J Real Estate Finan Econ
DOI 10.1007/s11146-014-9480-1

What is Subordination About? Credit Risk and Subordination Levels in Commercial Mortgage-backed Securities (CMBS)

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Abstract Subordination is designed to provide credit risk protection for senior CMBS tranches by allocating the initial credit losses to the more junior tranches. Subordination level should in theory reflect the underlying credit risk of the CMBS pool. In this paper, we test the hypothesis that subordination is purely about credit risk as intended. We find a very weak relation between subordination levels and both the *ex post* and *ex ante* measures of credit risk, rejecting our null-hypothesis. Alternatively, we find that subordination levels were driven by non-credit risk factors, including supply and demand factors, deal complexity, issuer incentive and a general time trend. We conclude that contrary to the traditional view, the subordination level is not just a function of credit risk. Instead it also reflects the market need of a certain deal structure and is influenced by the balance of power among issuers, CRAs and investors.

We are grateful to Peter DeMarzo, Michael Dewally, Mark Flannery, Sally Gordon, Dwight Jaffee, Tim Riddiough, Amit Seru, Walt Torous, Sean Wilkoff and participants at the 2007 RERI Research Conference, 2013 AREUEA Annual Meetings, the 2013 MFA Conference and the 2013 AREUEA International Conference for helpful comments. Special thanks are due to the Real Estate Research Institute (RERI) for its financial support. All remaining errors as well as the opinions expressed in this paper are our own responsibility. They do not represent the opinions of the Board of Governors of the Federal Reserve System or its staff.

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Published online: 27 July 2014

Keywords Commercial mortgage-backed securities (CMBS) · Subordination · Credit risk · Credit rating agency (CRA)

Introduction

Structured finance products, such as CMBS, offer investors the advantages of a senior-subordinated debt structure where cash flows from underlying commercial mortgage pool are allocated to various tranches of securities (bonds) according to predetermined rules. Typically, repayments of principal are distributed first to the senior tranches while losses due to default are allocated first to the subordinated tranches. This allows investors to buy the portion of the pool that provides the optimal combination of risk and return, with investors buying senior tranches expect to be well protected from credit risks while those holding subordinated tranches expect higher yield (An and Vandell 2013).

Subordination levels, defined as the proportion of principal outstanding of the junior tranches who will absorb the initial credit losses, determine how much credit support the deal structure provides the senior tranches. In a CMBS issuance, the issuer needs to provide a clear signal to investors that the subordination of a certain tranche is enough to insulate them from a certain level of credit risk.[1] CMBS issuers contract with credit rating agencies (CRAs) to determine the subordination levels required for each tranche in a given deal to achieve a certain credit rating, ranging from triple A (AAA) to single C.[2] From this perspective, we can easily see that subordination should be a straight-forward function of credit risk. The subordination level by design should reflect the underlying credit risk of the CMBS pool – the higher the credit risk in a given pool, the higher the subordination level a tranche of a given credit quality should have.

During the recent financial crisis the spread of AAA CMBS bonds soared to over 200 bps during 2008, due in part to worries about insufficient subordination protection. Subsequently, there have been heated debates on whether the CRAs had inappropriate credit ratings and subordination design (see, e.g., Griffin and Tang 2012; Bolton et al. 2012; Cohen and Manuszak 2013). The issuer of a CMBS deal has the incentive to increase their returns by maximizing the number of senior bonds produced by the deal by providing the minimum level of subordination required to receive a AAA rating. As the CRAs are paid by the issuers and not the investors, the argument is that CRAs' rating decisions become aligned over time with the issuers incentives, resulting in lower subordination and inflated ratings As a result the subordination level is a function not just of credit risk, but also of the balance of power among issuers, CRAs and investors.

In this paper, we follow these two lines of thoughts to empirically investigate the determinants of subordination. Our null hypothesis is that subordination is as intended a simple function of credit risk. Our alternative hypothesis is that subordination levels were driven by non-credit risk factors, including the ones that reflect the balance of power among issuers, the CRAs and investors. Our results in this paper lead us to reject

[1] In addition to a signaling effect, credit ratings may provide valuable regulatory arbitrage opportunities to certain investors (Stanton and Wallace 2012).

[2] Some unrated tranches are also issued in many CMBS deals.

the null hypothesis. We only find a very weak relation between subordination levels and both the *ex post* and *ex ante* measures of credit risk. Alternatively, we find that a number of non-credit risk factors do drive subordination levels.

Our test of the null hypothesis relies on predictive regressions. The rationale is as follows: if subordination is purely about credit risk, then subordination levels should predict credit risk of the CMBS pool, and the relationship should be positive.

We first regress the *realized* cumulative default loss of each CMBS deal on the subordination levels of its AAA and BBB tranches.[3] Interestingly, we find no significant relation between AAA subordination level and *ex post* default loss. For BBB tranches, there is only a weak relation between subordination level and *ex post* default loss in the post-2004 sample, as reflected by the marginal significance of the coefficient. The extremely low model fit in both the AAA and BBB regression also demonstrates that there lacks a close relation between subordination level and *ex post* default loss as we would expect. One may argue that this lack of close relation between subordination level and *ex post* default loss is due to the extreme difficulty for anyone to predict CMBS default loss. We show this is not the case: we find a very simple default loss model based on a few underwriting variables dominates subordination levels in predicting tranche default loss, no matter whether the tranche is AAA or BBB.

