SPY,\ INT,\ DEALS,\ CPNSPRD,\ CAPSPRD,\ RATE_i,\ STATE_i,\ ORIG_i,\ PTYPE_i) \qquad (13)$$

Equation (13) is estimated for Fixed Rate Balloon Loans only. Similarly, the model used to estimate the relationships for all other loans is specified as follows:

$$NONP\begin{Bmatrix}1\\0\end{Bmatrix} = f\,(LTV \text{ or } DSCR,\ LnSIZE,\ SPY,\ INT,\ DEALS,\ CPNSPRD,\ CAPSPRD,\ AMORT_i\,,\ RATE_i,\ STATE_i,\ ORIG_i,\ PTYPE_i) \qquad (14)$$

The sample used to estimate Equation (14) excludes all Fixed Rate Balloon Loans.

Hypothesis 3

Hypothesis 3 tests the value of a Cap Rate Spread underwriting standard above and beyond the result of using LTV and DSCR standards. Using a LTV cutoff of .8 and a DSCR cutoff of 1.25, only loans which would pass underwriter scrutiny under both of these standards are considered in using a model to estimate the parameters for Cap Rate Spread and the other covariates.

Consistent with the model under Hypothesis 2, the model used to estimate the relationships tested under Hypothesis 3 is specified as follows:

$$NONP\begin{Bmatrix}1\\0\end{Bmatrix} = f\,(LTV \text{ or } DSCR,\ LnSIZE,\ SPY,\ INT,\ DEALS,\ CPNSPRD,\ CAPSPRD,\ AMORT_i,\ RATE_i,\ STATE_i,\ ORIG_i,\ PTYPE_i) \qquad (15)$$

Equation (15) is estimated for only loans with *LTV* less than .8 and *DSCR* greater than 1.25 at the time of origination. As with the results from the prior probit models, the coefficient for Cap Rate Spread in this model will estimate the *z*-score or change in probability of Non-performance that is associated with a one-unit change in Cap Rate Spread. A significant negative relationship would support Hypothesis 3 indicating that Cap Rate Spread provides additional information even among loans considered safe by LTV and DSCR standards.

Hypothesis 4

The fourth and final Hypothesis contends that an underwriting standard utilizing Cap Rate Spread may help reduce the level of non-performing loans. While the selection of a floor beyond which loans would not be originated is somewhat arbitrary and subject to manipulation, the process illustrates the outcome potential of such an exercise. Underwriters of different firms face a wide range of investment objectives, loan approval pressures, system sophistication, and other underwriting standards. Each underwriter may choose to set their standards for LTV, DSCR, and Cap Rate Spread according to their individual firm's appetite for risk, the expected proportion of loans to be held on the company's own books, or other criteria. For this numerical model, the "safe" sample used to test Hypothesis 3 is again chosen to test further restrictive criteria for approving loans: a minimum Cap Rate Spread of 1%. Loans below this floor would not be approved even though they may have passed the LTV and DSCR requirements previously described. The outcome of this process will be a new set of loans which would have met all three standards. The remaining loans are those which would have passed the LTV and DSCR tests but failed the Cap Rate Spread test.

Evaluating each of these sets provides some interesting, though admittedly limited, insights into how a Cap Rate Spread-based underwriting rule would have performed through the recent financial crisis. Among the loans that would have been declined are many which are still performing today. Similarly, the set of loans which passed all three tests includes many non-performing loans. These two groups of loans-performing loans which would have never been originated and non-performing loans which passed all three ratio tests-are similar to the false positive (Type I) and false negative (Type II) errors reported with other forms of testing and analysis. It is important to point out that this numerical modeling approach is intended to simply provide insight into how Cap Rate Spread underwriting criteria may be incorporated into a comprehensive underwriting process. The error rates associated with the different sets of rules will be reported along with the changes to the quantities of loans originated throughout the sample period.

Robustness Checks

In addition to the primary methods outlined to test the hypotheses, several robustness checks will be conducted to test for sensitivity to choices made as part the research design. First, selected probit model specifications will also be conducted using a two-stage regression methodology designed to correct for possible endogeneity between the pricing of the loan (*NETCPN*) and the traditional ratios LTV and DSCR. If these factors are jointly determined in a process which trades off values of these against each other, results which assume their independence will be biased. Because Cap Rate Spread is calculated using Net Coupon Rate, endogeneity with LTV and/or DSCR would bias the estimated coefficients of the relationships between these right hand side variables and Non-performance. The first stage of the two-stage model will estimate the Net Coupon Rate of the loan using some overlapping variables along with a set of instrumental variables which identify the equation. The first stage of the model is as follows:

$$NETCPN = f\,(LTV,\ DSCR,\ INT,\ YQ_i,\ STATE_i,\ RATE_i,\ AMORT_i,\ PTYPE_i,\ ORIG_i). \qquad (12)$$

The predicted net coupon rate (*PREDNETCPN*) for each observation is used to calculate a predicted Cap Rate Spread where:

$$PREDCAPSPRD = CAPRT - PREDNETCPN. \qquad (13)$$

In the second stage of the model, the *CAPSPRD* used in prior models is replaced by the value derived from the predicted net coupon rate (*PREDNETCPN*). The resulting equation is as follows:

$$NONP\begin{Bmatrix}1\\0\end{Bmatrix} = f\,(LTV \text{ or } DSCR,\ LnSIZE,\ SPY,\ INT,\ DEALS,\ CPNSPRD,\ PREDCAPSPRD,\ AMORT_i\,,$$
$$RATE_i,\ STATE_i,\ ORIG_i,\ PTYPE_i) \qquad (18)$$

An additional concern in estimating the models in this dissertation is the assumption that the binary relationship between the right hand side variables and the incidence of Non-performance follows a standard normal distribution. It may also be the case that a logit model, which assumes a logistic distribution, better fits the true relationships. To test this assumption, select models are modified and estimated using a binary logistic method to test for sensitivity to the distribution assumption. Parameter estimates, direction and significance are expected to be similar to those estimated using probit models.

CHAPTER FOUR – ANALYSIS OF RESULTS

Descriptive Statistics

In order to provide a broad appreciation for the CMBS loan sample, basic statistical measures are reported for the variables used in this dissertation including minimum value, maximum value, mean, and standard deviation. Additionally, tables separating the sample by values for each of the dummy variables describe the size of each category and the mean values for the other key variables including LTV, DSCR and Cap Rate. Analyzing the distribution of the sample categorically reveals likely drivers of heterogeneity within the sample and provides a rationale for including the respective control variables for factors such as the regional variation captured by using $STATE_i$ indicator variables. The first table of descriptive statistics, Table 4, provides summary statistics describing the variables of interest for the full date range of the database – January 1993 to September 2011.

The size of loans underwritten for CMBS distribution varies considerably with an average loan amount of $12.4 million and a standard deviation of $43.2 million. The sample of loans includes several very large loans such as the Equity Office Portfolio at $6.87 billion, the Hilton Worldwide Portfolio at $2.87 billion, the Extended Stay Hotel Portfolio at $2.0 billion, Rockefeller Center at $1.69 billion, the largest of the Peter Cooper Village/Stuyvesant Town loans at $1.5 billion, and the La Quinta/Baymont Portfolio at $1.44 billion. Rather than remove these potential outliers, the log of loan size (*LnSIZE*) is used to better model the likely relationship between loan size and Non-performance (*NONP*).

Interest rates (*NETCPN*) charged on loans in the final sample range from a low of 2.65% to a high of 15% with a mean of 6.02% and a fairly tight distribution with a standard deviation of only .88%. The LTV ratios at the securitization cutoff date in the full database (not reported in Table 4) range from very small (.005) to very large (2.62) with a mean of .670. The database also included observations with LTVs of 0 despite data on these observations for loan amount and recent valuations. Observations where *LTV* is 0 or greater than 1 are eliminated from the sample. 90% of the observations in the sample fall between .39 and .80 with only 1% above .85. After the elimination of the observations with LTV at or below 0 and the other sample trimming measures, minimum value for LTV is .02, the maximum is 1.0 and the mean rises to .68 with a standard deviation of .12.

Debt service coverage ratios at cutoff in the full sample (not reported in Table 4) range from negative values as low as -.18 to extremely large (topping out at 136) with a mean of 1.63. Values below .9 and above 5 are eliminated. Ninety percent of the observations have *DSCR* between 1.06 and 2.35. 98% fall between 1.02 and 7.23. After eliminating the extreme values, *DSCR* for the final sample ranges from a low of .91 to a high of 5.00 with a mean of 1.46 and a standard deviation of .39. During the sample period the rates on 10-Year U.S. Treasuries ranged from a high of 7.92% in late 1994 to a low of 2.02% in late 2011. The mean interest rate at the time of origination for all observations in the sample is 4.49%.

The dependent variable in the empirical analysis is loan Non-performance (*NONP*). The mean for this variable across all observations is .21 and is a grouping of loan status indicators which all relate to a condition of Non-performance. The categories which are grouped in to the Non-performance category include delinquent, in foreclosure, grace, late, non-performing, and REO.

Those loans with a current status of defeased, matured, mixed, or special are not included in the sample.

The difference between the coupon rate of the loan (*NETCPN*) and the 10-Year Treasury note at the time of origination (*INT*), Coupon Spread (*CPNSPRD*), ranges from -1.92% to a high of 11.63% with a mean of 1.53% and a standard deviation of .80%. This measure is indicative of the bank's relative yield on the loan at the time of origination. The difference between the property Cap Rate and the coupon rate (*NETCPN*) is *CAPSPRD*, ranging from -10% to a high of 392% with a mean of 2% and a standard deviation of 9%. The measure relating to recent stock market returns is the 12 month change in the S&P index as a percentage. With a large proportion of values negative, the variable used the empirical tests is increased by 1 yielding all positive values with a mean of 1.12 (12% increase in the S&P index for the prior 12 months), a minimum of .47, a maximum of 1.62 and a standard deviation of .15.

A measure of recent CMBS origination activity is also incorporated into the analysis to account for the possibility that high or low volume may affect the origination decision process as underwriters are either rushed or have more time for due diligence. Periods of strong origination activity may lead to increased competition among underwriters attempting to fill bond pools with loans. The measure used is the number of CMBS loans originated in the period 12 months prior to the origination date of the observation (*DEALS*). The value is then scaled by dividing by 100. The mean value is .73 (73 loans originated in the 12 months prior to the origination date of the observation), the minimum is 0, the maximum is 5.37 (537 loans) and the standard deviation is .92 (92 loans).

In the two-stage modeling used to check the robustness of the assumptions around possible endogeneity between Coupon Rate, LTV and DSCR, a predicted Coupon Rate (*PREDNETCPN*) is estimated using ordinary least squares regression. The mean value of this predicted coupon rate is 6.02% with a minimum of 3.74%, a maximum of 10.63% and a standard deviation of .61%. This predicted coupon rate is then used to generate the *PREDCAPSPRD* variable used the second stage probit model which predicts Non-performance. The second stage variable, *PREDCAPSPRD,* has values very similar to the original *CAPSPRD* variable with a mean of 2%, a minimum of -8%, a maximum of 393% and a standard deviation of 9%.

