Subordinations Levels in Structured Financing*

Xudong An, Yongheng Deng† and Anthony B. Sanders‡

August 15, 2006

* The authors are grateful for helpful comments from Dwight Jaffee at University of California at Berkeley, Steve Swidler at Auburn University, Sally Gordon at Moody's and symposium participants at the Cambridge-UNC Charlotte Symposium 2006 on "Risk Management & Property Derivatives" in Cambridge, UK (July 2006). An and Deng gratefully acknowledge the financial support from the Lusk Center for Real Estate at USC.

† Lusk Center for Real Estate, School of Policy, Planning and Development, University of Southern California, Los Angeles, CA 90089. An, xudongan@usc.edu , 213-821-1351, 213-740-0373 (fax); Deng, ydeng@usc.edu , 213-821-1030, 213-740-6170 (fax)

‡ Faculty of Finance, Fisher College of Business, Ohio State University, Columbus, OH 43210. Sanders, sanders.12@osu.edu, (614) 688-8609, (614) 292-2418 (fax).

Abstract

Subordination levels are of critical importance in the classic senior-subordinated structure for securitized financing (such as collateralized debt obligations and commercial mortgage-backed securities). Subordination levels determine the amount of credit support that the senior bonds (or tranches) require from the subordinated bonds (or tranches) and are provided by the rating agencies. Thus, ratings agencies play an important role in the pricing and risk management of structured finance products.

The finance literature has numerous studies examining whether securities with higher risk (as predicted by asset pricing models, such as the CAPM) earn higher ex-post average returns. In a similar vein, it is of interest to examine whether securities (or tranches) with greater levels of subordination experience higher ex-post levels of delinquencies and default. In this paper, we examine whether bonds (or tranches) with greater levels of subordination do, in fact, experience higher ex-post levels of delinquencies and default.

Recent studies have found that rating agencies follow a “learning by doing” approach in subordination structuring (Riddiough and Chiang, 2004). As expected, the rating agencies were conservative in the early stages with regard to subordination levels given the paucity of information about delinquencies, defaults and prepayments on loans. As time progresses and more information is available regarding loan performance, subordination levels adjusted to new levels. This paper focuses on cross sectional differences in subordination levels. We examine if this relationship between subordination and ex-post delinquencies and defaults is conforming to rational expectation.

We perform both a deal level and a loan level analysis using commercial mortgage-backed securities (CMBS). Our results show that the expected loss for CMBS pools are a statistically significant factor in explaining both AAA and BBB bond subordinations; however, expected loss accounts for less than 30 percent of the variation. Even considering the rating agencies’ practice of incorporating differences in loan terms, borrower quality, deal structural and information quality into their subordination structure, the empirical fit is still too low. These findings indicate the difficulty in determining subordination levels apriori.

Subordinations Levels in Structured Financing

1. Introduction

The structured finance market has grown rapidly during the past two decades[1]. An attractive feature of structured finance to investors is the senior-subordinated debt structure where cash flows from underlying loan pool are allocated to various tranches of securities (bonds) according to rules. Typically, prepayments of principal are often distributed first to the senior tranches while losses due to default are allocated first to the subordinated tranches. Therefore, investors buying senior tranches expect to be well protected from credit risks while those holding subordinated tranches will get higher expected returns.

In this senior-subordinated structure, bond subordination levels are key variables because they determine how much credit support senior tranches have from the subordinated tranches. A stylized fact about subordination levels is that there exists a time series trend showing subordination levels declining systematically over time for one type of structured financing: commercial mortgage-backed securities (CMBS). This decline in subordination levels has been attributed to CMBS issuers' and rating agencies' "learning by doing" in subordination design (Riddiough and Chiang, 2004). Recent research by Downing and Wallace (2005) regarding CMBS suggests that, even for recently issued CMBS bonds, the observed subordination levels are higher than the optimal level, and that the market should see further reductions in subordination.

[1] For example, CMBS annual issuance in US has grown from less than $1 billion in 1985 to $169 billion in 2005. CMBS outstanding at the end of 2005 reached $550 billion, which accounts for about 21 percent of $2.6 trillion commercial mortgage outstanding.

A parallel question to how CMBS subordination design evolves over time is whether cross sectional differentials in subordination reflect differences in credit risks of CMBS pools. This is an interesting question because of two reasons: first, it is noteworthy that there is no standard for subordination design in the CMBS industry. Each rating agency is using a "learning by doing" approach as the industry develops. Second, using information at deal cutoff point (the time when information about the deal is measured) to infer CMBS deals' potential loss in a long horizon is a challenging task. Most rating agencies rely on the static approach, which attempts to assign subordination based on information observable at CMBS deal cutoff date. It is not clear whether this approach effectively captures potential dynamics of the default behaviors of many mortgage loans underlying CMBS pools. There are increasing volumes of studies have shown that it is the contemporaneous loan-to-value ratio (LTV) and debt-service-coverage ratio (DSCR) rather than original LTV and DSCR that determines commercial mortgage default risk (Ambrose and Sanders, 2003 and Ciochetti et al., 2003 among others).

In this paper, we examine both the static and dynamic approach in determining subordination levels. First, we examine how AAA and BBB bond subordination levels can be explained by both credit and non-credit variables at deal level. We pay special attention to the roles of original LTV and original DSCR, while existing literature suggest neither will be a good credit risk predictor for commercial mortgages. Second, we directly link AAA and BBB subordination levels with CMBS pool credit risks. The latter are measured as aggregate expected losses of commercial mortgage loans underlying each pool. Commercial mortgage loan expected loss is calculated by using the estimated commercial mortgage default probabilities and a set of predetermined loss severity rates by various property types.

Our analysis is based on a unique dataset which contains both CMBS deal level information and underlying commercial mortgage loan information. This dataset includes deal subordination levels and loan specific data such as loan-to-value (LTV) ratio, debt service coverage (DSCR) ratio, location of property, and loan outcomes in terms of prepayment, delinquency and default. Our dataset contains 193 CMBS conduit deals and approximately 30,000 commercial mortgage loans underlying those deals.

Our results show: 1) CMBS deal cutoff LTV, DSCR, property type and cutoff year are significant factors for CMBS bond subordination, and they explain about 85 percent of cross sectional variations in AAA subordination levels and over 65 percent of variations in BBB subordination levels; cutoff LTV and DSCR themselves explain about a quarter of the variations in subordination. 2) CMBS pool expected loss is a statistically significant factor in explaining both AAA and BBB bond subordinations; however, they account for less than 30 percent of the variation.

Previous studies on CMBS subordination include Riddiough and Chiang (2004) and Downing and Wallace (2005). Riddiough and Chiang (2004) discuss the development of commercial mortgage securitization and examine the active role of financial intermediaries (CMBS issuers and rating agencies) in subordination design and price setting. They find "learning by doing" behaviors in the development of this market. Downing and Wallace (2005) use a structural commercial mortgage-pricing model to infer the optimal CMBS bond subordination levels. They find subordination levels observed in the market are higher than their estimates and conclude that the market will likely see further reductions in subordination. There are two important differences between our study and the two aforementioned studies. First, these previous studies examine subordination at the CMBS deal level analysis, while we utilize all commercial mortgage loan level information and integrate underlying loan performance and deal level subordination design in our analysis. Second, the previous studies emphasize the time series properties of subordination while we focus on cross sectional differentials. The cross sectional analysis is important because CMBS investors need to differentiate "good" deals from "bad" deals.

In our analysis of CMBS subordination, we adopt a hazard model for commercial mortgage default based on the well developed mortgage default risk literature (e.g. Deng, Quigley and Van Order, 2000 and Ambrose and Sanders, 2003), which provides useful information on loan level default risk analysis for both the academic and industrial practitioners like rating agencies, commercial mortgage lenders and CMBS investors.

The section 2 briefly summarizes the mechanism of CMBS structure and subordination; section 3 explains our research questions and empirical approach; sections 4 and 5 describe the data and model results; concluding remarks are in a final section.

2. CMBS Product Design and Subordination

2.1 CMBS structure

Commercial mortgage-backed securities are an example of a structured finance product. Commercial mortgages are pooled together by CMBS issuers and several tranches of securities are created and sold to investors. A number of studies have shown that this pooling and tranching mechanism helps mitigate market imperfections and creates value (Riddiough, 1997, DeMarzo and Duffie, 1998, DeMarzo, 2005 and Gaur, Seshadri and Subrahmanyam, 2005). Intuitively, this mechanism enhances liquidity, diversification and risk management in the commercial mortgage market. This greatly enlarges the investor base and facilitates capital flow in commercial mortgage market. In many cases, a large number of loans are pooled together to create diversification effect. Finally, several entities with special expertise, such as commercial mortgage underwriter, CMBS issuer, master servicer, special servicer and rating agency are involved in the process to help achieve better risk management.