Proceeding to the *ex ante* measures of credit risk, we use a state-of-the-art loan level default risk hazard model to generate predicted default losses forecasted only with the information available at the time the deal was rated. This gives us a forward-looking estimate of tranche credit risk. We then regress the predicted default losses on the subordination levels. For either AAA or BBB tranches, there is not a significant relationship between subordination level and predicted default loss prior to 2004. There is a positive relationship between subordination level and predicted default loss since 2004. However, again, the model fits are very low (R-square 3 % in the AAA regression and less than 1 % in the BBB regression), indicating a lack of close relation between subordination level and predicted default loss.

Based on the aforementioned evidence, we reject our null hypothesis. Next we proceed to test our alternative hypothesis, that some non-credit risk factors have driven subordination levels. The non-credit risk factors tested include those related to the conflict of interest of the CRAs, those related to information asymmetry between CMBS issuers and the CRAs/investors, those related to the supply and demand of CMBS bonds, and a general time trend.

We confirm the importance of a number of non-credit risk factors in the next set of regression analysis. For example, we find that lagged credit spread slope, a potential barometer of relative popularity of different CMBS tranches, significantly affects subordination level. When the credit spread curve is steep, meaning that it is more profitable for issuers to carve out more senior tranches, AAA subordination levels decline. Similarly, we find that lagged average selling price of BBB tranches has a negative impact on subordination level.

Demand for CMBS tranches also affects subordination levels. For example, CDO issuance volume has a negative impact on both AAA and BBB subordination levels.

[3] We carefully match the time window on which we calculate deal loss with the duration of the tranche (AAA or BBB) that we analyze to make sure the cumulative default loss of the CMBS deal is in fact the risk bared by a particular tranche.

This can be explained by a classical demand side effect – to meet the increased demand for additional CMBS bonds to incorporate in CDOs that were popular in the capital market, issuance of CMBS bonds with low credit quality (low subordination protection) were increasing and the check-balance of CMBS bond quality diminished.

We also find deal complexity, measured by the number of tranches in a CMBS deal, has a negative impact on subordination levels. More complex CMBS deals have lower subordination levels. This echoes findings by Ghent et al. (2013) in the subprime ABS market and supports the notion that CMBS issuers take advantage of their informational advantage and use complex deals as devices to disguise investors and seek rent.

We further find that when CMBS issuers retain residual pieces (B-piece) of a CMBS issuance, the subordination levels of both AAA and BBB tranches are lower. This is consistent with an information asymmetry and adverse selection hypothesis: CMBS issuers choose to retain the residual pieces when the credit quality of the CMBS pool is high.

Finally, we find a strong time trend in subordination levels. The CRAs assign smaller and smaller subordination levels to CMBS bonds as the CMBS market develops. Further research is needed to identify whether this time trend reflects increased optimism among the CRAs or an increase in the negotiating power among the issuers.

Findings in this paper contribute to the heated debate on the efficacy of CRA credit ratings (see, e.g. Riddiough and Zhu 2009; Sangiorgi and Spatt 2011; Bolton et al. 2012; Bongaerts et al. 2012; Stanton and Wallace 2012). It also contributes to our understanding of how the structured finance products are designed (see, e.g., He et al. 2012; Furfine 2012; Ghent et al. 2013). The evidence presented in this paper shows that, in addition to credit risk, there are other market forces that affect subordination levels. Contrary to the traditional view, the subordination level is not simply a function of credit risk. Instead, it may also reflect the market demand for a given deal structure. This latter view is consistent with the view that clientele effect plays an important role in financial product design (see, e.g., Van Horne 1985).

The rest of the paper is organized as follows: section 2 briefly summarizes the mechanism of CMBS structuring and subordination in order to set up the stage; section 3 describes our data; sections 4 explains our predictive regressions to test the null hypothesis; section 5 explains our identification of non-credit risk determinants of subordination levels; concluding remarks are in a final section.

CMBS Product Design and Subordination

CMBS Structure

Commercial mortgage-backed security (CMBS) issuers create CMBS by pooling commercial mortgages and carving out tranches (bonds) out of the commercial mortgage pool. CMBS is an example of a structured finance product where assets are pooled and tranched. A number of studies have shown that this pooling and tranching mechanism helps mitigate market imperfections and creates value (Riddiough 1997, DeMarzo and Duffie 1999; Titman et al. 2004; DeMarzo 2005; Gaur et al. 2005). Intuitively, the pooling and tranching process enhances liquidity, diversification and risk management. By selling relatively "standard" and low-risk CMBS bonds (cash flows) rather than heterogeneous loans, the process greatly enlarges the investor base and facilitates capital flow in commercial mortgage market. The CMBS market can also provide a diversification effect for investors by pooling together a large number of loans. Finally, several entities with special expertise, such as commercial mortgage underwriters, CMBS issuers, master servicers, special servicers and rating agencies 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.[4] The proceeds from these loans are then used to service the coupon payments for a set of tranches in a senior-subordinate debt structure. The "waterfall" of payments are structured so that any return of principal generated by amortization, prepayment and default is allocated to the most senior tranche first 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). It is only after a tranche has had its entire outstanding balance either repaid due to returns on principal or written off due to allocated losses that the repayment of principal are re-directed to the next most senior tranche and the allocation of losses are re-directed to the next most junior tranche.[5] Any interest received from outstanding principal is paid to all tranches.[6]

The issuer then provides information on these loans to credit rating agencies (CRAs), and CRAs define the level of credit support, given the characteristics of the loans and the properties that collateralize the loans in the pool, that would be required for a tranche to receive a given credit rating under the senior-subordinated debt structure. The tranches may have varying credit ratings from AAA, AA (senior tranche), to BB, B (subordinated) and to unrated (first loss).[7] 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 as they benefit from the credit support provided by the subordinated tranches.