Using Cook's distance, a common technique for identification and inspection of outliers,, the critical value often used is D > 1 (Cook and Weisberg 1982) while another source suggests using D > (n/4) (Bollen and Jackman 1990). With a very large sample size, the Cook's distance test statistic is less than 1 but more than n/4 in most cases when evaluating size, LTV, and DSCR.

Table 4 ■ Summary Statistics for Full Sample.

Variable	Description	N	Min	Max	Mean	STD
SIZE	Loan Size as of Securitization *	47,883	55,158.00	6,867,198,760.00	12,432,105.14	43,198,328.16
NETCPN	Loan Coupon Rate as of Securitization	47,883	2.65	15.00	6.02	0.88
LTV	Loan to Value Ratio as of Securitization	47,883	0.02	1.00	0.68	0.12
DSCR	Debt Service Coverage Ratio as of Securitization	47,883	0.91	5.00	1.46	0.39
INT	10 Year Treasury Yield	47,883	2.02	7.92	4.49	0.54
NONP	Indicator Variable for Non-Performing Loans	47,883	0.00	1.00	0.21	0.41
CPNSPRD	Property Coupon Rate less 10 Year Treasury	47,883	-1.92	11.63	1.53	0.80
CAPSPRD	Property Cap Rate less Property Coupon Rate	47,883	-0.10	3.92	0.02	0.09
SPY	12 Month Change in S&P index plus 1	47,883	0.47	1.62	1.12	0.15
DEALS	CMBS originations in the last 12 months / 100	47,883	0.00	5.37	0.73	0.92
PREDNETCPN	Predicted Value of Coupon	47,883	3.74	10.63	6.02	0.61
PREDCAPSPRD	Property Cap Rate less Predicted Coupon Rate	47,883	-0.08	3.93	0.02	0.09
STATE	State Indicator Variable (See Table 5)					
RATE	Rate Type Indicator Variable (See Table 6)					
AMORT	Amortization Type Indicator Variable (See Table 7)					
PTYPE	Property Type Indicator Variables (See Table 8)					
ORIG	Originator Indicator Variable (See Table 9)					

Notes: Dependent variable is Non Performance (*Nonp*). * Models use the natural log of loan size (*LnSIZE*). *NETCPN, INT, CPNSPRD*, and *PREDNETCPN* are expressed in percentage terms (i.e. 2.65 = 2.56%). Measures derived from the Cap Rate including *CAPSPRD* and *PREDCAPSPRD* are expressed in decimal terms (i.e. .02 = 2%).

In order to control for geographic effects, dummy variables for the U.S. State have been included throughout into the empirical analysis. Several of the variables of interest fluctuate considerably by State and support the work of prior researchers who considered regional differences when attempting to understand CMBS loan performance. The state with the largest number of observations is California with 8,209 loans originated, 17.14% of the sample. For the empirical analysis, California is the excluded case and thus sets the model baseline. Table 5 presents the full list of 50 states plus the District of Columbia and the means and standard deviations for each of the key variables of interest: Non-performance, LTV, DSCR, and Cap Rate. As expected, states with below average rates of Non-performance appear to be associated with lower LTVs and higher DSCRs. California, for example has a .17 rate of Non-performance, average LTV is .63 and the average DSCR is 1.48. This compares to Arizona, 3% of the sample, with a .30 rate of Non-performance, average LTV is .69 and the average DSCR is 1.42. Incorporating $STATE_i$ dummy variables into the empirical analysis controls for fixed effects attributable to the State where the property as collateral for the loan is geographically located.

Table 5 ■ Summary Statistics by State.

	Overall		Non Performance		LTV		DSCR		Cap Rate	
State	N	%	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
All	47,883	100.00%	0.21	0.41	0.68	0.12	1.46	0.39	0.08	0.09
AK	92	0.19%	0.22	0.41	0.68	0.11	1.49	0.30	0.08	0.01
AL	520	1.09%	0.23	0.42	0.72	0.10	1.41	0.29	0.09	0.12
AR	219	0.46%	0.19	0.39	0.71	0.10	1.39	0.26	0.09	0.15
AZ	1,420	2.97%	0.30	0.46	0.69	0.11	1.42	0.30	0.07	0.05
CA	8,209	17.14%	0.16	0.37	0.63	0.13	1.48	0.42	0.07	0.04
CO	972	2.03%	0.24	0.43	0.69	0.10	1.44	0.34	0.08	0.07
CT	570	1.19%	0.20	0.40	0.70	0.11	1.46	0.35	0.08	0.06
DC	219	0.46%	0.13	0.34	0.65	0.13	1.51	0.53	0.07	0.05
DE	191	0.40%	0.18	0.39	0.71	0.10	1.44	0.30	0.08	0.10
FL	3,139	6.56%	0.25	0.43	0.69	0.10	1.45	0.34	0.08	0.07
GA	1,670	3.49%	0.23	0.42	0.71	0.09	1.42	0.27	0.08	0.10
HI	122	0.25%	0.20	0.40	0.70	0.09	1.42	0.24	0.09	0.09
IA	175	0.37%	0.27	0.44	0.71	0.09	1.41	0.28	0.08	0.03
ID	181	0.38%	0.27	0.45	0.67	0.11	1.47	0.29	0.08	0.08
IL	1,435	3.00%	0.22	0.41	0.69	0.11	1.45	0.36	0.08	0.07
IN	797	1.66%	0.24	0.43	0.72	0.09	1.39	0.26	0.09	0.16
KS	289	0.60%	0.19	0.40	0.71	0.10	1.43	0.30	0.08	0.15
KY	388	0.81%	0.22	0.42	0.71	0.10	1.44	0.31	0.08	0.04
LA	445	0.93%	0.16	0.36	0.71	0.11	1.43	0.29	0.11	0.24
MA	727	1.52%	0.16	0.36	0.68	0.11	1.48	0.43	0.08	0.10
MD	1,131	2.36%	0.16	0.36	0.69	0.12	1.47	0.35	0.08	0.04
ME	108	0.23%	0.13	0.34	0.72	0.09	1.42	0.25	0.08	0.02
MI	1,184	2.47%	0.28	0.45	0.71	0.11	1.46	0.36	0.09	0.11
MN	642	1.34%	0.24	0.43	0.70	0.10	1.42	0.33	0.08	0.06
MO	487	1.02%	0.19	0.39	0.72	0.09	1.43	0.29	0.09	0.22
MS	257	0.54%	0.27	0.45	0.71	0.10	1.44	0.27	0.09	0.10
MT	39	0.08%	0.18	0.39	0.66	0.12	1.44	0.28	0.08	0.02
NC	1,582	3.30%	0.29	0.45	0.72	0.09	1.41	0.25	0.08	0.11
ND	93	0.19%	0.15	0.36	0.71	0.11	1.43	0.26	0.08	0.01
NE	180	0.38%	0.18	0.39	0.70	0.10	1.44	0.24	0.08	0.01
NH	151	0.32%	0.21	0.41	0.70	0.11	1.43	0.29	0.09	0.14
NJ	1,304	2.72%	0.23	0.42	0.68	0.11	1.49	0.41	0.08	0.09
NM	282	0.59%	0.16	0.37	0.70	0.10	1.41	0.24	0.08	0.01
NV	854	1.78%	0.32	0.47	0.68	0.11	1.44	0.34	0.07	0.02
NY	3,273	6.84%	0.18	0.39	0.62	0.18	1.68	0.81	0.08	0.07
OH	1,553	3.24%	0.22	0.41	0.72	0.10	1.43	0.31	0.09	0.12
OK	436	0.91%	0.23	0.42	0.73	0.09	1.40	0.24	0.10	0.15
OR	585	1.22%	0.17	0.38	0.66	0.11	1.44	0.33	0.08	0.10
PA	1,516	3.17%	0.18	0.38	0.71	0.10	1.44	0.30	0.09	0.13
RI	72	0.15%	0.21	0.41	0.71	0.08	1.40	0.27	0.08	0.04
SC	636	1.33%	0.21	0.41	0.72	0.08	1.41	0.22	0.09	0.17
SD	58	0.12%	0.24	0.43	0.71	0.08	1.39	0.23	0.10	0.20
TN	741	1.55%	0.22	0.41	0.72	0.09	1.41	0.25	0.08	0.07
TX	4,883	10.20%	0.21	0.41	0.71	0.10	1.41	0.27	0.09	0.11
UT	429	0.90%	0.17	0.38	0.69	0.10	1.43	0.30	0.08	0.06
VA	1,529	3.19%	0.18	0.38	0.70	0.10	1.46	0.33	0.09	0.10
VT	40	0.08%	0.13	0.33	0.72	0.09	1.44	0.26	0.09	0.03
WA	1,277	2.67%	0.17	0.38	0.65	0.12	1.42	0.30	0.07	0.07
WI	640	1.34%	0.20	0.40	0.70	0.12	1.40	0.30	0.08	0.09
WV	110	0.23%	0.22	0.41	0.71	0.09	1.41	0.25	0.08	0.04
WY	31	0.06%	0.06	0.25	0.72	0.08	1.35	0.18	0.08	0.01

Table 6 presents summary statistics for the CMBS loan rate types in the sample. The loans in the sample are predominantly Fixed-rate loans (94.5%) with a small number of adjustable-rate loans tied to LIBOR (2.79%), the Prime Rate (0.1%), and U.S. Treasuries (2.58%). Of particular note is the difference between the mean Non-performance for the three primary rate types. Fixed-rate loans have a 21% rate of Non-performance while LIBOR indexed loans have a much higher rate of Non-performance at 33%, with U.S. Treasuries (UST) loans considerably lower at 8%. The LIBOR-indexed loans have a higher mean LTV at .72 compared to the Fixed rate loans where the average LTV is .68. UST indexed loans have the lowest LTV but also have the lowest DSCR. The variance in LTV is considerably larger for UST loans, but the FIXED Cap Rate variance deserves attention with a Cap Rate standard deviation at least five times that of the other rate types.

Table 6 ■ Summary Statistics by Rate Type.

	Overall		Non Performance		LTV		DSCR		Cap Rate	
Rate Type	N	%	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
All	47,883	100.00%	0.21	0.41	0.68	0.12	1.46	0.39	0.08	0.09
Fixed	45,264	94.53%	0.21	0.41	0.68	0.12	1.46	0.39	0.08	0.10
LIBOR	1,335	2.79%	0.33	0.47	0.72	0.10	1.41	0.32	0.08	0.02
Prime	48	0.10%	0.10	0.31	0.77	0.14	1.47	0.50	0.08	0.02
UST	1,236	2.58%	0.08	0.28	0.58	0.14	1.32	0.43	0.06	0.01

Notes: Fixed refers to loans with rates that do not change over the term of the loan. LIBOR refers to adjustable rate loans with rates indexed to the London Interbank Offered Rate, the average rate offered to other banks by a group of large London banks. Prime refers to adjustable rate loans with rates indexed the Prime rate, the rate offered to a bank's most favored clients. UST refers to adjustable rate loans tied to US Treasury securities of various maturities.

Table 7 presents summary statistics for the CMBS loan amortization types in the sample. More than half the loans in the sample are Balloon loans (52.35%) with payments of principal and interest but with a term shorter than the amortization period requiring a large final payment. The other amortization types are Fully Amortizing (9.03%), Interest Only (10.60%), Mixed (0.10%), and Partial Interest Only (28.01%). Comparing the two largest categories of loans, Balloon and Partial Interest Only, the statistics for Non-performance, LTV, DSCR and Cap Rate differ relative to each other in the expected manner. The Interest Only loans have the highest DSCR among the larger groups of loans, which is likely due to the lower levels of debt service required with an Interest Only loan. The variances across all statistics are relatively consistent among the different amortization types with only the standard deviation for Non-performance of the Mixed group significantly different from the other groups, with all five loans in the Mixed amortization type currently performing.