A typical CMBS is formed when an issuer deposits commercial mortgage loans into a trust[2]. The issuer then creates a series of tranches (bonds) backed by the loans and formed the so-called senior-subordinated debt structure. The tranches have varying credit qualities from AAA, AA (senior tranche), to BB, B (subordinated) and to unrated (first loss)[3] given that any return of principal caused by amortization, prepayment and default is allocated to the highest-rated tranche first and then the lower-rated tranches, while any losses that arise from a loan default is charged against the principal balance of the lowest rated tranche that is outstanding (first loss piece). Any interest received from outstanding principal is paid to all tranches[4].

Commercial mortgages found underlying CMBS deals are mostly restricted or deterred from prepayment by lockout, yield maintenance, defeasance and/or prepayment penalties. Commercial mortgages have substantially higher default rates than residential

[2] The loans could be bought from traditional lenders, portfolio holders or from conduit loan originators.
[3] Many CMBS deals also have an interest only (IO) tranche which absorbs excess interest payment.
[4] It is noteworthy that many CMBS deals vary from this simple structure. For more information, see Sanders (1999) and Darrell (2001). Also see Sanders (1999), Geltner and Miller (2001), Wheeler (2001) for other issues such as commercial mortgage underwriting, form of the trust, servicing, commercial loan evaluation, etc.

mortgages. Investors in subordinated tranches can get a as high as 500 bps spread over comparable maturity treasuries (depending on market conditions), while those who invest in AAA tranches get much lower spread since they are expected to be protected by the subordinated tranches.

2.2 Subordination

For each CMBS tranche, subordination level is defined as the proportion of principal outstanding of other tranches with lower rating. It reflects "credit support" of that tranche. Rating agencies play a key role in determining subordination levels at deal cutoff. Typically, the CMBS issuer proposes a debt structure, and the rating agencies work independently to examine whether the proposed structure can assure the tranches to reach certain ratings, such as AAA, AA, A, BBB etc. If not, rating agencies usually suggest the issuer to remove certain loans from the pool or change the amount of tranches in order to assign specific ratings to the tranches[5]. CMBS investors rely on the quality certification given by rating agencies and tell credit quality differences between different tranches mainly by their ratings[6].

Each rating agency has its own internal model in determining subordination levels. However, the general framework is approximately the same. Rating agencies perform three levels of analysis: 1) on the property level, based on commercial mortgage loan underwriters' cash flow report, rating agencies adjust property net operating income (NOI) based on their own judgments of whether the number in underwriting report is

[5] Usually two or more rating agencies are invited to CMBS rating and the proposing-revision process for subordination goes recursively. Moody's, Standard and Poor's and Fitch are currently three major CMBS rating agencies.
[6] Rating agencies also monitor each CMBS bond after its issuance, and like in corporate bond market, they upgrade and downgrade some bonds according to the change in the CMBS pool performance.

sustainable given the current market condition and deduct capital items such as capital reserves, tenant improvement and leasing commissions to form the so called net-cash flow (NCF). Rating agencies then calculate property value using their own capitalization rates, which could be different from the current market capitalization rate[7]. Rating agencies then calculate their "stressed" LTV and DSCR for each loan and feed their stressed LTVs and DSCRs into a loss matrix to form the basic credit support assessments. 2) On the loan level, rating agencies look at borrower quality, amortization, cash management, cross- and over-collateralization to make adjustment to their basic credit support assessments. After doing this, rating agencies aggregate their analysis into the pool level and assign subordination to each proposed CMBS tranches[8]. 3) Finally rating agencies perform portfolio level analysis, which examines pool diversity, information quality and legal and structural issues, and makes final adjustment to subordination levels for each CMBS bond.

It is noteworthy that there is no standard for subordination design. Each rating agency is using a "learning by doing" approach as the industry develops (Riddiough and Chiang, 2004). A stylized fact about subordination is that subordination levels have declined systematically since 1997. Researchers argue that this decline is the result of rating agencies being overly conservative at the beginning of the CMBS market development, and when the ratings agencies develop greater familiarity with the product and the market, they apply less stringent subordination criteria (Sanders, 1999, Geltner and Miller, 2001, Wheeler, 2001 and Downing and Wallace, 2005).

---

[7] For example, Moody's uses a stabilized cap rate to try to achieve a "through-the-cycle" property value.

[8] Although rating agencies perform property and loan analysis mainly on individual basis, they sometimes only review a random sample (40-60%) of the loans when number of mortgages in the pool is large, the pool was originated with uniform underwriting standards and the distribution of the loan balance is not widely skewed.

Recently, some rating agencies have started to employ a dynamic approach to assist the static approach in subordination design. Rather than relying on the static stressed LTV and DSCR and other information at deal cutoff, the dynamic approach attempts to incorporate a default probability model and loss severity model to predict commercial mortgage and CMBS pool expected loss over a relatively long horizon[9]. This is potentially a more desirable approach because the optimal subordination is essentially the expected default loss. However, the dynamic approach is still playing a complementary role in the industry and the static approach is the dominating methodology used in subordination design.

3. Research Question and Empirical Approach

There has been growing amount of interest in the economics of subordination in CMBS between both academics and industry practitioners in recent years. Through the analysis of subordination designs changes over time, researchers learn how the market solves the information problem as well as the learning process of market participants is in the newly innovated market (Riddiough and Chiang, 2004). From CMBS issuers' perspective, the optimal subordination design requires as less subordination as possible for a deal given the rating structure because the issuers can sell the senor tranches with a premium but the subordinated tranches with a discount. On the other hand, investors buying senior tranches always want as much subordination as possible to protect them from the pool default risk. Therefore the optimal subordination design requires rating agencies to deliver fair certification for CMBS products. However, rating agencies have

[9] For example, Moody's uses its Commercial Mortgage Metrics (CMM) to assist subordination design nowadays.

been experiencing "learning by doing" along with the development of the market, and there is no standard for optimal subordination design. For example, subordination criteria have become more liberal comparing to the conservative levels used in early years.

A parallel question to how CMBS subordination design evolves over time is whether cross sectional differentials in subordination reflect differences in credit risks of CMBS pools. One may argue that overall rating agencies have helped form more than enough credit support for senior tranches. However, it is not clear whether investors buying different CMBS bonds with the same rating are equally compensated for the risks taken. This question is important given rating agencies' usage of the static approach in subordination design.

CMBS bond subordination should reflect bond lifetime CMBS pool expected loss. Although rating agencies try to incorporate the analysis of future market trend into the subordination design, precisely predicting CMBS deals' potential loss in a long horizon is a very challenging job. For example, increasing volume of studies has shown that it is the contemporaneous loan-to-value ratio (LTV) and debt-service-coverage ratio (DSCR) rather than original LTV and DSCR that determines commercial mortgage default risk[10] (Vandell et al, 1993, Archer et al, 2001, Ambrose and Sanders, 2003, Ciochetti et al 2003, Ciochetti et al 2002, Chen and Deng, 2003 and Deng, Quigley and Sanders, 2005). Although rating agencies have been trying other static variables very different from

[10] It is argued that original LTV and DSCR might be endogenous to commercial mortgage default risk, e.g. because commercial mortgage loan origination is a negotiation process, when a lender/originator perceives that a commercial mortgage has higher risk than usual, one important instrument he would use is to adjust the amount of loan he issues, which results in a lower LTV and higher DSCR.

original LTV and DSCR[11], there have been concerns about the accuracy of using some "one-shot" static control variables in the long horizon prediction.

In order to address this concern, we propose an empirical test based on both a deal level analysis and a loan level analysis. In the deal level analysis, we examine how AAA and BBB bond subordination levels are related to deal level credit and non-credit variables. A linear regression model is estimated where the dependent variables are AAA and BBB bond subordination. We use variables observable at deal cutoff as our explanatory variables. These variables include credit risk factors well identified in the literature, such as property types, geographic diversification, loan size concentration and over-collateralization. We pay special attention to the roles of original LTV and original DSCR. Due to the reasons discussed in above, we expect these two factors to be insignificant on AAA and BBB subordination. We also include deal cutoff dummies based on the "learning by doing" argument. By estimating this model, we can infer what kind of factors explain the cross sectional variations in subordination.

In a loan level analysis, we directly link AAA and BBB subordination levels with the expected performance of CMBS deal underlying loans. Ideally, the subordination level should be equal to the expected deal loss over the lifetime of the bond, which is the aggregation of expected losses of underlying loans. Therefore, we should anticipate expected deal losses to have substantial explanatory power of cross sectional variations in subordination.