Subordination

For each CMBS tranche, subordination level is defined as the proportion of principal outstanding of the junior tranches. It reflects "credit support" of that tranche. The credit rating agencies (CRAs) determine subordination levels required for a tranche to earn a given rating at deal cutoff, such as AAA, AA, A, BBB, etc.,[8,9] This decision determines

[4] The loans could be bought from traditional lenders, portfolio holders or from conduit loan originators.

[5] This type of structure is often referred to as the "reverse waterfall" structure.

[6] It is noteworthy that some CMBS deals vary from this simple structure. For more information, see An and Vandell (2013). Also see Geltner and Miller (2001) for other issues such as commercial mortgage underwriting, form of the trust, servicing, commercial loan evaluation, etc.

[7] Many CMBS deals also have an interest only (IO) tranche, which absorbs excess interest payment.

[8] Throughout the paper, we use the S&P and Fitch rating scale (e.g., AAA). Moody's ratings (e.g., Aaa) are mapped into their S&P/Fitch equivalents.

[9] Moody's, Standard and Poor's and Fitch are currently three major CMBS rating agencies. There are other smaller CRAs such as Kroll Bond Ratings, and Realpoint that rate CMBS. Duff & Phelps Credit Rating Co. was another CRA that rated CMBS before Fitch acquired them.

how much an given deal can be issued at each rating, i.e. what proportion of the deal will be AAA rated versus less than AAA rated. In most cases, this debt structure is the final deal structure accepted by the issuer and provided to the investors. However, in case the issuer is not satisfied with the deal structure designed by the CRAs, he (she) may choose to remove certain loans from the pool and ask the CRAs to reevaluate the structure. Usually two or more CRAs are invited to CMBS rating and the proposing-revision process for subordination goes recursively. Once the deal structure is finalized, the CRAs provide their credit risk assessment – bond ratings for each CMBS tranche. CMBS investors typically rely on the ratings provided by the CRAs as a signal regarding the risk associated with each tranche, though these ratings are also important to investors subject to regulatory capital standards tied to credit ratings.[10]

In assessing subordination, the CRAs gather CMBS deal and underlying loan information and use models to estimate subordination levels needed for each CMBS deal. In fact, each CRA has its own internal model. However, the general framework is approximately the same. The CRAs perform typically three levels of analysis. First, the CRAs review the information provided on the underlying collateral of the loans that were provided by the commercial mortgage loan underwriters' cash flow report. They adjust property's net operating income (NOI) based on their own judgments of whether the number in underwriting report is 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).[11] The CRAs then calculate property value using their own capitalization rates, which could be different from the current market capitalization rate.[12] The CRAs may also 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. Second, the CRAs move to loan level analysis, examining borrower quality, amortization, cash management, cross- and over-collateralization to make adjustment to their basic credit support assessments. After doing this, the CRAs aggregate their analysis into the pool level and assign subordination to each proposed CMBS tranches.[13] Third, the rating agencies perform portfolio level analysis, which examines pool diversity (or concentration), information quality, legal and structural issues, any external credit enhancement and makes final adjustment to subordination levels for each CMBS tranche.

Data

Our data on CMBS deals come from CMAlert. CMAlert monitors CMBS issuance worldwide, and thus it provides issuance (cutoff) information about each CMBS deal.[14]

[10] CRAs also provide surveillance services, i.e., they 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.

[11] CRAs usually apply "haircuts" to loan underwriting NOI.

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

[13] 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.

[14] CMAlert does not provide on-time CMBS performance data.

Table 1 Cutoff year distribution of the CMBS deals in our sample

Year	# of Deals	$ Amount (billions)	# Tranches	Avg. Tranches per deal
1999	80	53.6	816	5
2000	80	46.5	910	10
2001	97	66.7	1,361	12
2002	71	52.4	1,170	14
2003	94	77.4	1,522	16
2004	85	93.1	1,743	16
2005	100	169.3	2,209	21
2006	94	196.7	2,275	22
2007	83	227.6	2,081	24
2008	9	12.1	210	25
2009	5	1.5	19	23
2010	19	10.8	129	4
2011	41	32.0	377	7
2012	44	28.4	386	9
Total	902	1068.2	15,208	17

The CMAlert data are at both the deal and tranche (bond) levels. At the deal level, CMAlert reports CMBS deal issuance (closing) date, deal name (name of the trust), total deal amount, denominator (US dollar or other foreign currency), region of distribution, type of deal (conduit, portfolio, fusion, etc.), offering type (rule 144A, private placement, SEC-registered, etc.), names of the issuer, trustee, book runner, seller, master servicer and special servicer, weighted average coupon (WAC), weighted average maturity (WAM), total number of loans and properties underlying the pool, weighted average loan-to-value (LTV) ratio, weighted average debt-service coverage ratio (DSCR), composition of loan types (e.g. percentage of office loans, percentage of hotel loans, etc.), the main location (state) of underlying loans, etc.