Table 7 ■ Summary Statistics by Amortization Type.

	Overall		Non Performance		LTV		DSCR		Cap Rate	
Amortization Type	N	%	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
All	47,883	100.00%	0.21	0.41	0.68	0.12	1.46	0.39	0.08	0.09
Balloon Amort	25,068	52.35%	0.20	0.40	0.68	0.12	1.48	0.39	0.08	0.11
Fully Amort	4,323	9.03%	0.19	0.40	0.62	0.15	1.43	0.46	0.08	0.05
Interest Only (IO)	5,077	10.60%	0.19	0.39	0.67	0.13	1.65	0.52	0.07	0.07
Mixed	5	0.01%	0.00	0.00	0.58	0.11	1.93	0.32	0.09	0.02
Partial IO	13,410	28.01%	0.23	0.42	0.72	0.09	1.36	0.27	0.08	0.08

Notes: Balloon Amortization loans have all payments with both principal and interest but have a balloon payment at the end of the term. Fully Amortization loans have principal and interest payments which result in a zero balance at the end of the term. Interest Only loans have only interest for the term of the loan. Mixed loans include some combination of the other amortization categories. Partial Interest Only (IO) Loans begin with interest only and switch to an amortization schedule at a later date.

Table 8 presents summary statistics for the CMBS loan property types in the sample. The predominant property types in the sample include Multifamily (26.29%), Unanchored Retail (18.11%) ,Anchored Retail (15.19%), and Office (16.35%). The remaining nine property type categories make up 24.06% of the loans in the sample. The level of Non-performance ranges from a low of 15% for Self Storage to a high of 25% for Full Service Hospitality. These two property type categories also have the highest average Cap Rate and the largest variance for Cap Rate.

The statistics for the other property type categories tend to follow expected patterns of high LTVs and low DSCRs associated with high rates of Non-performance with the exception of the two categories of hospitality (limited-service and full-service). These two property types, with the highest rates of Non-performance, are also among the lowest LTV and highest DSCR. Although these ratios point to lower risk loans among hospitality, the high Cap Rates of 11% and 10% for full- and limited-service respectively, suggest that investors recognized the risks present in these properties.

Table 8 ■ Summary Statistics by Property Type.

	Overall		Non Performance		LTV		DSCR		Cap Rate	
Property Type	N	%	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
All	47,883	100.00%	0.21	0.41	0.68	0.12	1.46	0.39	0.08	0.09
HealthCare	58	0.12%	0.16	0.37	0.65	0.13	1.70	0.57	0.09	0.04
HospFullSvc	878	1.83%	0.25	0.43	0.65	0.10	1.68	0.47	0.11	0.19
HospLtdSvc	1,541	3.22%	0.23	0.42	0.67	0.09	1.59	0.28	0.10	0.08
Industrial	3,045	6.36%	0.20	0.40	0.66	0.12	1.46	0.34	0.08	0.06
MixedUse	1,414	2.95%	0.21	0.41	0.66	0.13	1.42	0.36	0.07	0.08
MoblHmPark	1,468	3.07%	0.22	0.41	0.70	0.13	1.45	0.36	0.08	0.05
MultFamHsng	12,587	26.29%	0.22	0.41	0.68	0.14	1.44	0.48	0.08	0.09
Office	7,831	16.35%	0.22	0.42	0.69	0.11	1.44	0.35	0.08	0.08
Other	556	1.16%	0.17	0.38	0.64	0.15	1.56	0.54	0.09	0.08
RetlAnch	7,272	15.19%	0.20	0.40	0.70	0.11	1.44	0.33	0.08	0.09
RetlUnanch	8,672	18.11%	0.19	0.39	0.68	0.11	1.44	0.32	0.08	0.05
SlfSvcStrge	2,188	4.57%	0.15	0.36	0.66	0.12	1.52	0.43	0.10	0.23
Warehouse	373	0.78%	0.20	0.40	0.67	0.11	1.46	0.32	0.07	0.01

Table 9 presents summary statistics for the CMBS loan originators in the sample. A large number of originators (139) originated the loans in the sample while an expectedly small number (31) accounted for 80% of the loans in the sample period led by LaSalle Bank National

Association with 3,767 loans originated and Bridger Commercial Financing with 371 loans rounding out the top 31. The third largest group of loans fall into the category "Unknown Originator" with 3,514 loans. At the extremes, 11 originators have a Non-performance rate in excess of 50% while 38 originators do not have any non-performing loans. Many of the originators in both categories, however, originated very few loans.

The top 10 originators by number of loans share the same 21.1% mean rate of Non-performance with the overall sample but exhibit a considerable range of values with a low of 8.5% (Washington Mutual), a high of 29.2% (Bank of America), and a standard deviation of 7.0%. Several of the largest originators have since been acquired by others in the sample. In one case, an originator with a high rate of Non-performance, Wells Fargo (28.1%), purchased Wachovia, an originator with a very low rate (11.8%). Another acquisition, the 2008 purchase of CountryWide (29.3%) by Bank of America (29.2%), did not produce the same overall loan performance improvement for the acquirer. While many individual loans had LTVs exceeding .80, no originators in the sample have an average LTV of more than .80. A very similar observation is made with average DSCRs among the originators. Only 5 originators representing just 49 loans have average DSCRs of less than 1.25. This observation suggests that originators operated within LTV and DSCR targets at the portfolio level.

Table 9 ■ Summary Statistics by Originator.

	Overall		Non Performance		LTV		DSCR		Cap Rate	
Originator	N	%	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
All	47,883	100.00%	0.21	0.41	0.68	0.12	1.46	0.39	0.08	0.09
ABN AMRO	6	0.01%	0.33	0.52	0.64	0.10	1.76	0.52	0.12	0.03
AIG	31	0.06%	0.13	0.34	0.70	0.09	1.38	0.25	0.07	0.01
AMCC	213	0.44%	0.34	0.47	0.70	0.09	1.40	0.18	0.08	0.03
Allmerica	6	0.01%	0.00	0.00	0.60	0.09	1.43	0.27	0.09	0.01
American Mortgage Acceptance Co.	10	0.02%	0.00	0.00	0.63	0.17	1.62	0.47	0.07	0.01
Amresco	10	0.02%	0.40	0.52	0.73	0.06	1.32	0.12	0.10	0.01
Archon Financial	150	0.31%	0.36	0.48	0.69	0.14	1.56	0.34	0.14	0.29
Aries	1	0.00%	0.00	.	0.79	.	1.71	.	0.12	.
Artesia Mortgage Capital Corporation	661	1.38%	0.19	0.39	0.69	0.10	1.38	0.25	0.07	0.01
Atherton	5	0.01%	0.00	0.00	0.64	0.08	3.08	0.55	0.26	0.04
BSFI	3	0.01%	0.33	0.58	0.72	0.07	1.43	0.12	0.09	0.00
Bank of America, NA	1,335	2.79%	0.29	0.45	0.69	0.10	1.40	0.30	0.07	0.05
Barclays	285	0.60%	0.40	0.49	0.71	0.08	1.38	0.25	0.08	0.02
Basis Real Estate Capital II	4	0.01%	0.00	0.00	0.67	0.06	1.67	0.18	0.08	0.01
Bear Stearns Co. Inc.	1,250	2.61%	0.28	0.45	0.65	0.11	1.67	0.44	0.07	0.02
Beech Street Capital	5	0.01%	0.00	0.00	0.78	0.04	1.35	0.07	0.07	0.00
Bellwether Real Estate Capital	4	0.01%	0.00	0.00	0.75	0.00	1.45	0.06	0.07	0.00
Berkadia Commercial Mortgage	78	0.16%	0.15	0.36	0.67	0.07	1.45	0.23	0.07	0.01
Bloomfield	2	0.00%	0.00	0.00	0.70	0.05	1.43	0.12	0.08	0.03
Bridger Commercial Funding	371	0.77%	0.16	0.37	0.70	0.10	1.35	0.25	0.07	0.01
CAPMARK	324	0.68%	0.13	0.33	0.70	0.10	1.40	0.36	0.07	0.02
CBRE Capital Markets	87	0.18%	0.13	0.33	0.70	0.07	1.48	0.33	0.07	0.01
CBRE Melody & Company	80	0.17%	0.01	0.11	0.57	0.19	1.50	0.49	0.08	0.04
CCFC	82	0.17%	0.09	0.28	0.62	0.11	1.33	0.22	0.09	0.02
CDC Mortgage Capital	20	0.04%	0.15	0.37	0.69	0.13	1.55	0.46	0.08	0.01
CGM	686	1.43%	0.17	0.38	0.71	0.09	1.33	0.24	0.07	0.03
CIBC	1,087	2.27%	0.37	0.48	0.73	0.09	1.35	0.18	0.09	0.13
CMB	1	0.00%	1.00	.	0.74	.	1.36	.	0.09	.
CRF	351	0.73%	0.32	0.47	0.68	0.11	1.37	0.23	0.07	0.01

Originator	Overall N	Overall %	Non Performance Mean	Non Performance StDev	LTV Mean	LTV StDev	DSCR Mean	DSCR StDev	Cap Rate Mean	Cap Rate StDev
CWCapital	268	0.60%	0.10	0.30	0.70	0.10	1.38	0.37	0.07	0.01
Canada Life Assurance	2	0.00%	0.00	0.00	0.55	0.11	2.00	0.23	0.08	0.00
Centerline Mortgage Capital	7	0.02%	0.00	0.00	0.70	0.09	1.41	0.11	0.06	0.01
Chastain Capital Corporation	1	0.00%	0.00	-	0.70	-	1.22	-	0.09	-
Citigroup Inc.	438	0.99%	0.12	0.32	0.74	0.11	1.41	0.33	0.08	0.02
Columbia National Real Estate Finance	4	0.01%	0.00	0.00	0.67	0.05	1.27	0.03	0.06	0.01
Column Financial	3,673	8.28%	0.19	0.39	0.71	0.10	1.42	0.29	0.09	0.12
ContiFinancial	9	0.02%	0.00	0.00	0.66	0.09	1.32	0.18	0.08	0.01
CountryWide	854	1.92%	0.29	0.46	0.68	0.11	1.36	0.33	0.07	0.01
Credit Suisse	59	0.13%	0.31	0.46	0.69	0.12	1.49	0.38	0.10	0.01
DREFC	10	0.02%	0.10	0.32	0.70	0.05	1.39	0.10	0.11	0.01
Daiwa Real Estate	8	0.02%	0.00	0.00	0.69	0.08	1.43	0.21	0.11	0.03
Deutsche Bank	102	0.23%	0.25	0.44	0.69	0.13	1.37	0.27	0.10	0.17
Deutsche Bank (GACC)	30	0.07%	0.23	0.43	0.69	0.11	1.29	0.25	0.07	0.02
Deutsche Bank Berkshire Mortgage	7	0.02%	1.00	0.00	0.73	0.03	1.35	0.06	0.06	0.01
Deutsche Morgan Grenfell	12	0.03%	0.50	0.52	0.71	0.25	1.28	0.21	0.08	0.03
Deutshe Bank (GACC) / CGM	1	0.00%	0.00	-	0.75	-	1.60	-	0.24	-
Dexia	35	0.08%	0.31	0.47	0.69	0.08	1.36	0.22	0.07	0.01
Dime	80	0.18%	0.15	0.36	0.70	0.10	1.48	0.30	0.08	0.01
EHY	163	0.37%	0.28	0.45	0.72	0.10	1.44	0.35	0.07	0.02
EuroHypo AG	137	0.31%	0.39	0.49	0.72	0.10	1.43	0.38	0.08	0.03
FNFC	3	0.01%	0.00	0.00	0.56	0.06	2.40	0.02	0.14	0.03
Financial Federal Savings Bank	3	0.01%	0.00	0.00	0.75	0.08	1.31	0.01	0.07	0.01
Finova	1	0.00%	1.00	-	0.64	-	1.32	-	0.10	-
First Union	34	0.08%	0.50	0.51	0.75	0.07	1.23	0.17	0.09	0.01
GACC	97	0.22%	0.30	0.46	0.65	0.11	1.57	0.38	0.07	0.01
GMAC Commercial Mortgage Corp.	511	1.15%	0.35	0.48	0.70	0.10	1.44	0.27	0.08	0.05
General Electric Capital Corp.	1,270	2.86%	0.18	0.39	0.69	0.11	1.45	0.36	0.08	0.05
German American Capital	734	1.65%	0.24	0.42	0.72	0.10	1.36	0.34	0.09	0.10
Goldman Sachs	891	2.01%	0.18	0.38	0.70	0.11	1.49	0.37	0.09	0.16