The empirical analysis is specified using the following steps: first, we identify all commercial mortgage loans underlying the deals in the deal level regression; second, we

---

[11] Some rating agencies use their own stressed LTV and DSCR ratios, which may be very different from the original LTV and DSCR used here.

estimate a hazard model for conditional default probabilities of commercial mortgage loans. Hazard model has been proven to be a very effective tool to estimate and predict commercial mortgage default probabilities (Vandell, 1993, Huang and Ondrich, 2002, Ciochetti et al, 2002, 2003 and Chen and Deng, 2003). We follow the literature to include the most important variables such as the intrinsic value of call exercise and the intrinsic value of put exercise (contemporaneous LTV) as our covariates. We also incorporate property types, regional dummies and market environments such as credit spread, volatility of risk free rate and unemployment rate. Original LTV is also included as a test of the endogeneity hypothesis. Unfortunately, we do not have a contemporaneous DSCR variable available. However, if we assume a stabilized cap rate as is commonly done by rating agencies, we know this variable is perfectly correlated with contemporaneous LTV. Third, we make predictions of default probabilities for each loan using the model we just estimated, excluding insignificant variables. Next, we calculate expected losses of each loan over a specific time horizon based on default probability predictions and on assumptions of loss severities for each property type used as industry norm (expected loss = default probability × loss given default). We then aggregate expected losses of these loans into CMBS deals to calculate expected deal losses over certain horizons. Finally, we regress AAA and BBB subordination levels on expected deal losses to see how cross sectional variations of subordination can be explained by differences in deal credit risk. We should not expect a perfect correlation because there are other omitted factors such as legal and structural differences[12], information quality and borrower characteristics which

[12] As discussed previously, some deals may have special features on deal structure and legal arrangements. although they are all within the senior-subordinated framework.

affect pool credit risks but not included in our analysis. However, we should expect a high correlation given we have the most important variables included in our model.

We choose to use predict expected loss rather than the actual loss observed from the pools as explanatory variable in our subordination levels analysis because subordination is by definition designed to capture systematic credit risk. Actual pool loss contains idiosyncratic effects which are just noises to our analysis.

4. Data

We have constructed a dataset that contains information on both CMBS deals and their underlying commercial mortgage loans. Our database matches a CMBS deal database with a large commercial mortgage loan performance database from 1994 to 2003.

The database includes 718 CMBS deals and it covers virtually all CMBS deals during the period and contains detailed information on cutoff date, cutoff balance, cutoff LTV and DSCR, cutoff AAA and BBB subordination, as well as current values for these variables. It also has detailed information on geographic and property type distributions of properties underlying the loans. The data was collected through April 1, 2005.

We focus on conduit deals and those with all fixed rate loans underlying the pools. Conduit deal are the best suitable for our analysis because: 1) commercial mortgage loans underlying conduit deals are intended to be put into CMBS pools at origination, and they usually go into the pools after a short warehousing period[13]. Therefore, conduit deals have cutoff LTV and DSCR very close to weighted average of original LTV and DSCR

[13] In contrast, portfolio deals have underlying loans originally held in whole loan form by lenders or other investors and then sold to CMBS issuers.

of underlying loans. 2) Conduit deals have better information standards and thus they are more transparent to public than other types of deals (Riddiough, 1997).

We have a large loan history dataset of commercial mortgages from a major commercial mortgage data corporation[14]. There are about 50,000 loans originated during 1992-2003. The dataset contains detailed loan level information on origination date, original balance, original LTV and DSCR, mortgage rate, term, type and location of the property, paid off date, delinquency status, etc. Most importantly, it contains loan performance information (defaulted, prepaid, mature or current). The data reporting date is June 1, 2003.

We match the deal dataset and the loan history dataset by deal name. We also verify whether every loan supposed to be in the deal is in our sample, and excludes several deals with over 2 percent of loans missing. Finally we end up with 193 conduit deals associated with 30,049 loans. Table 1 lists the name and number of loans of all these deals. Number of loans underlying each deal varies from 28 to 421, with an average of 156. These deals are cutoff during 1995-2003 (Table 2), and the year distribution somehow reflects the increasing popularity of conduit deals.

We also use other data sources such as 1) interest rates from the Federal Reserve, 2) commercial property index from the National Association of Real Estate Investment Trusts (NAREIT) for the use of calculating option values[15], and 3) state level unemployment rates from the Bureau of Labor Statistics (BLS).

5. Results

[14] The provider prefers to be anonymous.
[15] We notice that the NAREIT index is for equity but not asset. However, that's the best we have.

5.1 Deal Level Subordination Analysis

Table 3 reports descriptive statistics of the 193 deals. Average deal cutoff balance is $924 million. AAA subordination level ranges from 12% to 37%, and weighted average LTVs at cutoff are between 43% and 77%. The geographic diversification variable is measured by the entropy[16] where the higher the value of the entropy, the more evenly distributed the loans are in geography (see Table 3 for details). The property concentration variable is also an entropy measure. Over-collateralization is percentage of loans with over-collateralization, and the prepayment constraint variable measures the weighted average mortgage term (in months) covered by lockout, yield maintenance, defeasance or prepayment penalty.

Table 4 reports regression results of both AAA and BBB subordinations. Most property types have an impact on subordination levels as expected. For example, when there are more anchored retail properties, there are less subordination requirements because loans for anchored retail properties have much lower risks than other types such as office, hotel and industrial. Hotel loans are very risky and thus proportion of hotel loans has positive significant impact on subordination. However, the percentage of multifamily loans has no impact on subordination, which contradicts to the common perception that multifamily loans are of low risk.

The biggest surprise comes from cutoff LTV and cutoff DSCR. Cutoff LTV is highly significant with positive sign and cutoff DSCR is significant with negative sign. However, we explained previously that cutoff LTV and DSCR should not be good credit risk predictors. We also estimate the subordination levels with cutoff LTV and cutoff

[16] The entropy measures the degree to which the probability of the system is spread out over different possible states. The more states are available to the system with higher probability, the greater the entropy.

DSCR as the only explanatory variables (model 1 in table 4). It turns out that these two variables have substantial explanatory power on subordination. They account for about 24 and 21 percent of cross sectional variation in subordination of AAA and BBB bonds respectively. In real world, rating agencies are using stressed LTV and DSCR rather than cutoff LTV and DSCR in subordination design, but we see cutoff LTV and DSCR have substantial explanatory power of subordination levels. We hypothesize that cutoff LTV and DSCR are highly correlated with rating agencies' stressed LTV and DSCR.

It is also surprising that the Herfindahl index for loan size concentration and estimated LTV at maturity, which is a proxy of balloon risk, is not significant. In addition, the coefficient of the geographic diversification variable has opposite sign to our expectation.

Certainly, this static analysis is not definitive because we are not clear such model will reflect CMBS pool credit risks over a relatively long horizon. We need further investigation based on commercial mortgage loan performance as an alternative to the static analysis.

Finally, our results show that subordination level contracts over time, which is consistent with the argument that rating agencies and CMBS issuers tend to be conservative in subordination design at early stage of CMBS market development, and are becoming less stringent with subordination levels.

5.2 Default Risk Analysis

The loan level analysis lost a few loan observations due to missing values in LTV and other variables. Table 5 shows the origination year distribution of 28,124 loans left in our sample. Parallel to the year distribution of deals, we have fewer loans originated in 1994 and 1995. The 28,124 loans finance properties widely distributed among 10 regions (see Table 6), with the highest share of Southern/Atlantic. Southern/West Coast, Western/Southern Pacific and Northeast/Mid-Atlantic also have over 10 percent loans populated. A further analysis show that these loans are originated in 51 US states plus two US territories, Puerto Rico and Virgin Islands, among which California (17.81%), Texas (10.98%), Florida (7.65%) and New York (6.04%) are the four most populated states. The loans are within 332 MSAs, with Los Angeles, CA, New York City, NY and Dallas, TX accounting for over 3 percent each.

In terms of loan numbers, the most populated property type is multifamily, which accounts for almost one-third of the sample (see Table 7). Retail and office also have significant shares. Table 8 shows characteristics of loans at origination. Original LTVs vary from less than 1% to 113%. As usually seen, most of these commercial mortgage loans have prepayment constraints, and lockout covers nearly 50 percent of the maturity terms (see Table 9).

We identify 912 defaults (defined as over 60 days of delinquency), which is 3.24% of the whole sample (see Table 10). This is much higher than residential default rate in a 9-year horizon (1995-2003). The sample only contains 2.37% prepayments, which is much lower than prepayment rate in residential mortgages.

Figure 1 plots the empirical conditional default probabilities at various seasoning (measured in months) of the pool, comparing to the residential default rate benchmark – the 100% SDA. The default probabilities in our sample in most periods are two to three times of the 100% SDA, which demonstrates that commercial mortgages could be much riskier than residential mortgages.

Table 11 reports means and variances of time varying variables at origination and at termination. The intrinsic values of call and put exercises are calculated following Deng, Quigley and Van Order (2000), and the volatility of 10 year treasury security rate, credit spread and credit spread volatility are calculated following Ambrose and Sanders (2003). Specifically, the intrinsic value of call exercise is calculated as the ratio of present values of remaining mortgage payment based on market mortgage rate and on coupon rate. For calculating the intrinsic value of put exercise, we use the National Association of Real Estate Investment Trusts (NAREIT) REITs index by property type to approximate the property value process of each loan, and then calculate the ratio of present value of remaining mortgage payment based on market mortgage rate and property value. The put exercise value is just this ratio minus 1. Volatility of the 10-year treasury rate is defined as the standard deviation of the 10-year rate measured over the past 24 months. Figure 2 shows the treasury rates and yield curve during our study period, and figure 3 shows the volatility of the 10-year treasury rate. Credit spread is defined as the spread between AAA and Baa rated corporate bond yields, and credit spread volatility is calculated similar to the volatility of the 10-year treasury rate. Figure 4 and 5 plot the credit spread and credit spread volatility. State level monthly unemployment rate from the BLS are matched into our data. The variable prepayment constraint is a time varying dummy variable indicating, in each month, whether the mortgage is covered by any type of prepayment constraint – lock out, yield maintenance or prepayment penalty. We see that the average put option value for defaulted loans is significantly higher than loans at large.