At the tranche (bond) level, CMAlert provides information on the name of the tranche, the issuance amount, denominator, ratings (name of the credit rating agencies and ratings assigned by the corresponding CRAs), subordination level, coupon, interest rate benchmark, spread, maturity date, expected life, selling price, etc. The tranche data is linked to the deal data through a unique deal ID for each CMBS deal.

In this paper, we focus on CMBS deals issued and sold within the U.S. Over $1 trillion of CMBS was issued from 1999 to 2012, accounting for about a quarter of all U.S. commercial real estate (CRE) lending. The total number of deals is 902, and there are a total of 15,208 tranches contained in these CMBS deals.[15] Among the CMBS tranches, 4,676 are rated AAA, 1,592 are rated AA, 1,844 are A, 2,988 are BBB, 1,681 are BB, and 1,506 are B. There are also 53 CCC, 48 tranches with junk ratings and 820 unrated tranches. We report the number of CMBS deals and the total issuance amount in each year in Table 1. We also show the average number of tranches in those CMBS deals by cutoff year. As we can see as the overall activity in the market, measured both

[15] We exclude government agency deals and deals backed by commercial real estate leases.

Table 2 Descriptive statistics of the CMBS deals

	Average or percent
Total deal amount (millions)	1,184 (1,057)
Number of underlying properties	148.6 (165.2)
Number of underlying loans	121.7 (356.8)
Deal weighted average LTV	63.4 (9.4)
% of office mortgages	34.5 %
% of hotel mortgages	17.5 %
% of multi-family mortgages	24.0 %
% of nursing/retirement mortgages	16.2 %
% of retail mortgages	37.5 %
Share of the largest 5 loans	44.4 (28.5)
Lock out coverage	14.8 %
Yield maintenance coverage	33.7 %
Prepayment penalty coverage	35.9 %
Defeasance coverage	27.1 %
More than one book runners	35.4 %
Special servicer = servicer	38.2 %
Securitization program as beneficiary	71.0 %

Standard deviations for continuous variables are included in parentheses

by the number and the size of deals we also saw the complexity of the deals increase, with the average number of tranches per deal peaking at 25 in 2007.

Table 2 contains descriptive statistics of the CMBS deals in our sample. The deals on average were backed by approximately 120 loans, which were in turn backed by 150 properties. Office (35 %) and retail (38 %) accounted for the most common property types, The five largest loans accounted for 44 % of the balance of the average deal and the weighted average LTV is 63 %. We find that for 38 % of the deals the master servicer has chosen itself as the special servicer. The average subordination level is about 20 percent for AAA tranches and about 5 percent for the BBB tranches (Table 3). The average spread at origination is about 66 basis points for AAA tranches and 230 basis points for the BBB tranches. The average subordination levels of the AAA and BBB tranches by cohort (cutoff year) are plotted in Fig. 1. We observe a clear downward pattern in both AAA and BBB subordination levels from 1999 to 2007.

Each CMBS deal is backed by commercial mortgage loans that provide financing for established income-generating properties (multifamily, office, retail, industrial,

Table 3 Means of the CMBS tranches (Bonds)

	AAA	BBB
Subordination rate	20.3	5.4
Spread	66.2	237
Rating shopping	14.1 %	13.6 %
Expected life of the tranche	8.1	9.1
Ex-post pool losses*	2.1 %	2.4 %

* The ex-post pool losses are calculated based on the smaller sample of the merged CMAlert and Morningstar data

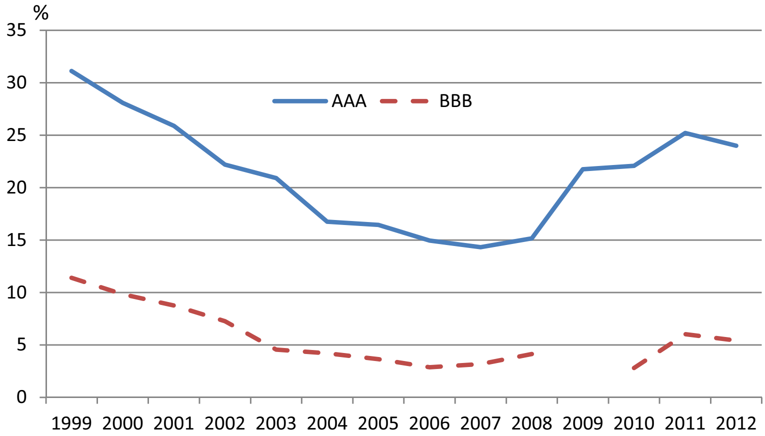

Fig. 1 Average AAA and BBB subordination levels by cohort (Issuance Year). *Note*: There was not a single BBB CMBS bond issuance in the year of 2009. Data source: CMAlert.com

hotel, healthcare, etc.). Depending on the type of the deal, there are typically 50–400 loans underlying a CMBS deal from different borrowers. However, there are deals that contain only one large loan (large-loan deals),[16] and deals that contain loans from a single borrower (single-borrower deals). CMBS loans generally have a principal balance between \$2 million and \$15 million; and they usually have a 30-year amortization term with a balloon payment due within 5 to 10 years (interest-only loans became more prevalent by 2006 and 2007). Individual mortgages are usually non-recourse; and, in the event of default, the mortgage is turned over to a CMBS special servicer for workout with the borrower or liquidation. As discussed previously, there is virtually no prepayment risk associated with mortgages that back a CMBS: borrowers that wish to pre-pay are typically constrained to do so through some form of prepayment constraint such as lock-out, prepayment penalty, yield maintenance and defeasance.[17]