	Overall		Non Performance		LTV		DSCR		Cap Rate	
Originator	N	%	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
Grandbridge Real Estate Capital	24	0.05%	0.67	0.48	0.63	0.16	1.83	0.80	0.07	0.01
Greenwich Capital	951	2.14%	0.25	0.43	0.73	0.08	1.41	0.25	0.08	0.03
HSBC Bank USA, NA	3	0.01%	1.00	0.00	0.60	0.15	1.38	0.34	0.06	0.01
Hanover	2	0.00%	0.00	0.00	0.68	0.07	1.37	0.01	0.09	0.02
Heller Financial	10	0.02%	0.30	0.48	0.70	0.07	1.38	0.15	0.09	0.01
Holliday Fenoglio Fowler L.P.	47	0.11%	0.00	0.00	0.74	0.04	1.34	0.13	0.07	0.01
ITLA	1	0.00%	0.00	-	0.36	-	1.94	-	0.09	-
IXIS	302	0.68%	0.13	0.34	0.69	0.08	1.40	0.30	0.07	0.01
JHREF	39	0.09%	0.10	0.31	0.62	0.11	1.92	0.55	0.10	0.10
JPMorgan Chase & Co.	2,790	6.29%	0.22	0.41	0.69	0.11	1.44	0.33	0.09	0.12
John Hancock Real Estate Finance	23	0.05%	0.26	0.45	0.63	0.12	1.77	0.50	0.09	0.01
KeyBank NA	815	1.84%	0.09	0.28	0.70	0.11	1.38	0.29	0.08	0.12
KeyCorp Real Estate Capital Markets	143	0.32%	0.38	0.49	0.66	0.12	1.47	0.32	0.07	0.01
LJ Melody	2	0.00%	1.00	0.00	0.76	0.01	1.31	0.01	0.09	0.00
LNR Partners	7	0.02%	0.14	0.38	0.23	0.18	2.47	0.98	0.07	0.02
LaSalle Bank National Association	3,767	8.49%	0.24	0.43	0.71	0.10	1.41	0.28	0.08	0.06
Ladder Capital Finance	71	0.16%	0.03	0.17	0.62	0.09	1.68	0.47	0.07	0.01
Laureate Capital Corp.	1	0.00%	0.00	-	0.78	-	1.25	-	0.10	-
Lehman Brothers	980	2.21%	0.18	0.38	0.71	0.10	1.39	0.29	0.08	0.06
Lincoln	11	0.02%	0.27	0.47	0.62	0.15	1.46	0.34	0.09	0.01
Llama	8	0.02%	0.38	0.52	0.66	0.12	1.32	0.14	0.09	0.01
M & T Realty Capital Corporation	8	0.02%	0.00	0.00	0.72	0.05	1.38	0.12	0.07	0.00
M&I Marshall & Ilsley Bank	3	0.01%	0.00	0.00	0.73	0.06	1.35	0.06	0.07	0.00
M&T Reality Capital Corporation	4	0.01%	0.00	0.00	0.79	0.00	1.22	0.01	0.07	0.00
MBIC	17	0.04%	0.00	0.00	0.59	0.13	1.44	0.49	0.09	0.01
MMA Mortgage Investment Corporation	2	0.00%	0.00	0.00	0.74	0.00	1.21	0.00	0.06	0.00
MONY	8	0.02%	0.00	0.00	0.67	0.05	1.14	0.08	0.22	0.36
Massachusetts Mutual Life Insurance	116	0.26%	0.52	0.50	0.44	0.10	1.34	0.23	0.07	0.09
Merrill Lynch & Co. Inc.	1,134	2.56%	0.18	0.39	0.70	0.10	1.40	0.26	0.08	0.09
Midland	39	0.09%	0.36	0.49	0.68	0.09	1.37	0.26	0.09	0.02

	Overall		Non Performance		LTV		DSCR		Cap Rate	
Originator	N	%	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
Morgan Guaranty Trust	47	0.11%	0.47	0.50	0.64	0.13	1.32	0.22	0.09	0.02
Morgan Stanley	557	1.26%	0.17	0.37	0.68	0.09	1.56	0.36	0.08	0.05
Morgan Stanley Mortgage Capital Holding	1,546	3.48%	0.22	0.41	0.68	0.11	1.48	0.38	0.11	0.28
NACC	89	0.20%	0.16	0.37	0.69	0.09	1.47	0.41	0.10	0.03
NCB Capital Corporation	248	0.56%	0.20	0.40	0.45	0.26	2.51	1.21	0.07	0.04
NCCI	507	1.14%	0.35	0.48	0.70	0.11	1.47	0.37	0.07	0.02
NLIC	120	0.27%	0.10	0.30	0.69	0.09	1.51	0.36	0.07	0.01
NREC	1	0.00%	0.00	-	0.66	-	1.67	-	0.07	-
National City	19	0.04%	0.37	0.50	0.68	0.12	1.42	0.37	0.07	0.01
National Consumer Cooperative Bank	232	0.52%	0.15	0.35	0.43	0.26	2.65	1.27	0.06	0.02
National Realty Funding LC	46	0.10%	0.13	0.34	0.67	0.09	1.40	0.23	0.09	0.01
NationsBanc	50	0.11%	0.22	0.42	0.67	0.14	1.43	0.24	0.09	0.02
Nationwide	112	0.25%	0.15	0.36	0.66	0.13	1.60	0.56	0.08	0.01
Natixis Real Estate Capital Inc.	120	0.27%	0.19	0.40	0.70	0.07	1.26	0.16	0.07	0.02
Natl Consumer Co-Op Bank	45	0.10%	0.16	0.37	0.25	0.13	3.60	0.94	0.07	0.02
Nomura	499	1.12%	0.20	0.40	0.70	0.11	1.43	0.29	0.08	0.03
NorthMarq Capital	54	0.12%	0.15	0.36	0.69	0.08	1.46	0.23	0.07	0.01
Northland/Marquette Capital Group Inc.	26	0.06%	0.00	0.00	0.66	0.09	1.47	0.25	0.07	0.01
ORIX Real Estate Capital Markets	2	0.00%	1.00	0.00	0.70	0.06	1.58	0.38	0.11	0.02
Oak Grove Commercial Mortgage	1	0.00%	0.00	-	0.60	-	1.60	-	0.07	-
PCF II	45	0.10%	0.13	0.34	0.62	0.13	1.58	0.38	0.07	0.01
PMCF	72	0.16%	0.18	0.39	0.69	0.09	1.44	0.18	0.09	0.03
PNC	1,109	2.50%	0.18	0.38	0.72	0.09	1.39	0.25	0.09	0.11
Peachtree	4	0.01%	0.00	0.00	0.54	0.14	2.72	0.91	0.16	0.10
Primary Capital Advisors	10	0.02%	0.00	0.00	0.75	0.04	1.30	0.07	0.07	0.01
Prime Capital Funding	651	1.47%	0.15	0.36	0.63	0.12	1.54	0.40	0.07	0.01
Principal Commercial Funding	572	1.29%	0.13	0.34	0.62	0.13	1.63	0.46	0.08	0.04
Prudential	816	1.84%	0.36	0.48	0.69	0.10	1.46	0.32	0.08	0.04
Regions Bank	3	0.01%	0.00	0.00	0.66	0.05	1.62	0.11	0.08	0.01
Residential Funding Corp.	19	0.04%	0.53	0.51	0.70	0.09	1.32	0.14	0.10	0.01

	Overall		Non Performance		LTV		DSCR		Cap Rate	
Originator	N	%	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
Royal Bank of Canada	100	0.21%	0.19	0.39	0.72	0.08	1.28	0.17	0.06	0.01
Salomon	94	0.20%	0.33	0.47	0.71	0.10	1.36	0.29	0.09	0.01
Secore Financial Corp.	1	0.00%	0.00	.	0.69	.	1.26	.	0.10	.
Sovereign Bank	152	0.32%	0.09	0.28	0.64	0.13	1.40	0.33	0.07	0.01
Starwood Property Mortgage	2	0.00%	0.00	0.00	0.39	0.09	2.89	1.79	0.07	0.03
State Farm	11	0.02%	0.18	0.40	0.59	0.13	1.56	0.39	0.10	0.04
Sun Trust Bank	132	0.28%	0.08	0.27	0.68	0.11	1.36	0.20	0.07	0.01
Teachers Insurance and Annuity	140	0.29%	0.23	0.42	0.62	0.11	1.62	0.40	0.08	0.03
The Community Preservation Corporation	4	0.01%	0.00	0.00	0.67	0.08	1.59	0.21	0.07	0.00
The Royal Bank of Scotland	28	0.06%	0.00	0.00	0.62	0.10	2.04	0.54	0.08	0.01
UBS AG	836	1.75%	0.16	0.36	0.72	0.10	1.36	0.23	0.08	0.07
UCMFI	176	0.37%	0.14	0.35	0.60	0.12	1.38	0.39	0.08	0.01
Union Central Life	25	0.05%	0.12	0.33	0.61	0.11	1.31	0.18	0.08	0.01
Union Labor Life	14	0.03%	0.21	0.43	0.58	0.14	1.35	0.28	0.09	0.01
Unknown	3,514	7.34%	0.15	0.36	0.69	0.11	1.48	0.37	0.08	0.03
Wachovia Bank NA	2,494	5.21%	0.12	0.32	0.70	0.11	1.45	0.34	0.08	0.11
Walker & Dunlop	14	0.03%	0.00	0.00	0.72	0.05	1.29	0.04	0.07	0.01
Washington Mutual Bank	1,786	3.73%	0.08	0.28	0.57	0.14	1.36	0.43	0.06	0.01
Wells Fargo Bank, NA	2,815	5.88%	0.28	0.45	0.63	0.13	1.61	0.45	0.08	0.09
Wingate	3	0.01%	0.33	0.58	0.64	0.09	1.65	0.26	0.12	0.02

Empirical Results

Cap Rate Spread: Full Sample

The first model estimates the relationship between Cap Rate Spread, its covariates, and CMBS loan Non-performance. The parameters are estimated using two versions of the model with one including LTV and another with DSCR. The results are presented in Table 10. The LTV coefficient in the LTV model is positive as expected, estimated to be 1.05 and significant at the 1% level. Due to the shape of the cumulative normal distribution, the effects of the coefficients are dependent upon the starting point along the curve.