We estimate a flexible baseline hazard model following the method in Deng, Quigley and Van Order (2000) for default risk. We only focus this analysis on default risk due to the following two reasons: first, prepayment is very rare in commercial mortgage as seen in our sample[17]; second, theoretically prepayment has little impact on subordination. Table 12 presents the maximum likelihood estimates.

The value of put option exercise is highly significant for default, and it has a positive sign as we expect. Different from the competing risks story in residential mortgages, the value of call option is positively related to default exercise. This is possibly because given prepayment constraint and distressed loans workout practice in commercial mortgages, some borrowers could simply choose to default when it's optimal to refinance and they could get a new mortgage to pay off the principal when original lender/servicer comes to "workout" the loan[18]. Credit spread and unemployment rate, which are good proxies for overall and local economic environments respectively, are significant and have positive effect on default. For different property types, hotel loans have higher default rates, other things being equal. Office loans have lower default rates. It is interesting that multifamily loans do not show lower default rates with statistical significance, which may be consistent with our previous results of deal subordination. Loans in Midwest and in Southern part of the country are riskier, while those in Western/Southern Pacific, including California, have lower default risks. This is consistent with regional real estate market performance.

[17] This could be mainly because of the prepayment constraint.
[18] Although this is not legal practice, it is not rare.

Consistent with the existing literature, original LTV does not have a positive impact on default risk. We also analyze the correlations of original LTV and put and call values. We find that the correlations are very low, which exclude the possibility that the values of put and call exercises capture the effect of original LTV on default risk.

Our final goal is to directly link subordination to CMBS pool credit risk. We use the default probability model estimated above to predict conditional default probabilities for each loan over 85-month period. We then calculate cumulative default probabilities in each month. The cumulative default rate in the first year is about 0.1 percent and it grows to over 2 percent in year 3 and over 4 percent in year 5 (see Table 13).

Next, we calculate expected losses of each loan over certain horizons based on loss severity assumptions documented in the Appendix table. Then, we aggregate loan level expected losses into CMBS deal level. Table 14 shows the expected losses of the 174 CMBS deals at 1 year, 2 year, 3 year, 5 year and 7 year.

Finally, we regress AAA and BBB subordination levels of CMBS deals on the predicted 2-year, 3-year, 5-year and 7-year expected losses respectively. If subordination differentials well reflect differences in CMBS pool credit risks, the expected losses should have strong explanatory power for the AAA and BBB subordination levels. In table 14 (panel 1 for AAA subordination and panel 2 for BBB subordination), we do see that the 2-year, 3-year, 5-year and 7-year expected losses are all have significant positive correlation with subordination.

Our findings suggest that rating agencies' static approach in subordination design does capture some variations in CMBS pool credit risks. However, we find the fittings of above models range from 8 percent to 29 percent, which implies that over 70 percent of subordination variation is not explained by the predicted losses. As discussed earlier, we do not expect a perfect fitting, because our sample does not contain some of the static control variables rating agencies control such as differences in loan terms, borrower quality, deal structural and legal issues, and information quality. However, we believe expected losses calculated here should be the major determinants of subordination and it is hard to imagine that other factors should account for as high as 70 percent of the subordination variations.

Our deal level and loan level analyses suggest that the dynamic approach that incorporates more sophisticated default probability models (such as the hazard model) will likely be more desirable in the future research.

6. Conclusion

Subordination plays an important role in the senior-subordinated structure of securitized transactions such as CMBS. Optimal subordination design is in the interests of CMBS investors, issuers and rating agencies because subordination levels determine how investors buying senior CMBS bonds are protected from credit risk and how much an issuer can get out of a certain commercial mortgage pool. Rating agencies essentially decide subordination levels for each CMBS deal.

Recent studies show rating agencies follow a "learning by doing" approach in subordination design, and they have been overly conservative in the early stage of the market development (Riddiough and Chiang, 2004 and Downing and Wallace 2005). Parallel to the question of how CMBS subordination design evolves over time, whether cross sectional differentials in subordination reflect differences in credit risks of CMBS pools is an important question.

Rating agencies have traditionally used a static approach on subordination design, in which information collected at the deal cutoff point is used to infer credit support needed for CMBS bonds to reach certain ratings. Given CMBS bond subordination should reflect bond lifetime CMBS pool expected loss, it is not clear whether those "one-shot" static variables captures potential dynamics of the default behaviors of many mortgage loans underlying CMBS pools.

We perform two layers of analysis to examine whether cross sectional differentials in CMBS subordination levels reflect differences in CMBS pool credit risks. Our deal level analysis of subordination levels show that CMBS deal cutoff LTV, DSCR, property type composition and cutoff year are significant factors for CMBS bond subordination, and they explain about 85 percent of cross sectional variations in AAA subordination levels and over 65 percent of variations in BBB subordination levels; surprisingly, cutoff LTV and DSCR themselves explain about a quarter of the variations in subordination. Our loan level analysis based on default probability hazard model and certain assumptions of loss severities show that CMBS pool expected loss is a statistically significant factor in explaining both AAA and BBB bond subordinations; however, they account for less than 30 percent of the variation. Even taking account of rating agencies' practice of incorporating differences in loan terms, borrower quality, deal structural and legal issues and information quality into their subordination design, the less than 30 percent of fitting is still too low.

Combining our deal level and loan level analysis, we were able to demonstrate the dynamic approach that incorporates more sophisticated default probability models (such as the hazard model that is well developed in the literature) might be desirable for ratings agencies to employ.

Historically, CMBS subordination has not reached boundary condition in general, because historical subordination levels have been systematically higher than needed (Downing and Wallace, 2005). When rating agencies apply less stringent subordination standards in recent years, optimal subordination design will become a more important concern.

References

Ambrose, Brent W., and Anthony B. Sanders (2003), "Commercial Mortgage-backed Securities: Prepayment and Default," *Journal of Real Estate Finance and Economics*, 26 (2-3): 179-196.

Archer, Wayne R., Peter J. Elmer, David M. Harrison and David C. Ling (2002), "Determinants of Multifamily Mortgage Default," *Real Estate Economics*, 30 (3): 445-473.

Chen, Jun and Deng, Yongheng, (2003), "Commercial Mortgage Workout Strategy and Conditional Default Probability: Evidence from Special Serviced CMBS Loans," University of Southern California Lusk Center for Real Estate Working Paper No. 2003-1008.

Ciochetti, Brian A., Yongheng Deng, Bin Gao, and Rui Yao (2002), "The Termination of Commercial Mortgage Contracts through Prepayment and Default: A Proportional Hazards Approach with Competing Risks," *Real Estate Economics,* 30 (4): 595-633.

Ciochetti, Brian A., Yongheng Deng, Gail Lee, James Shilling and Rui Yao (2003), "A Proportional Hazards Model of Commercial Mortgage Default with Originator Bias," *Journal of Real Estate Finance and Economics*, 27 (1): 5-23.

DeMarzo, P. (2005), "The Pooling and Tranching of Securities: A Model of Informed Intermediation," *Review of Financial Studies*, 18: 1-35.

DeMarzo, P. and Darrell Duffie (1999), "A Liquidity-Based Model of Security Design," *Econometrica*, 67: 65-99.

Deng, Yongheng, John M. Quigley, and Robert Van Order (2000), "Mortgage Terminations, Heterogeneity and the Exercise of Mortgage Options," *Econometrica,* 68 (2): 275-307.

Deng, Yongheng, John M. Quigley, and Anthony B. Sanders (2005), "Commercial Mortgage Terminations: Evidence from CMBS," working paper presented at the 2005 Annual American Real Estate and Urban Economics Association (AREUEA) Meetings.

Downing, Christopher and Nancy Wallace (2005), "Commercial Mortgage Backed Securities: How Much Subordination is Enough?" working paper.

Gaur, Vishal, Sridhar Seshadri and Marti G. Subrahmanyam (2005), "Intermediation and Value Creation in an Incomplete Market," FMA European Conference 2005 working paper.

Geltner, David, Norman G. Miller (2001), *Commercial Real Estate Analysis and Investment*, Mason, OH: South- Western Publishing, 2001.

Huang, Wenyi and Jan Ondrich (2002), “Stay, Pay or Walk Away: A Hazard Rate Analysis of FHA-Insured Multifamily Mortgage Terminations,” *Journal of Housing Research*, 13 (1): 85-117.

Riddiough, Timothy J. (1997), “Optimal Design and Governance of Asset-Backed Securities,” *Journal of Financial Intermediation*, 6: 121-152.

Riddiough, Timothy J. and Risharng Chiang (2004) “Commercial Mortgage-Backed Securities: An Exploration into Agency, Innovation, Information, and Learning in Financial Markets,” Real Estate Research Institute Working Paper.