Our data on CMBS loans is from Morningstar's subsidiary Realpoint. For each loan, Realpoint provides detailed information such as the name of the CMBS deal that the loan is from, loan origination date, original amount, LTV, DSCR, lender, and collateral information including property type, location, etc. In addition, Realpoint monitors the status of each loan so that we can identify whether a CMBS loan is defaulted, prepaid, matured, or current in each month.

We match the Realpoint loan data with the CMAlert deal data through deal information to identify loans underlying each CMBS deal.[18]

[16] Fusion deals usually contain a single large loan combined with a number of smaller loans. They are designed to provide a diversification benefit to offset the concentration risk represented by the large loan.

[17] For example, defeasance, the more popular form of prepayment constraint in recent years, requires the borrower to deposit treasuries into the trust that mimic the terms of the underlying mortgage in order to prepay the loan.

[18] Since the deal IDs from the two databases do not match, we have to manually build a crosswalk between the two databases based on deal issuance information. We lose quite a number of observations during the process of this match due to a combination of differences in coverage between CMAlert and Morningstar and difficulties in establishing matches between deals in both datasets. However, we find no statistical significant difference between the matched sample and the raw sample in many dimensions such as the size, the weighted LTV, subordination, loss rate, etc. So, we are not concerned with sample selection issues.

Table 4 Descriptive statistics of the CMBS loans

Variables	Average or percent
Pacific	20.2 %
Mountain	9.1 %
West North central	3.9 %
West South central	12.3 %
East North central	11.7 %
East South central	4.3 %
South Atlantic	22.4 %
New England	3.5 %
Balance (millions)	9.717
Underwritten LTV	69.1 % (12.0 %)
Underwritten DSCR	1.50 (0.56)
Current DSCR	1.49 (0.62)
Current Occupancy Rate	92.5 (11.3)
Yield Curve Slope	0.80 (1.13)
Credit Spread	0.89 (0.17)
Lock-Out Coverage	0.92
Yield maintenance coverage	0.50
Months to complete initial action of Foreclosure	4.3 (2.5)

Standard deviations for continuous variables are included in parentheses

We report summary statistics of the CMBS loans in Table 4. While we only identify loans of a subset of the CMAlert CMBS deals, the sample we are working with is largely similar to the original CMAlert data in composition. It also includes important contemporaneous loan level variables such as current occupancy rates and current DSCR.

Other data we used in the analysis include: interest rates from the Federal Reserve; commercial property indices from the National Council of Real Estate Investment Fiduciaries (NCREIF), the National Association of Real Estate Investment Trusts (NAREIT) and CBRE; and state level unemployment rates from the Bureau of Labor Statistics (BLS).

Credit Risk and Subordination Level

From CMBS issuers' perspective, a lower subordination for a given rating structure is desirable as it increases the proportion of the deal that can be issued as senior tranches. These are sold by the issuer at a premium while subordinated tranches must be sold at a discount. On the other hand, investors buying senior tranches wills always prefer as much subordination as possible to protect them from default risk of the CMBS pool. Therefore, the optimal subordination design requires a fair coverage of CMBS credit risk. In other words, if a CMBS pool contains higher default risk, then higher subordination level should be provided to its senior tranches.

In order to test the positive relation between subordination level and credit risk, we conduct the following predictive regression analysis[19]:

$$Credit\ risk = f(\text{subordination level}) \tag{1}$$

Measuring the credit risk of a CMBS tranche is challenging. We take several different approaches. The first approach we adopt is to look at the realized default loss of each CMBS deal and calculate the cumulative default loss of the deal during the life of each tranche. This *ex post* measure of credit risk is model independent. We then regress the *ex post* credit risk of the *tranche* on tranche subordination level. The regression takes the following form:

$$C_i = \alpha + \beta_1 b_i + \beta_2 b_i \cdot yr2004 + \varepsilon_i \tag{2}$$

Here C_i is the *ex post* credit risk, b_i is the tranche subordination level, and $yr2004$ is a dummy variable indicating that the CMBS is issued after 2003.