As illustrated by Pampel (2000), the probit coefficients are difficult to interpret in their "raw" form but may be transformed into more manageable terms. The LTV coefficient of 1.05 represents the change in the probit / *z*-score for a 1 unit change in LTV. This effect equates to different changes in probability depending upon the starting point due to the shape of the cumulative normal distribution. The effect will be greatest where the probability of the dependent variable is closest to .5 and diminish as probability Non-performance moves in either direction.

The mean level of Non-performance in the CMBS loan is .21 meaning that 21% of loans have a status of Non-performance. This value of .21 translates to a *z*-score of -.81 with a probability density of .29. Multiplying this coefficient for LTV of 1.05 by the probability density for Non-performance at its mean (.29) the result is .30 which represents the change in probability for a 1 unit change in LTV. This relationship suggests that an increase in LTV of .05, from .70 to .75

would increase the probability of Non-performance by 1.5% (.05 x .30 = .015). The same approach may be used for the interpretation of the other probit coefficients in this dissertation.

The coefficient for *LnSIZE*, the natural log of loan size, in the estimation of Equation (12) for the LTV and DSCR models and all subsequent estimations is positive and significant, suggesting that as loans increase in size, the probability of Non-performance also increases. The size and significance of the coefficient for loan size (*LnSIZE*) in the LTV model of Table 10 is .04 and less than 1% respectively.

The coefficient for CMBS origination volume (*DEALS*) is significant and negative, suggesting that as origination volume increases, the risk of Non-performance decreases. This result seems to contradict the conventional wisdom that increased deal volume enables lower quality loans to slip through. An alternative explanation for this finding may be attributed to increased experience and competence of underwriters who have recently completed more transactions or underwriting teams who have, in the wake recent origination volume, increased their staffing levels or implemented standards designed to deal with the surge in origination volume. This alternative hypothesis suggests the possibility of a negative relation between origination volume and Non-performance.

The *CPNSPRD* (Coupon Spread) coefficients in both LTV and DSCR models of Table 10 are significant and positive with increased gaps between the current 10-Year Treasury note and the coupon rate on the loan associated with higher levels of Non-performance. A higher Coupon Spread proxies the pricing of riskier loans at origination and the evidence of increased risk for Non-performance justifies the pricing.

The final variable in the estimation of the LTV and DSCR models reported in Table 10 is *CAPSPRD* (Cap Rate Spread). The parameter estimates for *CAPSPRD* are negative as expected in both models but only significant in the LTV model. A third model, not reported in Table 10, includes both LTV and DSCR produces results similar to those of the LTV only model, the coefficient for DSCR insignificant. Results from Table 10 provide limited support for the hypothesis that the Cap Rate Spread is related to Non-performance among all CMBS loan types. The results from the LTV and DSCR models are inconsistent since Cap Rate Spread is not significant in the DSCR model.

Table 10 ■ Cap Rate Spread Model Results for LTV and DSCR.

	LTV Model			DSCR Model		
LTV	1.05	***	(230.41)			
DSCR				-0.24	***	(109.81)
LnSIZE	0.04	***	(31.07)	0.05	***	(36.27)
SPY	-0.04		(0.67)	-0.08	*	(2.81)
INT	0.24	***	(263.32)	0.22	***	(213.18)
DEALS	-0.04	***	(22.08)	-0.04	***	(24.18)
CPNSPRD	0.10	***	(94.57)	0.08	***	(59.40)
CAPSPRD	-0.25	***	(8.75)	-0.07		(0.73)
Numer of observations	47,883			47,883		
McFadden's Pseudo R-squared	0.07			0.07		

Notes: Dependent variable is nonp (non performance). Model includes dummy variables (coefficients not reported) for loan ammortization types. These categorical variables include the following: Balloon, Fully Amortizing, Interest Only, Mixed, and Partial Interest Only. Model includes dummy variables (coefficients not reported) for loan originators. These categorical variables include institutions such as the following: Bank of America, Countrywide, Goldman Sachs, Merrill Lynch, Sun Trust, Wachovia, and Wells Fargo. Model includes dummy variables (coefficients not reported) for Property Type. These categorical variables include the following: Healthcare, Hospitality Full Service, Hospitality Limited Service, Industrial, Mixed Use, Mobile Home Park, Multifamily Housing, Office, Other, Retail Anchored, Retail Unanchored, Self Service Storage, and Warehouse. Model includes dummy variables (coefficients not reported) for Rate Type. These categorical variables include rate types such as the following: Fixed, Libor, Euribor, and Prime. Model includes dummy variables (coefficients not reported) for State. These categorical variables include states such as the following: Georgia, Michigan, New York, and Texas. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. Chi squared statistic in parentheses.

Cap Rate Spread: Fixed Rate Balloon Loans

The CMBS market throughout the sample period originated a wide variety of loans with differing combinations of Rate Type, Amortization Type, and other features. Although loans with many different sets of characteristics are present in the sample, more than half of the sample (24,918 of the 47,883 total) is designed as the standard Fixed Rate Balloon loan. The typical Fixed Rate Balloon loans should create a more homogenous group, influenced by similar unmeasured risk and underwriting variables. To investigate the Cap Rate Spread relationship further, the sample is split into two groups: Fixed Rate Balloon loans, and all other loans.

Estimation with LTV: Fixed Rate Balloon Loans Only

The Fixed Rate Balloon loan subset includes only those loans with both characteristics: a Rate Type of Fixed and an Amortization Type of Balloon. This is the most common type of loan packaged and sold to the CMBS market. In addition to all other Rate and Amortization Types, the subset of other loans includes Fixed Rate loans and Balloon loans paired with non-Balloon Amortization Types and non-Fixed Rate Types respectively. Table 11 presents the results for the two sample subsets, with the Fixed Rate Balloon loans in Panel A and all other loans in Panel B. The results for Fixed Rate Balloon loans support a significant role for Cap Rate Spread in both the models for LTV and DSCR. In the Panel A of Table 11 for the LTV model, the estimated coefficients for LTV, loan size, interest rates, recent origination volume, Coupon Spread, and Cap Rate Spread are consistent with the results in both significance and direction to those in Table 10 for the full sample. With the Fixed Rate Balloon subset, the effect size for Cap Rate Spread in the LTV model is nearly double that of the full sample (-.25 compared to -.48), suggesting that the risk of Non-performance attributable to the Cap Rate Spread is considerably greater for Fixed rate Balloon loans.

Estimation with DSCR: Fixed Rate Balloon Loans Only

The DSCR model in Panel A of Table 11 also presents results that are largely consistent with those of the full sample in Table 10, with the exception of the finding for the Cap Rate Spread. For the standard Fixed Rate Balloon loans, *CAPSPRD* (Cap Rate Spread) has a negative and significant impact on the risk of Non-performance in the DSCR model. This finding suggests that the Cap Rate Spread is a predictor of Non-performance for Fixed Rate Balloon loans, and that estimations considering alternative less-standard mortgage structures veil this relationship. The Panel A model fit statistics reported by the McFadden's pseudo R-square are the same between Table 10 and Table 11 at .07 for all specifications.

All Other Amortization Types

Panel B of Table 11 reports the model results for the subset of the database with all other types of loans that do not combine Fixed Rate and Balloon Amortization. This collection of different types of loans shares some of the same parameter estimates with the full sample reported in Table 10 with a few notable exceptions. A relationship between Non-performance and recent stock market performance is not detected in the LTV model for the full sample and is just barely significant by standard criteria in the DSCR model of Table 10. In contrast, a Non-performance relationship with the stock market is significant at the 5% and 1% level in the LTV and DSCR models, respectively, in Panel B. The relationship between recent stock market returns and Non-performance is negative, suggesting that as the level of recent stock market returns rises, the level of CMBS loan Non-performance falls among these other types of loans.

Results describing the stock market relationship reported in Table 11 Panel B provide an interesting possible direction for future research. The results may be due to stock market momentum and/or sentiment among underwriters whereby loans originated following periods of higher stock market returns may only be sold to debt investors who are more discriminating and thus requiring more stringent underwriting and higher quality loans. Following periods of lower stock market returns, more investors may flock to the apparent security of bonds, debt and MBS causing a demand driven push to originate marginal, lower quality loans approved by less stringent underwriters.

In contrast to Panel A, the Cap Rate Spread coefficient of the DSCR model in Panel B is positive. For this group of non-Fixed Rate Balloon loans, Non-performance rises as the Cap Rate Spread increases. This result suggests that among this subset of loans, the absolute level of Cap Rate is binding in the relationship with Non-performance. This finding is consistent with the conventional wisdom associating high Cap Rates with high risk real estate but is at odds with the theory that a low Cap Rate Spread increases the probability of Non-performance.

Table 11 ■ Cap Rate Spread Model Results for Loan Groups.

Panel A -Fixed Rate Balloon Loans	LTV Model			DSCR Model		
LTV	0.94	***	(97.88)			
DSCR				-0.27	***	(69.59)
LnSIZE	0.05	***	(20.13)	0.06	***	(26.16)
SPY	0.07		(1.44)	0.02		(0.08)
INT	0.28	***	(213.31)	0.26	***	(175.31)
DEALS	-0.04	***	(11.88)	-0.05	***	(15.47)
CPNSPRD	0.12	***	(91.28)	0.10	***	(59.37)
CAPSPRD	-0.48	***	(17.62)	-0.28	***	(7.22)
Numer of observations	24,918			24,918		
McFadden's Pseudo R-squared	0.07			0.07		

Panel B - Other Loans	LTV Model			DSCR Model		
LTV	1.36	***	(185.32)			
DSCR				-0.24	***	(61.28)
LnSIZE	0.02	***	(3.58)	0.02	**	(5.74)
SPY	-0.42	**	(17.39)	-0.40	***	(16.25)
INT	0.19	***	(55.36)	0.15	***	(36.93)
DEALS	-0.04	**	(11.09)	-0.03	***	(7.99)
CPNSPRD	0.07	**	(18.19)	0.04	***	(7.51)
CAPSPRD	0.12		(0.79)	0.34	**	(6.00)
Numer of observations	22,965			22,965		
McFadden's Pseudo R-squared	0.07			0.07		

Notes: Dependent variable is nonp (non performance). Panel A includes fixed rate balloon loans. Panel B includes all other loans. Model includes dummy variables (coefficients not reported) for loan originators. These categorical variables include institutions such as the following: Bank of America, Countrywide, Goldman Sachs, Merrill Lynch, Sun Trust, Wachovia, and Wells Fargo. Model includes dummy variables (coefficients not reported) for Property Type. These categorical variables include the following: Healthcare, Hospitality Full Service, Hospitality Limited Service, Industrial, Mixed Use, Mobile Home Park, Multifamily Housing, Office, Other, Retail Anchored, Retail Unanchored, Self Service Storage, and Warehouse. Model includes dummy variables (coefficients not reported) for State. These categorical variables include states such as the following: Georgia, Michigan, New York, and Texas. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. Chi squared statistic is in parentheses.