Sanders, Anthony B. (1999), “Commercial Mortgage-Backed Securities,” in *The Handbook of Fixed-Income Securities*, edited by Frank J. Fabozzi. McGraw-Hill Co., 2000.

Vandell, Kerry, Walter Barnes, David Hartzell, Dennis Kraft, and William Wendt (1993), “Commercial Mortgage Defaults: Proportional Hazards Estimations Using Individual Loan Histories,” *Journal of the American Real Estate and Urban Economics Association(AREUEA)*, 21 (4): 451-480.

Wheeler, Darrell (2001), “A Guide to Commercial Mortgage-Backed Securities,” in *Guide to Mortgage-Backed and Asset-Backed Securities*, edited by Lakhbir Hayre. New York, NY: John Wiley & Sons, Inc., 2001.

Figure 1: Conditional Default Probabilities of Commercial Mortgage Loans

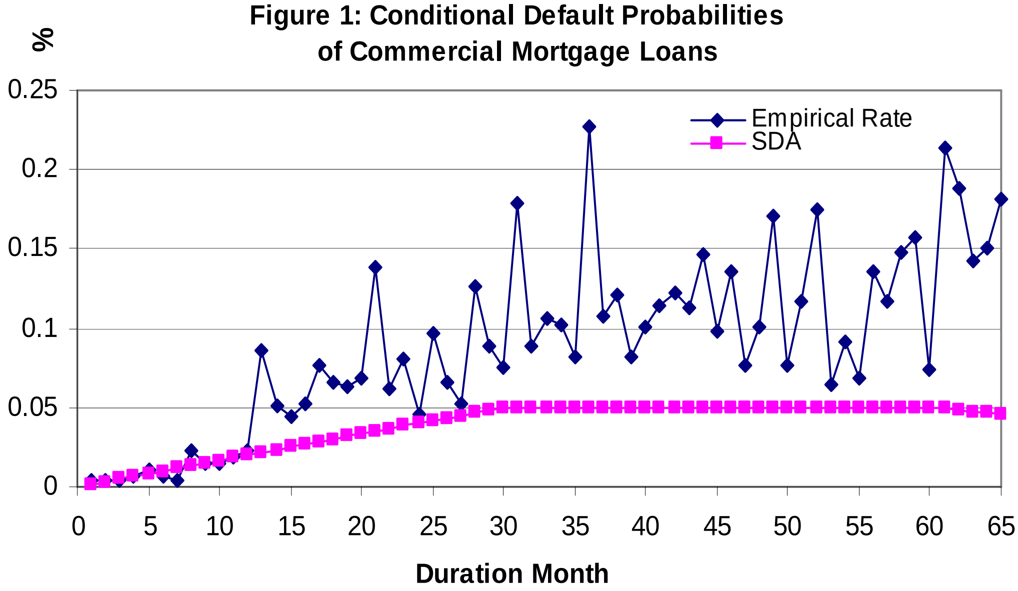
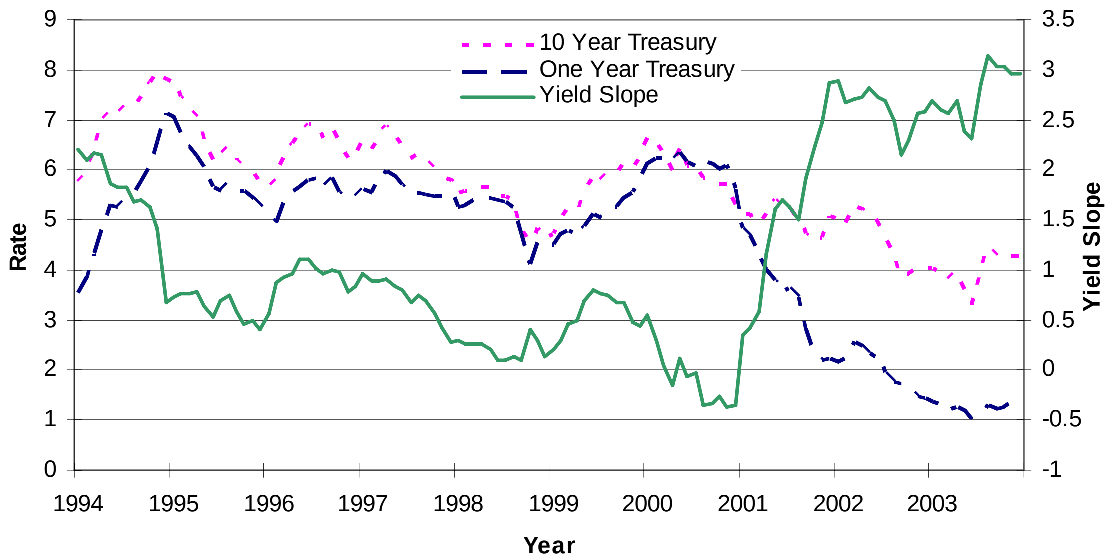


Figure 2: Interest Rates and Yield Slope



NOTE: Yield slope is defined as 10 year treasury rate minus 1 year treasury rate.

Figure 3: Volatility of 10 Year Treasury Rate

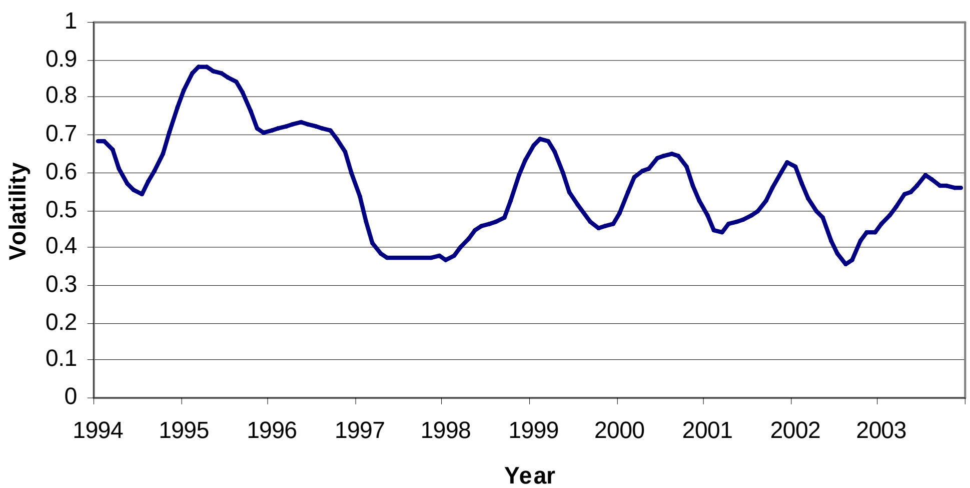
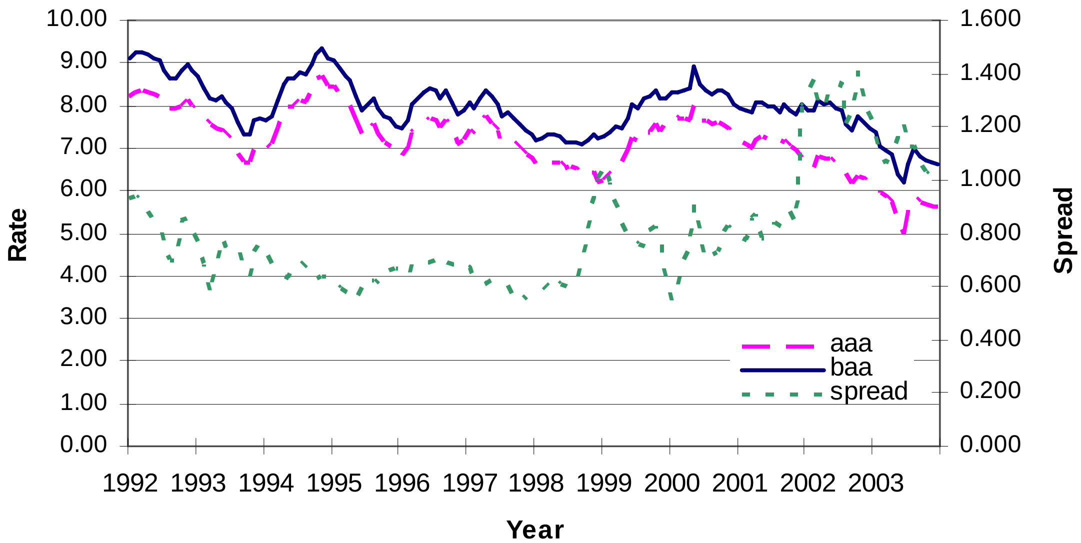


Figure 4: Bond Rates and Credit Spread



NOTE: Credit spread is defined as the difference between AAA corporate bond rate and BAA corporate bond rate.