Figures 2 and 3 plot the patterns of CMBS AAA and BBB spreads and corporate credits spread, as well as close relationship between the issuance of CMBS and commercial real estate CDO. We therefore include the interaction of b_i and $yr2004$ dummy to account for any structural break in the CMBS market after 2003, given the big changes in the structured finance markets in general and the CMBS market in particular since then. For example, the asset-backed securities (ABS) market (especially the subprime ABS market) has exploded and the collateralized debt obligations (CDO) market has developed rapidly; conduit lending, where commercial mortgage loans are originated for the sole purpose of securitization, has become the dominant source of CMBS loans; and defeasance has become a popular means of prepayment constraint. Finally, the CMBS market saw wide spread use of AAA tranches with different levels of credit support start in 2004. The tranche with the lowest level of credit support that would produce a AAA rating from CRAs was referred to as the junior AAA tranche. Deals also include a senior AAA tranche with levels of credit support, set by the issuer and not the CRAs, as high as 30 percent. Many deals also had a mezzanine tranche with credit support between those of the senior and junior AAA. The development of this tranche structure was part of the increasing complexity of structured finance deals seen during this period.[20]

We run the regressions separately for AAA and BBB tranches. For both AAA and BBB tranches we limit our analysis to the tranche with the lowest subordination rate for that given deal that received that particular rating. This allows us to isolate our analysis on the subordination rate chosen by the CRAs, independent of the development of the senior/mezzanine/junior AAA structure. We exclude all the deals issued after 2009 in this set of analysis as not even the shortest maturity AAA tranches issued after 2009 have matured, and thus we cannot calculate the cumulative default loss during the full life of those tranches.

We report the regression results, labeled model 1, in Table 5. Surprisingly, we see that for AAA tranches, subordination level has no significant relation with *ex post*

[19] This predictive regression approach is used in other studies such as Plazzi et al. (2010).

[20] The development of the senior/mezzanine/junior AAA CMBS structure may also reflect investors' demands for CMBS bonds with a lower risk profile than those provided by the AAA subordination rate set by the CRAs.

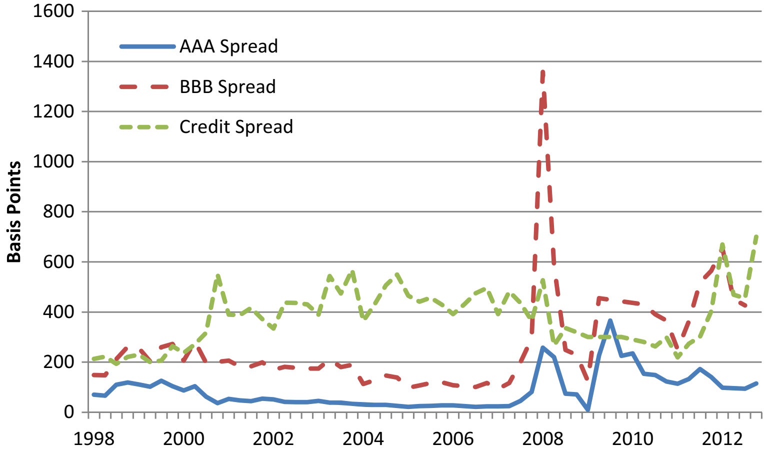

Fig. 2 CMBS AAA and BBB spreads and corporate credit spread. *Note*: CMBS data is from CMAlert.com. The credit spread (corporate Baa minus corporate Aaa spread) data is from the Fed

credit risk before and after 2004. For BBB tranches, subordination level has a marginally significant positive relation with *ex post* credit risk only after 2003. The R-Squares show that the model fits are extremely low suggesting that subordination levels do not predict *ex post* credit risk. The R-Square of the AAA tranches regression is only 0.5 percent and that of the BBB tranches is only 1 percent.

Is the low predicting power of subordination levels due to the unpredictability of *ex post* credit risk of CMBS tranches? We try to address this question by running some additional regressions on *ex post* credit risk. We add a few underwriting variables to equation (2) and run the following regression:

$$C_i = \alpha + \beta_1 b_i + \beta_2 b_i \cdot yr2004 + \beta_3 NumProps_i + \beta_4 WLTV_i + \beta_5 TOP5Loan_i + \beta_6 LogAmt_i + \varepsilon_i \quad (3)$$

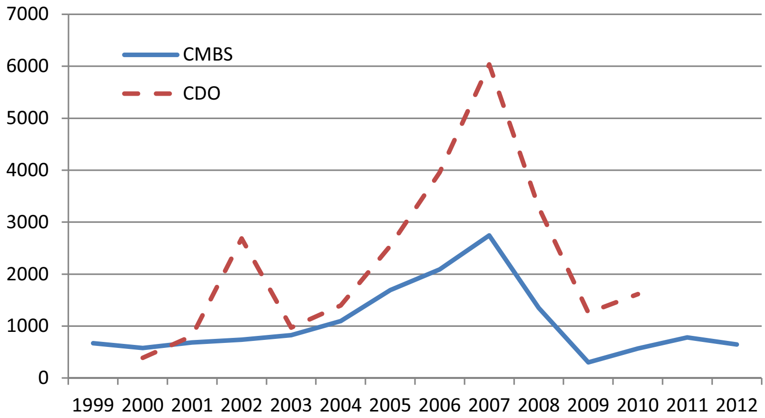

Fig. 3 CMBS and commercial real estate CDO issuance ($Million)

Table 5 OLS estimates of the *Ex Post* default loss regression, dependent variable: realized CMBS deal loss during the life of the tranche

	AAA Model 1	BBB Model 1
Intercept	0.0221***	0.0236***
	(0.0009)	(0.0010)
Subordination level	−0.0008	0.0019
	(0.0014)	(0.0015)
Subordination level * issuance year ≥ 2004	0.0010	0.0030*
	(0.0014)	(0.0015)
N	292	223
Adjusted R-Square	0.0052	0.0104

Standard errors are in parentheses. * for p<10 %, ** for p<1 % and *** for p<0.1 %. The regression sample is a subset of the CMAlert deal sample where the data is matched between CMAlert and Morningstar

Here $Num\Pr ops_i$ represents the number of properties in the CMBS loan collateral, $WLTV_i$ represents the weighted LTV of the CMBS deal, $Top5Loan_i$ represents the share of the largest 5 loans in the CMBS pool, and $LogAmt_i$ represents the log of the tranche dollar amount.