Cap Rate Spread and Non-performance: Conservative Loans

For Cap Rate Spread to aid in evaluating commercial mortgage risk, it must provide information beyond the analysis techniques already in use by industry experts and academic researchers. Conservative underwriting standards relying upon LTV and DSCR will still permit the origination of some subsequently non-performing loans. Starting with the sample used in Panel A of Table 11, fixed rate balloon loans, the sample is filtered further, selecting only those loans which would meet typical underwriter requirements in both areas, LTV and DSCR. Using only loans which would pass a conservative set of LTV and DSCR criteria, .80 and 1.25 respectively, the Cap Rate Spread coefficient now provides an indication of the additional information provided by this measure even among loans normally considered very conservative.

Although the sample includes only loans with LTV less than .8 and DSCR greater than 1.25, the specifications estimated retain these variables as these variables likely continue to be related to Non-performance even in these “safe” ranges. Table 12 presents the results of the model with this sample of presumably safe loans and indicates that Cap Rate Spread is a significantly related to Non-performance in the direction expected. The effect size of Cap Rate Spread approaches LTV and even exceeds that of DSCR in this restricted set of loans as expected since these loans have already been filtered to eliminate those with the most extreme LTV and DSCR values.

The effects are important in this group because this is a group of loans which would escape even the conservative underwriter’s scrutiny insofar as the LTV and DSCR measures are concerned. As with the full sample of fixed rate balloon loans, as the Cap Rate Spread falls, the incidence of Non-performance rises. This result is consistent in scale, direction, and significance to those of

Panel A of Table 11. Cap Rate Spread appears to provide an additional measure of risk identification.

Table 12 ■ Cap Rate Spread Model Results - LTV < .80 and DSCR > 1.25.

	LTV Model		DSCR Model	
LTV	1.08 ***	(101.59)		
DSCR			-0.31 ***	(75.57)
LnSIZE	0.03 **	(5.26)	0.04 ***	(8.02)
SPY	0.07	(1.10)	0.02	(0.10)
INT	0.26 ***	(155.07)	0.24 ***	(126.09)
DEALS	-0.05 ***	(11.63)	-0.05 ***	(15.34)
CPNSPRD	0.08 ***	(15.01)	0.05 ***	(7.05)
CAPSPRD	-0.90 ***	(8.13)	-0.47 **	(4.64)
Numer of observations	20,534		20,534	
McFadden's Pseudo R-squared	0.07		0.08	

Notes: Dependent variable is nonp (non performance). Sample includes fixed rate balloon loans with LTV < .8 and DSCR > 1.25. Model includes dummy variables (coefficients not reported) for loan originators. These categorical variables include institutions such as the following: Bank of America, Countrywide, Goldman Sachs, Merrill Lynch, Sun Trust, Wachovia, and Wells Fargo. Model includes dummy variables (coefficients not reported) for Property Type. These categorical variables include the following: Healthcare, Hospitality Full Service, Hospitality Limited Service, Industrial, Mixed Use, Mobile Home Park, Multifamily Housing, Office, Other, Retail Anchored, Retail Unanchored, Self Service Storage, and Warehouse. Model includes dummy variables (coefficients not reported) for State. These categorical variables include states such as the following: Georgia, Michigan, New York, and Texas. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. Chi Squared statistic is in parentheses.

Robustness Checks

The empirical models tested in this dissertation make some key assumptions which may affect the parameter estimates and potentially bias the results and conclusions of the research. The first of these assumptions is that of independence of the factors LTV and DSCR, which may be jointly determined with the price (*NETCPN*) of the loan. The second assumption relies upon the cumulative standard normal distribution to accurately describe the relationship between the probability of Non-performance and the independent variables in the models used to test the research hypotheses. Each of these assumptions is challenged in a series of robustness checks, with results reported in the section below.

Interest Rate Endogeneity

The pricing of commercial mortgages involves a myriad of factors and risk mitigation tools that range from the interest rate and ratio requirements of the loan to yield-maintenance provisions and contractual covenants. Among the group of numerical considerations, factors such as the coupon rate, LTV, and DSCR requirements are likely intertwined in the underwriting decision-making process. A loan with a higher LTV or lower DSCR may be approved with a higher interest rate. Conversely, loans with very conservative ratio results may be underwritten with lower interest rates. This potential endogeneity may introduce bias in estimates of the Cap Rate Spread in specifications including both the loan coupon rate (or calculated values relying upon it) and the LTV or DSCR ratios.

The LTV should be related to Coupon Rate through the recognition among underwriters that a loan with a higher LTV is riskier. As such, it is reasonable to expect that higher LTVs are associated with higher rates. Borrowers requiring very high loan amounts relative to the value of the collateral are sure to receive offers from lenders that feature commensurately higher interest rates. Similarly, borrowers with a target or required level of interest will likely face limits on the amount they may be borrowed and thus constrain the LTV possible for the deal.

The relation between loan interest rates and DSCR is even clearer, as higher interest rates directly affect the DSCR by increasing the payment required for a given loan amount. A complex interplay between the Coupon Rate, DSCR, and loan amount may also surface, as attempts by lenders to compensate for the risk of a low DSCR tend to exacerbate the very ratio of concern. As a risk-averse lender raises the rates to a low-DSCR borrower, the DSCR is even further reduced when this outcome is not offset by a lower loan amount. Although the focus of this analysis is constrained to LTV, DSCR and the Coupon Rate, many other factors may also be adjusted as underwriters price commercial loans. Factors such as yield-maintenance protections, rate type, amortization period, and other contractual provisions may also be modified by lenders to counteract the risks of high LTV or low DSCR when their ability to adjust the loan interest rate is limited.

To reduce the possibility of bias related to the endogeneity of loan rate and the ratios, a two-stage model is specified wherein the loan coupon rate is predicted as a function of the ratios LTV and DSCR, the 10-Year Treasury rate, indicator variables used in the other specifications, and a set of indicator variables not included in the second-stage of the specification. In order to identify the first-stage of the two-stage model, indicator variables for the time period are included in the first-stage of the model. The results of the first-stage of the model are presented in Table 13. All primary covariates are significant in the first-stage model including DSCR, LTV, and the 10-Year Treasury rate. Of the 72 quarterly indicator variables, 53 (73.6%) are significant at the 1% level, 2 (2.8%) are significant at the 5% level, 4 (5.6%) are significant at the 10% level, and the remaining 13 (18.1%) fail to satisfy a significance test at any of the customary levels. The second-stage of the specification predicts Non-performance as a function of Cap Rate Spread and other covariates but replaces the Cap Rate Spread used in prior specifications with Predicted Cap Rate Spread.

Table 13 ■ First Stage Model Results for Predicted Cap Rate Spread.

Variable	Estimates	
DSCR	-0.43 ***	(-37.11)
LTV	-0.97 ***	(-26.18)
INT	0.27 ***	(15.62)
Numer of observations	47,883	
R-squared	0.48	

Notes: Dependent variable is the loan coupon rate. Model includes dummy variables (coefficients not reported) for time period (year/quarter), loan amortization types, loan originators, property type, rate type, and state. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. T statistic is in parentheses.

The remainder of this second-stage model mirrors that of the model reported in Table 10. When comparing the results of the second-stage model presented in Table 14 to those of the ordinary model of Table 10, the direction and significance of the estimates are all consistent between the specifications, suggesting little sensitivity in the results to model choice in this regard. The McFadden's Pseudo R-squared provides no evidence that one model specification is a better fit to the data, with the single-stage and two-stage model values the same for both the LTV and DSCR model specifications.

Table 14 ■ Second Stage Model Results for Predicted Cap Rate Spread.

	LTV Model		DSCR Model	
LTV	1.05 ***	(229.70)		
DSCR			-0.24 ***	(110.16)
LnSIZE	0.04 ***	(30.82)	0.05 ***	(36.10)
SPY	-0.04	(0.65)	-0.08 *	(2.84)
INT	0.24 ***	(263.57)	0.22 ***	(212.63)
DEALS	-0.04 ***	(22.04)	-0.04 ***	(24.22)
CPNSPRD	0.10 ***	(91.47)	0.07 ***	(55.56)
PREDCAPSPRD	-0.22 ***	(7.37)	-0.04	(0.26)
Numer of observations	47,883		47,883	
McFadden's Pseudo R-squared	0.07		0.07	

Notes: Dependent variable is nonp (non performance). Model includes dummy variables (coefficients not reported) for loan ammortization types. These categorical variables include the following: Balloon, Fully Amortizing, Interest Only, Mixed, and Partial Interest Only. Model includes dummy variables (coefficients not reported) for loan originators. These categorical variables include institutions such as the following: Bank of America, Countrywide, Goldman Sachs, Merrill Lynch, Sun Trust, Wachovia, and Wells Fargo. Model includes dummy variables (coefficients not reported) for Property Type. These categorical variables include the following: Healthcare, Hospitality Full Service, Hospitality Limited Service, Industrial, Mixed Use, Mobile Home Park, Multifamily Housing, Office, Other, Retail Anchored, Retail Unanchored, Self Service Storage, and Warehouse. Model includes dummy variables (coefficients not reported) for Rate Type. These categorical variables include rate types such as the following: Fixed, Libor, Euribor, and Prime. Model includes dummy variables (coefficients not reported) for State. These categorical variables include states such as the following: Georgia, Michigan, New York, and Texas. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. Chi squared statistic is in parentheses.

To test for model sensitivity among the Fixed Rate Balloon Loan subsample, the two-stage approach is also applied to the model approach previously reported in Table 11. As with the prior two-stage specification, the Coupon Rate for the individual loans is predicted in the first-stage. The predicted loan Coupon Rate (*PREDNETCPN*) is then used in the construction of the Cap Rate Spread (*PREDCAPSPRD*) entered into the second-stage equation. The results of the second-stage model for specification testing loan groups are presented in Table 15. The estimates for the group of Fixed Rate Balloon loans are presented in Panel A and are consistent with the results in Panel A of Table 11. The estimates for other loans are presented in Panel B and are also consistent with the results in Panel B of Table 11. The results presented in Table 15 provide additional support with results for Cap Rate Spread that are insensitive to potential endogeneity between loan rates and the LTV / DSCR ratios.

Table 15 ■ Second Stage Model Results for Predicted Cap Rate Spread for loan groups.