Figure 5: Volatility of Credit Spread

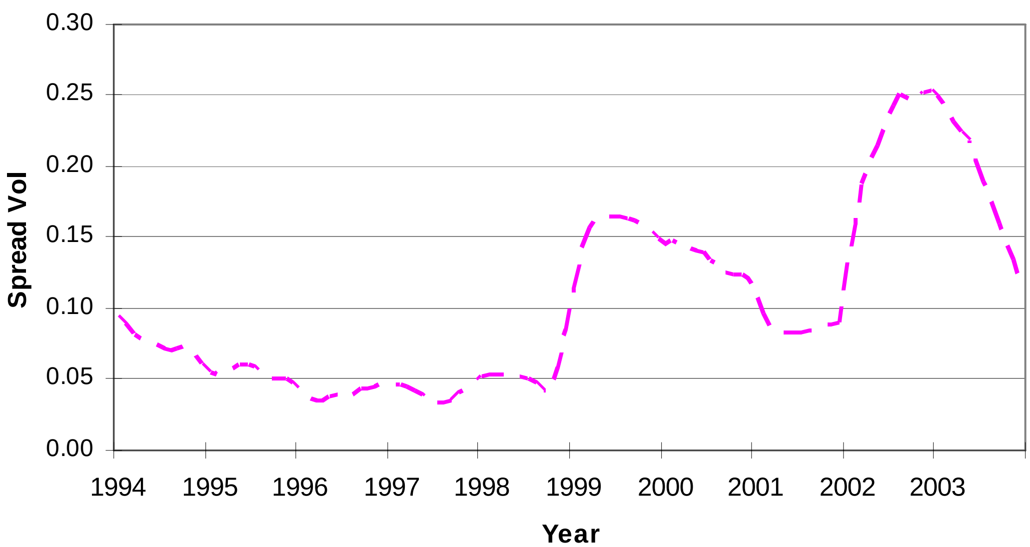


Table 1: CMBS Conduit Deals in Our Sample

Deal Name	Loan Number	Percent	Deal Name	Loan Number	Percent
AMRESCO 1997-C1	96	0.32	JPMCC 2001-CIBC3	125	0.42
ASC 1995-D1	61	0.20	JPMCC 2002-C1	129	0.43
ASC 1996-D2	124	0.41	JPMCC 2002-C2	108	0.36
ASC 1996-D3	114	0.38	JPMCC 2002-C3	87	0.29
BACM 2000-2	128	0.43	JPMCC 2002-CIBC4	121	0.40
BACM 2001-PB1	134	0.45	JPMCC 2002-CIBC5	116	0.39
BACM 2002-PB2	118	0.39	JPMCC 2003-C1	103	0.34
BACM 2003-1	112	0.37	JPMCC 2003-ML1	122	0.41
BSCMS 2000-WF1	181	0.60	JPMC 2000-C10	168	0.56
BSCMS 2000-WF2	145	0.48	JPMCC 2001-CIBC1	165	0.55
BSCMS 2001-TOP2	140	0.47	JPMCC 2001-CIBC2	143	0.48
BSCMS 2001-TOP4	152	0.51	JPMC 2000-C9	140	0.47
BSCMS 2002-PBW1	126	0.42	JPM 1997-C5	269	0.90
BSCMS 2002-TOP6	150	0.50	JPM 1999-C7	145	0.48
BSCMS 2002-TOP8	120	0.40	JPM 1999-C8	128	0.43
BSCMSI 1998-C1	146	0.49	JPMC 1999-PLS1	65	0.22
BSCMSI 1999-C1	114	0.38	LBCC 1996-C2	109	0.36
BSCMSI 1999-WF2	285	0.95	LBCMT 1998-C1	259	0.86
CASC 1998-D7	199	0.66	LBUBS 2000-C3	173	0.58
CCA1-2	92	0.31	LBUBS 2000-C4	167	0.56
CCA1-3	108	0.36	LBUBS 2000-C5	110	0.37
CCIC 2002-CCL1	53	0.18	LBUBS 2001-C2	141	0.47
CCMSC 2000-1	91	0.30	LBUBS 2001-C3	134	0.45
CCMSC 2000-2	81	0.27	LBUBS 2001-C7	114	0.38
CCMSC 2000-3	95	0.32	LBUBS 2002-C1	142	0.47
CCMSC 1999-2	92	0.31	LBUBS 2002-C2	111	0.37
CDCMT 2002-FX1	58	0.19	LBUBS 2002-C4	114	0.38
CMAC 1998-C1	312	1.04	LBUBS 2003-C3	110	0.37
CMAC 1999-C1	242	0.81	MCFI 1996-MC1	162	0.54
CMAT 1999-C1	230	0.77	MCFI 1997-MC1	158	0.53
CMAT 1999-C2	81	0.27	MCFI 1997-MC2	181	0.60
CMB-FUNB 1999-1	205	0.68	MCFI 1998-MC1	249	0.83
CMLBC 2001-CMLB-1	120	0.40	MCFI 1998-MC3	232	0.77
COMM 2003-LNB1	92	0.31	MLFA 2002-CAN7	49	0.16
COMM 2000-C1	112	0.37	MLFA 2002-CAN8	66	0.22
COMM 1999-1	221	0.74	MLFA 2003-CAN9	63	0.21
CSFB 2000-C1	211	0.70	MLFA 2003-CAN10	55	0.18
CSFB 2001-CF2	182	0.61	MLFA 2000-CAN3	53	0.18
CSFB 2001-CK1	142	0.47	MLFA 2000-CAN4	63	0.21
CSFB 2001-CK3	169	0.56	MLFA 2001-CAN5	55	0.18
CSFB 2001-CKN5	195	0.65	MLFA 2001-CAN6	40	0.13
CSFB 2001-CK6	240	0.80	MLMI 1996-C2	300	1.00
CSFB 2001-CP4	130	0.43	MLMI 1997-C1	219	0.73
CSFB 2002-CKP1	156	0.52	MLMI 1997-C2	147	0.49
CSFB 2002-CKN2	204	0.68	MLMI 1998-C2	401	1.33
CSFB 2002-CKS4	156	0.52	MLMI 1998-C3	139	0.46

CSFB 2002-CP3	103	0.34	MLFA 1998-CAN1	32	0.11
CSFB 2002-CP5	141	0.47	MLMI 1999-C1	106	0.35
CSFB 2003-C3	249	0.83	MLFA 1999-CAN2	43	0.14
CSFB 2003-CK2	101	0.34	MLMT 2002-MW1	101	0.34
CSFB 1995-M1	28	0.09	MSCI 2003-IQ4	119	0.40
CSFB 1999-C1	152	0.51	MSCI 2000-LIFE1	131	0.44
DLJ 2000-CF1	128	0.43	MSCI 1996-WF1	148	0.49
DLJCMC 2000-CKP1	230	0.77	MSCI 1997-C1	160	0.53
DLJ 1997-CF1	118	0.39	MSCI 1997-HF1	169	0.56
DLJ 1997-CF2	126	0.42	MSCI 1997-WF1	126	0.42
DLJ 1998-CF2	302	1.01	MSCI 1998-CF1	323	1.07
DLJ 1998-CG1	301	1.00	MSCI 1998-HF2	262	0.87
DLJ 1999-CG2	343	1.14	MSCI 1998-HF1	351	1.17
DLJ 1999-CG3	160	0.53	MSCI 1998-WF1	299	1.00
FUBOA 2001-C1	182	0.61	MSCI 1998-WF2	218	0.73
FULB 1997-C1	283	0.94	MSCI 1999-FNV1	166	0.55
FULB 1997-C2	421	1.40	MSCI 1999-RM1	221	0.74
FUNB 2000-C1	143	0.48	MSCI 1999-WF1	266	0.89
FUNB 2000-C2	162	0.54	MSDWC 2001-PPM	84	0.28
FUNB 2001-C2	107	0.36	MSDWC 2001-TOP1	165	0.55
FUNB 2001-C3	125	0.42	MSDWC 2001-TOP3	158	0.53
FUNB 2001-C4	137	0.46	MSDWC 2001-TOP5	143	0.48
FUNB 2002-C1	106	0.35	NFC 1998-1	201	0.67
FUNB-CMB 1999-C2	223	0.74	NFC 1998-2	376	1.25
FUNB 1999-C4	156	0.52	NFC 1999-1	331	1.10
GCCFC 2002-C1	112	0.37	PCMT 2003-PWR1	100	0.33
GCCFC 2003-C1	72	0.24	PMAC 1999-C1	177	0.59
GECCMC 2000-1	102	0.34	PNCMA 2000-C1	209	0.70
GECCMC 2001-1	151	0.50	PNCMAC 2000-C2	185	0.62
GECCMC 2001-2	126	0.42	PNCMAC 1999-CM1	207	0.69
GECMC 2001-3	133	0.44	PSSFC 1998-C1	254	0.85
GECMC 2002-1	137	0.46	PSSFC 1999-C2	220	0.73
GECCMC 2002-2	111	0.37	PSSFC 1999-NRF1	257	0.86
GECCMC 2002-3	131	0.44	RMF 1997-1	48	0.16
GECCMC 2003-C1	134	0.45	SBM7 2002-KEY2	66	0.22
GMAC 2000-C1	136	0.45	SBMS 2000-C1	266	0.89
GMAC 2000-C2	129	0.43	SBMS 2000-C3	181	0.60
GMAC 2000-C3	174	0.58	SBMS 2001-C1	182	0.61
GMAC 2001-C1	101	0.34	SBMS 2001-C2	139	0.46
GMAC 2001-C2	96	0.32	SBM7 2002-KEY2	66	0.22
GMAC 2002-C1	108	0.36	SBMS 1999-C1	213	0.71
GMAC 2002-C2	109	0.36	Solar Trust 2001-1	47	0.16
GMAC 2002-C3	108	0.36	SOLAR 2003-CC1	77	0.26
GMAC 2003-C1	104	0.35	WBCMT 2002-C1	156	0.52
GMAC 1997-C1	355	1.18	WBCMT 2002-C2	104	0.35
GMAC 1999-C3	138	0.46	WBCMT 2003-C3	130	0.43
GSMSCII 2003-C1	74	0.25	WBCMT 2003-C4	140	0.47
GSMSCII 1999-C1	304	1.01	WBCMT 2003-C5	152	0.51
HMAC 2000-PH1	235	0.78	WBCMT 2003-C4	140	0.47
HMAC 1999-PH1	181	0.60	WMCM 2003-C1	212	0.71