We provide the regression results in Table 6. Model 2 represents the aforementioned regression (Equation 3). Interestingly, we see that three of the added underwriting variables, weighted LTV, share of the largest 5 loans and log tranche amount are significant in the AAA regression and the model fit is boosted from 0.5 percent to 11

Table 6 OLS estimates of the *Ex Post* default loss regression: alternative specifications, dependent variable: realized CMBS deal loss during the life of the tranche

	AAA		BBB	
	Model 2	Model 3	Model 2	Model 3
Intercept	0.022***	0.022***	0.024***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)
Subordination level	−0.004**		−0.003	
	(0.002)		(0.002)	
Subordination level * issuance year ≥ 2004	−0.002		0.002	
	(0.002)		(0.001)	
Number of underlying properties	0.001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Deal weighted average LTV	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Share of the largest 5 loans	−0.002*	−0.002*	−0.003*	−0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Log of tranche amount	−0.003**	−0.003**	−0.005**	−0.004*
	(0.001)	(0.001)	(0.002)	(0.002)
N	292	292	223	223
Adjusted R-Square	0.1144	0.0990	0.1262	0.1042

Standard errors are in parentheses. * for p<10 %, ** for p<1 % and *** for p<0.1 %

percent. For BBB tranches, weighted LTV, share of the largest 5 loans and log tranche amount also help predict ex post default loss. With these three significant variables, the model fit also increased significantly from 1 percent to nearly 13 percent.

Next, we leave out subordination level from equation (3) and keep only the underwriting variables in the *ex post* credit risk regression. The regression becomes:

$$C_i = \alpha + \beta_3 NumProps_i + \beta_4 WLTV_i + \beta_5 Top5Loan_i + \beta_6 LogAmt_i + \varepsilon_i \quad (4)$$

This is model 3 in Table 6. We can see that those significant underwriting variables in model 2 remain significant, and the model fits only decreased slightly from model 2, which are still significantly higher than those of model 1 where only subordination level is used to predict *ex post* credit risk.

Taking the regression results in Tables 5 and 6 together, we find that subordination levels of AAA and BBB CMBS tranches do not predict *ex post* credit risk. Moreover, a very simple regression model that uses only a few underwriting variables available at CMBS issuance (cutoff) does a better job in predicting *ex post* credit risk.

Considering that subordination levels are determined at CMBS issuance, we seek *ex ante* measure of credit risk in equation (1). The *ex ante* credit risk measure we use is the predicted default loss. In order to obtain the predicted default loss of each CMBS tranche, we build default risk models based on loan level data and use those models to predict CMBS default loss.

At the CMBS loan level, a state-of-the art default probability model coupled with loss severity assumptions provide us a tool to predict CMBS loan default loss. The default probability model we estimate is a standard Cox proportional hazard model that is widely used in the mortgage literature (see, e.g. Vandell et al. 1993; Seslen and Wheaton 2010; An et al. 2013). The model specification is similar to that in An et al. (2013).

We present the maximum likelihood estimates in Table 7. Contemporaneous DSCR and the contemporaneous occupancy rate are both significant and negatively related to default probability, as we expect. 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. Loans in Midwest and in Southern part of the country are riskier, while those in Western/Southern Pacific, including California, have lower default risks. Consistent with the existing literature, original LTV is not significant.

We then use the default probability model estimated above to predict conditional default probabilities for each loan over its lifetime. We produce two alternative estimates of the probability of default. For our baseline forecast, we assume both the loan level (current DSCR and current occupancy rate) and the market (term spread, credit spread, and state unemployment rate) remain constant for the life of the loan. For our adverse case we assume that each of these measures worsen significantly over the first 3 years of the loan and then remain flat for the remainder of the loan.[21]

Next, we calculate expected losses of each loan over certain horizons based on loss severity assumptions documented in the Appendix Table (exp*ected loss*=

[21] Under our alternative scenario we assume state unemployment rates increase 3 percentage points, credit spreads rise 30 basis points while the term spread falls by the same amount, occupancy rates fall by 15 percentage points and the DSCR falls by 0.15 over the first three years of the loan.