Panel A -Fixed Rate Balloon Loans	LTV Model			DSCR Model		
LTV	0.94	***	(97.60)			
DSCR				-0.27	***	(69.52)
LnSIZE	0.05	***	(19.89)	0.06	***	(26.00)
SPY	0.07		(1.57)	0.02		(0.09)
INT	0.28	***	(214.05)	0.26	***	(175.55)
DEALS	-0.04	***	(11.78)	-0.05	***	(15.42)
CPNSPRD	0.13	***	(90.48)	0.10	***	(58.21)
PREDCAPSPRD	-0.46	***	(16.96)	-0.26	**	(6.58)
Numer of observations	24,918			24,918		
McFadden's Pseudo R-squared	0.07			0.07		
Panel B - Other Loan Types	**LTV Model**			**DSCR Model**		
LTV	1.24	***	(142.73)			
DSCR				-0.20	***	(39.11)
LnSIZE	0.04	***	(12.33)	0.04	***	(12.76)
SPY	-0.38	***	(14.31)	-0.37	***	(13.40)
INT	0.20	***	(60.53)	0.18	***	(48.99)
DEALS	-0.03	***	(8.52)	-0.03	***	(7.12)
CPNSPRD	0.06	***	(12.08)	0.04	**	(6.08)
PREDCAPSPRD	0.19		(1.84)	0.37	***	(7.38)
Numer of observations	22,965			22,965		
McFadden's Pseudo R-squared	0.08			0.07		

Notes: Dependent variable is nonp (non performance). Panel B includes the following amortization types: Amortizing, Interest Only, Mixed, and Partial Interest Only. Model includes dummy variables (coefficients not reported) for loan originators. These categorical variables include institutions such as the following: Bank of America, Countrywide, Goldman Sachs, Merrill Lynch, Sun Trust, Wachovia, and Wells Fargo. Model includes dummy variables (coefficients not reported) for Property Type. These categorical variables include the following: Healthcare, Hospitality Full Service, Hospitality Limited Service, Industrial, Mixed Use, Mobile Home Park, Multifamily Housing, Office, Other, Retail Anchored, Retail Unanchored, Self Service Storage, and Warehouse. Model includes dummy variables (coefficients not reported) for State. These categorical variables include states such as the following: Georgia, Michigan, New York, and Texas. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. Chi squared stastic is in parentheses.

Normal and Logistic Distributions

The empirical results presented thus far using probit models may be sensitive to the distribution assumption of this approach. The probit technique assumes that the relationship takes the form of the cumulative distribution function of the normal distribution. If this assumption is false, estimates from probit models may suffer from bias and lead to erroneous conclusions. To test for sensitivity to the distribution function choice, an alternative specification is used for two of the empirical models. The Cap Rate Spread models with results presented in Table 10 for both LTV and DSCR are performed again using a logit (logistic regression) model instead of a probit model.

The results of this process are presented in Table 16. The direction and significance of the estimates resulting from the logistic model are nearly identical to those resulting from the probit model in Table 10. The direction, significance, and model fit, as indicated by the McFadden's pseudo R-squared, suggest little difference between the probit and logit models with this sample and primary research question.

Table 16 ■ Logistic Cap Rate Spread Model.

	LTV Model		DSCR Model	
LTV	1.87 ***	(226.51)		
DSCR			-0.43 ***	(105.98)
LnSIZE	0.07 ***	(29.64)	0.08 ***	(35.60)
SPY	-0.08	(0.79)	-0.15 *	(3.14)
INT	0.42 ***	(257.92)	0.38 ***	(207.45)
DEALS	-0.06 ***	(20.95)	-0.07 ***	(22.97)
CPNSPRD	0.16 ***	(92.56)	0.13 ***	(58.94)
CAPSPRD	-0.44 ***	(8.94)	-0.12	(0.82)
Numer of observations	47,883		47,883	
McFadden's Pseudo R-squared	0.07		0.06	

Notes: Dependent variable is nonp (non performance). Model includes dummy variables (coefficients not reported) for loan ammortization types. These categorical variables include the following: Balloon, Fully Amortizing, Interest Only, Mixed, and Partial Interest Only. Model includes dummy variables (coefficients not reported) for loan originators. These categorical variables include institutions such as the following: Bank of America, Countrywide, Goldman Sachs, Merrill Lynch, Sun Trust, Wachovia, and Wells Fargo. Model includes dummy variables (coefficients not reported) for Property Type. These categorical variables include the following: Healthcare, Hospitality Full Service, Hospitality Limited Service, Industrial, Mixed Use, Mobile Home Park, Multifamily Housing, Office, Other, Retail Anchored, Retail Unanchored, Self Service Storage, and Warehouse. Model includes dummy variables (coefficients not reported) for Rate Type. These categorical variables include rate types such as the following: Fixed, Libor, Euribor, and Prime. Model includes dummy variables (coefficients not reported) for State. These categorical variables include states such as the following: Georgia, Michigan, New York, and Texas. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. Chi squared statistic in parentheses.

Although LTV and DSCR are correlated as expected, these variables are not the primary variables of interest and thus may be included together in the empirical tests in order to further improve the explanatory possibilities of the model. In addition to the robustness checks for endogeneity of coupon rates with LTV / DSCR and the distribution assumption, select models were modified to introduce interaction effects between LTV, DSCR, Cap Rate Spread, and market interest rates. The result of this process provided evidence of a significant interaction between Cap Rate Spread, and DSCR. Three models are estimated and presented with DSCR, LTV and both in the models reported in Table 17. The interaction terms included in the models are as follows: Cap Rate Spread with LTV, Cap Rate Spread with DSCR, LTV with DSCR, and Cap Rate Spread with Int (10-Year Treasury yield).

In the first model with only LTV, the interaction terms for Cap Rate Spread with DSCR and LTV with DSCR are significant. The second model which replaces LTV with DSCR, has similar results with the same interaction terms significant yet the LTV with DSCR interaction term reverses sign. This is likely due to the change from including LTV to including DSCR in the model. The third model includes both LTV and DSCR and again has a significant positive result for the Cap Rate Spread with DSCR interaction term. The LTV with DSCR term remains significant at the 10% level and again returns to a negative sign. In this final model with LTV, DSCR and the Cap Rate Spread with DSCR interaction term, DSCR is insignificant. Of particular note is the result for Cap Rate Spread. This variable, the focus of other models throughout this dissertation is insignificant in all cases when the Cap Rate Spread with DSCR variable is included in the model. DSCR is significant at the 1% level, Cap Rate Spread is insignificant, and the interaction term is significant at the 5% level. An interaction term for LTV and DSCR is also significant at the 1% level.

Extending the interaction testing to the subsets for Fixed Rate Balloon and all other loans, the coefficients for Cap Rate Spread and the Cap Rate Spread with DSCR in the LTV model are both significant at the 10% and 5% levels respectively. However, in the Fixed Rate Balloon model including DSCR, neither Cap Rate Spread nor the Cap Rate Spread with DSCR interaction term coefficients are significant. With the other loans, the Cap Rate Spread and Cap Rate Spread with DSCR coefficients are both highly significant in both the LTV and DSCR models. These results provide further evidence of the importance of Cap Rate Spread and its interaction with DSCR in CMBS loan underwriting decisions.

Table 17 ■ Interaction Model.

	LTV Model		DSCR Model		LTV and DSCR Model	
LTV	1.19 ***	(223.99)			1.25 ***	(49.92)
DSCR			-0.33 ***	(163.86)	0.02	(0.17)
LnSIZE	0.04 ***	(24.85)	0.04 ***	(28.53)	0.04 ***	(24.89)
SPY	-0.05	(.85)	-0.04	(0.74)	-0.05	(0.85)
INT	0.24 ***	(229.41)	0.25 ***	(250.05)	0.24 ***	(228.35)
DEALS	-0.04 ***	(23.12)	-0.04 ***	(21.55)	-0.04 ***	(23.13)
SPNSPRD	0.09 ***	(79.46)	0.09 ***	(77.21)	0.09 ***	(79.61)
CAPSPRD	-0.89	(.41)	-0.44	(0.10)	-0.91	(0.42)
CAPSPRD x LTV	0.15	(.02)	0.14	(0.01)	0.16	(0.02)
CAPSPRD x DSCR	1.08 ***	(12.03)	0.78 **	(6.47)	1.08 ***	(12.15)
LTV x DSCR	-0.17 ***	(7.87)	0.48 ***	(75.22)	-0.20 *	(3.50)
CAPSPRD x INT	-0.20	(1.52)	-0.20	(1.57)	-0.19	(1.51)
Numer of observations	47,883		47,883		47,883	
McFadden's Pseudo R-squared	0.07		0.07		0.07	

Notes: Dependent variable is nonp (non performance). Model includes dummy variables (coefficients not reported) for loan originators. These categorical variables include institutions such as the following: Bank of America, Countrywide, Goldman Sachs, Merrill Lynch, Sun Trust, Wachovia, and Wells Fargo. Model includes dummy variables (coefficients not reported) for Property Type. These categorical variables include the following: Healthcare, Hospitality Full Service, Hospitality Limited Service, Industrial, Mixed Use, Mobile Home Park, Multifamily Housing, Office, Other, Retail Anchored, Retail Unanchored, Self Service Storage, and Warehouse. Model includes dummy variables (coefficients not reported) for State. These categorical variables include states such as the following: Georgia, Michigan, New York, and Texas. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. Chi Squared statistic is in parentheses.

Research Limitations

The study by Archer, Elmer, Harrison, and Ling (2002) discusses survivor bias, a common problem with loan performance databases. The authors methodically present the issues of both left- and right-censoring of their data. Left-censoring can happen when loans are paid off early or when loans default and the property is sold prior to the observation point. As a result, these loans, which were originated alongside other loans in the final sample, are not included in the final sample. Similarly, databases provided by banks, insurance companies, and regulatory agencies are also prone to right-censoring of the data. The problem with right censoring is not missing loans, but rather loans that are present in the sample but have not yet defaulted. These limitations plague empirical studies in many domains that rely upon secondary data gathered and maintained primarily for the purposes of operating an ongoing business or governmental concern.

To reduce the effects of left-censoring, Archer, Elmer, Harrison, and Ling (2002) removed loans from their sample that had seasoned for more than 24 months prior to securitization by the RTC or FDIC. The authors point out that the problems of left censoring may be mitigated in the case of a multivariate analysis since, as they postulate, the marginal effects of the default factors likely influence the censored and uncensored loans equally.

Another typical issue with this type of data is accuracy. As a screen for the accuracy of key variables such as LTV and DSCR, values may be assessed to identify those which may be considered unreasonable. For example, outliers that fall far from industry standards may be eliminated from the sample on the grounds that they are either mistakes or represent atypical arrangements at the time of origination. For their sample, Archer, Elmer, Harrison, and Ling (2002) set cutoff criteria for the loan contract rate, original LTV, and DSCR to eliminate the potential effects of outliers. Although a similar process was used with this research to deal with outliers, the nature of CMBS loans and databases which provide the sources for secondary data research are prone to lack data and contain errors.

In one example of the potential for bias related to uncertainty in the data, the validity of parameter estimates in models including LTV rely upon the assumption that each property is encumbered by only one loan. If, however, some loans in the CMBS loan database are second mortgages these loans may experience more stress than other loans with the same LTV where the loan reported for the observation is the only loan for the property.

Another potential bias in the research is due to missing data. The most notable example is due to missing or invalid values for net operating income (NOI), a variable needed to compute Cap Rate and thus Cap Rate Spread. NOI is missing in 21,945, roughly 30% of the original sample of 73,196 U.S. loans originated starting in 1993. If this large number of loans differs from the remaining sample in a non-random manner in characteristics related to the measured relationships, the final results of this research may be severely biased. One possible extension of this research would be to supplement the Bloomberg data with additional sources which would fill in the NOI gaps and add other loan and originator data elements which may further add to the research possibilities herein.