JPMCC 2001-C1	169	0.56	**Total (193 deals)**	**30049**	**100.00**

NOTE: CMBS deal data are from CMBS.COM. Raw data include information on 718 CMBS deals collected on April 1, 2005. Only 311 conduit deals cut off after 1995, with all fixed rate loans, and with AAA subordination levels recorded are selected. We further match these deals with our commercial mortgage database, and exclude those deals with over 2 percent of loans unidentified. Final sample includes 193 deals associated with 30,049 commercial mortgage loans.

Table 2: CMBS Conduit Deals by Cutoff Year

Year	Frequency	Cumulative Frequency	Percent	Cumulative Percent
1995	2	2	1.04	1.04
1996	6	8	3.11	4.15
1997	16	24	8.29	12.44
1998	20	44	10.36	22.8
1999	30	74	15.54	38.34
2000	29	103	15.03	53.37
2001	35	138	18.13	71.50
2002	34	172	17.62	89.12
2003	21	193	10.88	100.00

NOTE: The 193 deals are associated with 30,049 commercial mortgage loans. All deals are conduit deals, with all fixed rate loans.

Table 3: Descriptive Statistics of CMBS Conduit Deals in Our Sample

Variable	Mean	Std Dev.	Minimum	Maximum
Cutoff LTV	0.63	0.04	0.43	0.77
Cutoff DSCR	1.47	0.21	0.92	3.13
Estimated LTV at maturity	0.58	0.10	0.22	1.54
AAA subordination	0.23	0.05	0.12	0.37
BBB subordination	0.09	0.03	0.00	0.17
Over-collateralization	0.00	0.03	0.00	0.33
Geographic diversification	0.86	0.08	0.36	0.97
Share of loans in the most populated state (in loan amount)	0.22	0.09	0.09	0.66
Share of loans in the top 5 populated states (in loan amount)	0.57	0.11	0.31	1.00
Share of loans in California (in loan amount)	0.16	0.09	0.00	0.45
Herfindahl index of loan size concentration	0.02	0.01	0.00	0.06
Share of amount of the largest loan	0.07	0.04	0.02	0.27
Share of amount of the 5 largest loan	0.24	0.09	0.09	0.60
Property type diversification	0.03	0.00	0.02	0.04
Share of multifamily loans (in loan amount)	0.24	0.12	0.00	1.00
Share of retail, anchored loans	0.24	0.13	0.00	0.56
Share of retail, unanchored loans	0.08	0.09	0.00	0.65
Share of office loans	0.21	0.10	0.00	0.48
Share of industrial loans	0.07	0.05	0.00	0.25
Share of healthcare loans	0.02	0.07	0.00	0.82
Share of full service hotel loans	0.02	0.03	0.00	0.18
Prepayment constraint	0.93	0.18	0.16	1.00
Deal cutoff balance (000s)	$924,000	$352,000	$77,962	$2,370,000
Number of assets at cutoff	156.32	75.06	28.00	422.00
Gross WAC	7.68	0.99	5.15	10.25
Net WAC	7.59	0.97	5.12	10.11
Number of deals		193		

NOTE: Cutoff LTV and cutoff DSCR are from the raw data, which are calculated as weighted average of loan LTV and DSCR of all loans in each specific CMBS pool at cutoff. Estimated LTV at maturity is a variable from the raw data, which is used to measure balloon risk. Geographic diversification is defined as state entropy, which is calculated as:

$$-\sum_{i=1}^{10} P_i \times \log_{10} P_i$$

where P_i is the share of loans in one of the 9 most populated states and the share for the rest. Property type diversification is calculated similarly. Prepayment constraint is defined as number of mortgage month covered by any of the four prepayment constraint types (lock out, yield maintenance, defeasance and prepayment penalty) divided by mortgage term.

Table 4: Estimates of the Deal Level Subordination Models
Dependent variable: AAA/BBB subordination at cut off

	AAA Subordination		BBB Subordination	
	Model 1	Model 2	Model 1	Model 2
Intercept	0.04	0.05	0.01	0.07
	(0.08)	(0.04)	(0.05)	(0.04)
Cutoff LTV	0.42***	0.34***	0.19***	0.18***
	(0.09)	(0.05)	(0.05)	(0.04)
Cutoff DSCR	-0.06**	-0.02**	-0.04***	-0.01
	(0.02)	(0.01)	(0.01)	(0.01)
Estimated LTV at Maturity		0.00		0.01
		(0.02)		(0.01)
Over-collateralization		0.08		0.06
		(0.05)		(0.05)
Geographic diversification		0.08***		-0.01
		(0.02)		(0.02)
Share of loans in California		0.01		-0.01
		(0.02)		(0.02)
Herfindahl index of loan size concentration		0.03		-0.06
		(0.16)		(0.15)
Share of multifamily loans		0.03		-0.02
		(0.02)		(0.02)
Share of retail, anchored loans		-0.06**		-0.06**
		(0.02)		(0.02)
Share of office loans		0.02		-0.04
		(0.02)		(0.02)
Share of industrial loans		-0.06		-0.03
		(0.04)		(0.03)
Share of retail, unanchored loans		-0.07*		-0.08**
		(0.03)		(0.02)
Share of healthcare loans		-0.01		0.00
		(0.03)		(0.03)
Share of full service hotel loans		0.10*		0.02
		(0.04)		(0.04)
Prepayment constraint		-0.01		-0.01
		(0.01)		(0.01)
YR 97		-0.02*		-0.03**
		(0.01)		(0.01)
YR 98		-0.03**		-0.02*
		(0.01)		(0.01)
YR 99		-0.04***		-0.02*
		(0.01)		(0.01)
YR 00		-0.08***		-0.03***
		(0.01)		(0.01)
YR 01		-0.10***		-0.05***
		(0.01)		(0.01)
YR 02		-0.10***		-0.05***

		(0.01)		(0.01)
YR 03		-0.11***		-0.06***
		(0.01)		(0.01)
N	193	193	193	193
Adjusted R-Square	0.2446	0.8686	0.2064	0.6600

NOTE: These are OLS estimates. Standard errors are in parentheses. *** for p<0.001; ** for p<0.01; * for p<0.05

Table 5: Commercial Mortgage Loans Underlying CMBS Conduit Deals by Origination Year

	Number of loans	Cumulative number	Percent	Cumulative Percent
1994	52	52	0.18	0.18
1995	269	321	0.96	1.14
1996	1,407	1,728	5.00	6.14
1997	4,025	5,753	14.31	20.46
1998	7,133	12,886	25.36	45.82
1999	4,027	16,913	14.32	60.14
2000	3,346	20,259	11.90	72.03
2001	4,151	24,410	14.76	86.79
2002	2,909	27,319	10.34	97.14
2003	805	28,124	2.86	100.00

NOTE: These are commercial mortgage loans underlying the 193 CMBS conduit deals. 1925 loans are excluded due to missing values of LTV and other variables. Data collecting date is June 1, 2003.

Table 6: Regional Distribution of the Commercial Mortgage Loans

Region	Number of loans	Percent
Midwest/Eastern	2,708	9.63
Midwest/Western	1,056	3.75
Northeast/Mid-Atlantic	3,259	11.59
Northeast/New England	1,308	4.65
Southern/Atlantic	5,875	20.89
Southern/East Coast	916	3.26
Southern/West Coast	3,675	13.07
Western/Mountain	2,669	9.49
Western/Northern Pacific	2,353	8.37
Western/Southern Pacific	3,497	12.43
Missing	808	2.87
Total	28,124	100

NOTE: These are commercial mortgage loans underlying the 193 CMBS conduit deals. 1925 loans are excluded due to missing values of LTV and other variables. Data collecting date is June 1, 2003.

Table 7: Property Type Composition of the Commercial Mortgage Loans

	Number of loans	Percent
Multifamily	8,871	31.54
Retail	7,746	27.54
Office	4,186	14.88
Industrial	2,401	8.54
Hotel	1,495	5.32
Other	3,425	12.18
Total	28,124	100

NOTE: These are commercial mortgage loans underlying the 193 CMBS conduit deals. 1925 loans are excluded due to missing values of LTV and other variables. Data collecting date is June 1, 2003.

Table 8: Characteristics of the Commercial Mortgage Loans at Origination

Variable	Mean	Std Dev.	Minimum	Maximum
Original Balance (000s)	$5,857.41	$9,362.98	$67.48	$295,000.00
Original LTV (%)	69.02	11.54	0.66	112.50
Gross coupon rate (%)	7.76	0.86	4.35	12.88
Net coupon rate (%)	7.68	0.84	4.23	12.78
Amortization term (months)	324.54	52.34	33.00	720.00
Maturity term (months)	128.07	35.36	33.00	360.00
Number of loans		28,124		

NOTE: These are commercial mortgage loans underlying the 193 CMBS conduit deals. 1925 loans are excluded due to missing values of LTV and other variables. Data collecting date is June 1, 2003.

Table 9: Prepayment Constraint Coverage of the Commercial Mortgage Loans

Variable	Month	Coverage
Maturity Term	3,601,947	
Lockout	1,702,134	47.26
Yield Maintenance	692,094	19.21
Prepayment Penalty	70,458	1.96

NOTE: These are for the 28,124 loans underlying the 193 CMBS deals. Most of these loans have defeasance clause. Unfortunately, we don't have that information in our commercial mortgage loan database.

Table 10: Termination Status of the Commercial Mortgage Loans

	Frequency	Percent
Default	912	3.24
Prepay	667	2.37
Mature	51	0.18
Current	26,494	94.20
Total	28,124	100

NOTE: These are commercial mortgage loans underlying the 193 CMBS conduit deals. 1925 loans are excluded due to missing values of LTV and other variables. Default is defined as over 60 days of delinquency. Status observation point is June 1, 2003.

Table 11: Descriptive Statistics of Time Varying Variables

	At Origination				At Termination			
Variable	All loans		Defaulted loans		All loans		Defaulted loans	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Call option	0.024	0.002	0.047	0.002	0.153	0.003	0.111	0.005
Call option square	0.003	0.000	0.004	0.000	0.027	0.000	0.017	0.000
Put option	-0.551	3.123	-0.400	0.050	-1.083	4.481	-0.638	0.293
Put option square	3.427	21178	0.210	0.105	5.653	37240	0.699	1.135
Vol. of 10 year treasury	0.854	0.819	0.525	0.209	2.349	0.165	1.658	1.253
Credit spread	0.800	0.052	0.698	0.017	1.150	0.010	1.002	0.061
Vol. of credit spread	0.102	0.004	0.078	0.002	0.212	0.001	0.153	0.004
Unemployment rate	4.827	1.298	4.567	1.065	5.812	0.847	5.109	1.416
Prepayment constraint	0.994	0.007	0.997	0.003	0.843	0.132	0.907	0.085
Number of loans	28,124		912		28,124		912	

NOTE: Call option value is calculated as the percent difference between the present value of existing mortgage payment stream under current market rate and present value under mortgage coupon rate. Put option value is calculated as the percent difference between the current market value of the mortgage and the current market value of the property. Current property market value is estimated using the National Real Estate Investment Trusts (NAREIT) property value index. Credit spread is defined as the yield differential between AAA corporate bonds and BAA corporate bonds, and its volatility is approximated by its standard deviation in the past 24 month. Volatility of 10 year treasury rate is calculated similarly. Prepayment constraint is a time varying dummy variable. In each month, we examine whether the loan is covered by any one of the prepayment constraints (lockout, yield maintenance and prepayment penalty). If so, the prepayment constraint is assigned a value of 1. Unemployment rate is the state unemployment rate obtained from the Bureau of Labor Statistics (BLS).

Table 12: Maximum Likelihood Estimates of the Flexible Baseline Default Models

	Model 1	Model 2
Original LTV	-0.01	-0.01
	(0.01)	(0.01)
Call option	9.00***	8.66***
	(1.19)	(1.23)
Call option square	-11.18**	-8.12
	(5.38)	(5.54)
Put option	0.49***	0.54***
	(0.13)	(0.12)
Put option square	0.00	0.00
	(0.05)	(0.04)
Vol. of 10 year treasury		0.22
		(0.22)
Credit spread		1.64***
		(0.47)
Vol. of credit spread		-3.44***
		(0.79)
Unemployment rate		0.08**
		(0.04)
Prepayment constraint		-0.49***
		(0.12)
Multifamily dummy	-0.20	-0.20
	(0.13)	(0.13)
Retail dummy	0.10	0.09
	(0.13)	(0.13)
Office dummy	-0.30*	-0.30*
	(0.16)	(0.16)
Industrial dummy	0.20	0.21
	(0.16)	(0.16)
Hotel dummy	0.92***	0.83***
	(0.15)	(0.15)
Midwest/Eastern	0.66***	0.70***
	(0.16)	(0.16)
Midwest/Western	0.46**	0.56***
	(0.2)	(0.22)
Northeast/Mid-Atlantic	0.18	0.20
	(0.16)	(0.17)
Northeast/New England	0.12	0.24
	(0.21)	(0.23)
Southern/Atlantic	0.38***	0.44***
	(0.14)	(0.15)
Southern/East Coast	0.77***	0.80***
	(0.18)	(0.19)
Southern/West Coast	0.55***	0.56***
	(0.15)	(0.15)
Western/Mountain	0.17	0.22

	(0.17)	(0.17)
Western/Southern Pacific	-0.74***	-0.76***
	(0.2)	(0.21)
Likelihood	-31,013	-30,977
B.I.C.	62,476	62,425
A.I.C.	62,228	62,166
N	28,124	28,124

NOTE: Standard errors are in parentheses. *** for p<0.001; ** for p<0.01; * for p<0.05. The hazard model is estimated using maxim likelihood method as in Deng, Quigley and Van Order (2000). A flexible baseline is estimated simultaneously with other covariates. For property types, we use the "other" type as the reference group, and for regional dummy we use "Western/Northern Pacific" as the reference group.

Table 13: Predicted Cumulative Default Rate of Commercial Mortgage Loans

	Mean	Std Dev.	Minimum	Maximum
1 year cum. default rate	0.14	0.13	0.00	2.08
2 year cum. default rate	0.95	0.93	0.00	12.67
3 year cum. default rate	2.08	1.85	0.00	20.69
5 year cum. default rate	4.08	3.23	0.02	34.99
7 year cum. default rate	6.45	4.30	0.20	44.25
Number of deals			28,124	

NOTE: The numbers are in percent. We use the estimated model 2 in table 13 to predict the hazard rate in each of the 85 duration month for each loan. We then calculate the cumulative default rates for each loan. Insignificant variables like "original LTV" are dropped from the prediction equation.

Table 14: Expected Cumulative Loss of CMBS Pools

	Mean	Std Dev.	Minimum	Maximum
1 year expected cum. loss	0.06	0.03	0.02	0.31
2 year expected cum. loss	0.41	0.21	0.11	1.38
3 year expected cum. loss	0.91	0.43	0.37	2.53
5 year expected cum. loss	1.75	0.71	0.93	4.80
7 year expected cum. loss	2.75	0.95	1.68	7.27
Number of deals		174		

NOTE: The numbers are in percent. Expected loss is just default probability times loss given default. Our loss given default assumptions follow Moody's study on loss severity, which assigns different loss ratios for different types of properties. See Appendix table for details. We aggregate expected loss for each loan into CMBS deal level.

Table 15: Estimates of the Subordination – Expected Loss Relationship Models
Dependent variable: AAA/BBB subordination level of CMBS deal

Panel 1: AAA subordination	Model 1	Model 2	Model 3	Model 4
Intercept	0.21***	0.21***	0.18***	0.17***
	(0.01)	(0.01)	(0.01)	(0.01)
2 year expected cum. loss	6.85***			
	(1.66)			
3 year expected cum. loss		3.80***		
		(0.81)		
5 year expected cum. loss			3.56***	
			(0.45)	
7 year expected cum. loss				2.79***
				(0.33)
N	174	174	174	174
Adjusted R-Square	0.0845	0.1076	0.2658	0.2941

Panel 2: BBB subordination	Model 1	Model 2	Model 3	Model 4
Intercept	0.07***	0.07***	0.05***	0.05***
	(0.00)	(0.00)	(0.00)	(0.01)
2 year expected cum. loss	4.26***			
	(0.95)			
3 year expected cum. loss		2.51***		
		(0.46)		
5 year expected cum. loss			2.08***	
			(0.26)	
7 year expected cum. loss				1.58***
				(0.19)
N	174	174	174	174
Adjusted R-Square	0.0988	0.1427	0.2715	0.2835

NOTE: Standard errors are in parentheses. *** for p<0.001; ** for p<0.01; * for p<0.05. These are OLS estimates.

Appendix Table: Loss Severity Assumptions Used in CMBS Pool Expected Loss Calculations

Property type	Loss ratio (%)
Multifamily	32.3
Retail	43.6
Office	38.1
Industrial	35.0
Hotel	52.5
Other	60.6