CHAPTER FIVE – NUMERICAL ANALYSIS

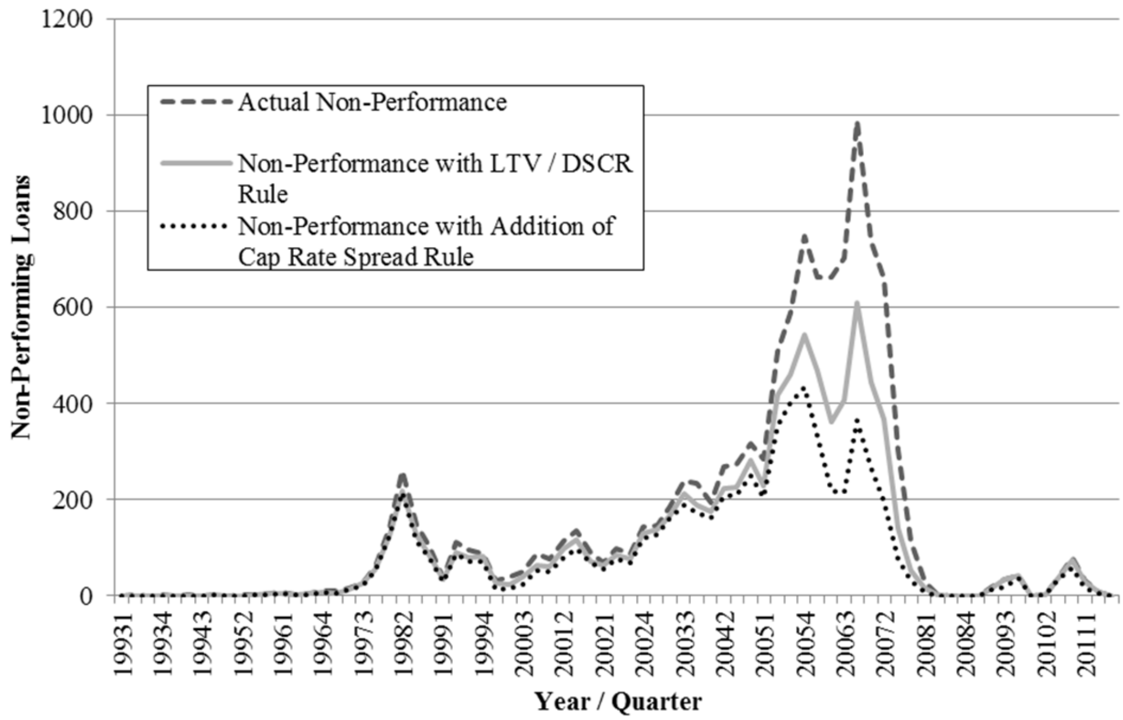
Applications

In practice, underwriters may be advised to select a decision rule or screening criteria related to Cap Rate Spread that is utilized alongside LTV and DSCR when making approval and/or pricing decisions on commercial mortgage loans. While the level selected by individual underwriters will vary according to the business model and risk tolerance of each firm, it may be illustrative to select a cutoff point and demonstrate the effect this prescription may have had on the rate of loan Non-performance for past loans. For demonstration purposes, a level of 1% is selected as a minimum Cap Rate Spread required for loans which would be approved for origination.

To ensure that the Cap Rate Spread is evaluated for its additional power to reduce loan Non-performance, the conservative LTV and DSCR rules are first applied. To visually present the result of increasingly restrictive underwriting criteria, a chart is constructed beginning with the rate of Non-performance for all loans, proceeding to the level of Non-performance with the conservative LTV and DSCR rules, and ending with the level of Non-performance by adding the Cap Rate Spread rule. The chart displays the much reported rise in Non-performance for those loans originated throughout the 2000s with the peak occurring in early-2007.

By introducing the LTV and DSCR criteria, the risk of Non-performance follows the same pattern but at levels markedly lower than what actually happened. The lowest line, for the addition of the Cap Rate Spread rule, is lower still and also demonstrates a slightly different pattern with the second major peak of the 2000s lower than the first. This result may suggest that Cap Rate Spread may have helped as an early warning signal to avoid the second major peak.

Figure 3 ■ Loan Performance with LTV/DSCR and Cap Rate Spread Rules



A Cap Rate Spread criteria requiring loans to have a value greater than .01 would have prevented the origination of an additional 1,798 CMBS loans reducing the rate of Non-performance from 14.9% with only the LTV and DSCR criteria to just 11.6% by adding the Cap Rate Spread criteria. Of course, the imposition of additional criteria will also lead to erroneously rejecting loans which would have performed well. Back testing with the same sample of CMBS loans, this Type I error rate rises from 19% with only the LTV and DSCR criteria to 34% with the addition of the Cap Rate Spread.

Ultimately, CMBS loan underwriters must individually determine an acceptable level of Non-performance appropriate to their business model and tolerance for risk. Using intuition, experience, tools, and rules, each underwriter must choose a balance between the competing risks of rejecting potentially profitable loans and accepting loans which will fail. This research result is important because it helps deepen our understanding of the relationships between property income and loan performance and provides an additional tool that underwriters may employ in assessing CMBS loan risk.

CHAPTER SIX – CONCLUSIONS AND IMPLICATIONS FOR FUTURE RESEARCH

Conclusions

Standard measures such as LTV and DSCR are the mainstay of commercial mortgage underwriting risk assessment. Despite the continued reliance upon these trusted measures, commercial mortgage Non-performance and ultimate default rose significantly during the financial crisis of the late 2000s. This rise in defaults, coupled with a boom in the securitization of commercial mortgages, provides motivation for studying loan and origination factors known at origination and their relationships with future Non-performance. In this dissertation, an additional factor is proposed that appears to have a relation to Non-performance: the Cap Rate Spread. This spread between the unlevered rate of return on the building and the coupon rate of the loan provides an indication of how profitable a project is to the mortgagee and how insulated they are against shocks to their NOI. A borrower with a high Cap Rate Spread has a greater ability to make continued loan payments during an economic downturn. Although Cap Rate Spread and DSCR are expected to rise together in most circumstances, periods of especially low interest rates may lead to loans with high DSCR and low Cap Rate Spread. These loans originated during low interest rate periods may be a particular risk of Non-performance.

The use of Cap Rate Spread is demonstrated as an additional underwriting standard on those loans which would have passed conservative criteria based on LTV and DSCR. These "safe" loans should provide fertile ground for exploring the marginal benefit of a Cap Rate Spread underwriting policy. Back-testing with the sample of CMBS loans originated in the 1993 – 2011 time period will show the quantity of loans which, though meeting the LTV and DSCR criteria, would have been rejected on a Cap Rate Spread basis, as well as the rate of error in rejecting loans that would have continued performing though the sample period.

The research relies primarily upon a probit methodology to estimate the parameters related to the probability of Non-performance in a sample of 47,883 individual loans that ultimately were packaged into CMBS. The evidence revealed through empirical testing suggests that Cap Rate Spread does provide significant additional information beyond that of the traditional ratios of LTV and DSCR. With the full database, results for models including LTV contained significantly negative coefficients for Cap Rate Spread suggesting that as Cap Rate Spread widens, the risk of Non-performance falls. When DSCR is included in the model, however, the Cap Rate Spread coefficient is no longer significant.

With the sample split into two groups, a homogenous group of the most common loans, Fixed Rate Balloon, and all other loans, the results for the Fixed Rate Balloon loans are consistent for both the LTV and DSCR models. With the group of Fixed Rate Balloon loans, the coefficient for Cap Rate Spread is negative and significant in all specifications including a two-stage model with a Cap Rate Spread measure based on a predicted Coupon Rate. The results are also robust to changing the distribution assumption from normal to logistic by modeling with the logit approach rather than probit. For the group of other loans, the coefficient for Cap Rate Spread is positive and significant in the DSCR model but is insignificant in the LTV model suggesting that Cap Rate Spread adds no additional information beyond LTV or that the set of variables in the model do not adequately represent the Non-performance process.

The final aim of this dissertation is to suggest and model the outcome of using a Cap Rate Spread underwriting standard when evaluating and approving commercial mortgage loans. Modeling the potential outcome of an underwriting tool such as Cap Rate Spread, an arbitrary cutoff point is set at 1% and analyzed for the effect on originations during the sample period of requiring a value greater than the cutoff in order for a loan to be approved. To better understand the marginal effects of such a policy, only loans which would have also passed conservative LTV and DSCR tests are considered. Loans that meet tests requiring LTV less than .8 and DSCR greater than 1.25 are further restricted with a Cap Rate Spread criteria that require loans to have a value greater than 1%. Such a policy would have prevented the origination of an additional 1,798 CMBS loans reducing the rate of Non-performance from 14.9% with only the LTV and DSCR criteria to just 11.6% by adding the Cap Rate Spread criteria.

If the null hypothesis with respect to loan performance is that loans will perform, a false positive (Type I) error would be the equivalent of blocking the origination of a loan which would have performed through the sample period. Back testing with the same sample of CMBS loans, this Type I error rate rises from 19%, with only the LTV and DSCR criteria, to 34% with the addition of the Cap Rate Spread. This prescription must be used with caution because the performance of the loans is only known through the end of the observation period. This truncated sample period does not include future Non-performance of the currently performing loans and thus may be biased by loans originated in later periods which did not experience economic conditions which may likely lead to Non-performance.

The appropriate Cap Rate Spread floor for use as an underwriting standard will necessarily vary according to the risk-tolerance and profitability of the individual originators or the investors purchasing the pools of mortgages through their CMBS shares. Loans or CMBS pools using a Cap Rate Spread floor policy that is otherwise similar to other loans or pools may provide an additional measure of protection against subsequent Non-performance or default. While no one Cap Rate Spread floor would be appropriate for all originators, all originators should consider incorporating this simple criteria into their broader program of underwriting tools.

Future Research Directions

Are there some situations where LTV, DSCR, or Cap Rate Spread is the binding constraint or the decision rule that would override in situations where the other rules disagree as to the approval of a loan? For example, there may be some situations when, even though the ratios LTV and DSCR suggest a loan is too risky for origination, the loan's Cap Rate Spread would support a favorable origination decision. The presentation in Figure 3 shows the possibility of the reverse, loans which would be approved on the basis of their LTV and DSCR ratios but may be declined due to a low Cap Rate Spread. The economic conditions and loan characteristics which determine the binding constraint from among LTV, DSCR and Cap Rate Spread is an area for further investigation. Visual inspection of the trends in levels seems to indicate that the relationship between interest rates and Cap Rate Spread changed after 2007. This potential structural break warrants further study to understand whether this apparent change is significant and to test theories which may explain the change, if any, to this relationship.

As pointed out previously, a simple rule to block the origination of loans likely to experience trouble in the future must be combined with information needed to balance the potential profits of lending with the potential losses of loan defaults. Any decision rule is likely to reject loans which would have performed well and accept loans which will later default. Research combining the profitability of particular loans or general loan characteristics with the institutional costs of default may help illuminate this interesting but unexplored aspect of loan performance and default. Extending this research to include additional information about the loan originators such as type of firm, extent to which originators retain an equity stake in target CMBS, and depth and experience of underwriting organizations may further demonstrate the importance of Cap Rate Spread in predicting CMBS loan performance.

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