Table 7 MLE estimates of the flexible baseline default probability model

Variables	Coefficient	Standard error	Odds ratio
Pacific	−0.463***	(0.119)	0.639
Mountain	0.215*	(0.117)	1.240
West North Central	0.489***	(0.161)	1.631
West South Central	0.559***	(0.127)	1.748
East North Central	0.0267	(0.109)	1.027
East South Central	0.349**	(0.139)	1.418
South Atlantic	0.202*	(0.107)	1.225
New England	−0.0305	(0.176)	0.970
Log Balance	0.292***	(0.0252)	1.340
Underwritten LTV	0.400***	(0.0420)	1.492
Underwritten DSCR	−0.0999***	(0.0350)	0.905
Current DSCR	−1,134***	(0.0428)	0.322
Current Occupancy Rate	−0.261***	(0.0178)	0.771
Yield Curve Slope	−0.138***	(0.0406)	0.871
Credit Spread	0.450***	(0.0237)	1.568
Lock-Out Coverage	−0.611***	(0.0803)	0.543
Yield maintenance coverage	−0.378***	(0.0538)	0.686
Months to complete initial action of Foreclosure	0.100***	(0.0315)	1.105
State Unemployment Rate	0.599***	(0.0352)	1.820
N	685,153		
−2LogL	65,708		
AIC	65,746		
SBC	65,865		

Standard errors are in parentheses. * for p<5 %, ** for p<1 % and *** for p<0.1 %. Continuous variables have been standardized before model estimation

loan amount×*default probabilty*×*loss given default*). Then, we aggregate loan level expected losses into CMBS deal level to form our *ex ante* credit risk measure.[22] The expected loss rates are reported at different horizons in Table 8. The average cumulative default loss under the baseline forecast reaches 15.7 percent in the seventh year. It reaches 51.5 percent under the alternative forecast.

Based on these models, we obtain the predicted default loss of each CMBS deal at each point in time, $\widehat{C_{l,t}}$. Finally, we run the predictive model of equation (2) by replacing C_i by $\widehat{C_{l,t}}$, where N is the expected life of the CMBS tranche. So the regression is:

$$\widehat{C_{l,t}} = \alpha + \beta_1 b_i + \beta_2 b_i \cdot yr2004 + \varepsilon_i \tag{5}$$

[22] A caveat of this aggregation is that we are ignoring default correlations that are due to unobservable common risk factors. However, since we've already included many of the common risk factors in the default hazard model, we don't see the inclusion of such default correlations will change our results materially.

Table 8 Predicted cumulative expected loss rate of CMBS loans

	Mean	Std Dev.	Minimum	Maximum
Baseline				
1 year cum. loss rate	0.10	0.06	0.00	0.66
2 year cum. loss rate	0.37	0.23	0.00	2.38
3 year cum. loss rate	0.71	0.46	0.00	4.63
5 year cum. loss rate	1.43	0.93	0.01	9.24
7 year cum. loss rate	2.07	1.34	0.01	13.36
Adverse				
1 year cum. loss rate	0.13	0.08	0.00	0.86
2 year cum. loss rate	0.68	0.43	0.00	4.39
3 year cum. loss rate	1.79	1.15	0.01	11.62
5 year cum. loss rate	4.31	2.79	0.02	27.75
7 year cum. loss rate	6.54	4.22	0.04	42.22
Number of loans	17,519			
Number of deals	442			

The numbers are in percent. We use the estimated default hazard model in Table 8 to predict the hazard rate in each of the 40 duration quarters for each loan. We then calculate the cumulative loss rates for each loan

We report our regression results in Table 9. Interestingly, in both the AAA and BBB regressions, subordination level is significant only post-2004. In fact, we notice that subordination level is only marginally significant in the BBB regression. More importantly, as we see from the R-squares of the regressions, neither of these two regressions have much explanatory power in the baseline loss scenario and in the adverse loss scenario, suggesting that the subordination rates are not good predictors of *ex ante* credit risk.[23]

To briefly summarize the findings in this section: we find that subordination levels of AAA and BBB CMBS tranches have a very weak relation with the credit risk of the CMBS tranche, either using the *ex post* credit risk measure or the *ex ante* credit risk measures. Therefore, we reject our null hypothesis that subordination is purely about credit risk.

Determinants of Subordination Levels: Credit Risk and Non-Credit Risk Factors

Our empirical analysis in section 4 shows that subordination levels do not have the close relation with credit risk as in our null hypothesis. Then the question is what determines subordination levels. In order to answer this question, we run regressions to identify determinants of subordination levels.

First, we extend the work of An et al. (2008) to regress subordination levels of AAA and BBB tranches of each CMBS deal on identifiable credit risk factors of the CMBS pool, including the weighted LTV, number of properties in the CMBS pool, pool composition in property type, prepayment constraint coverage, etc. We also include

[23] We are aware that some CMBS deals may have external credit enhancement but we do not believe that those external credit enhancements explain over 95 percent of the variations in ex ante credit risk.

Table 9 OLS estimates of the *Ex Ante* default loss regression, based on loan level model, dependent variable: expected CMBS deal loss during the life of the tranche based on loan level loss models

	AAA	BBB
Baseline expected cumulative losses		
Intercept	0.026***	0.026***
	(0.001)	(0.001)
Subordination level	0.001	0.001
	(0.001)	(0.001)
Subordination level * issuance year ≥ 2004	0.004**	0.003*
	(0.001)	(0.001)
N	292	223
Adjusted R-Square	0.0340	0.0080
Alternative expected cumulative losses		
Intercept	0.083***	0.085***
	(0.003)	(0.003)
Subordination level	0.003	0.002
	(0.004)	(0.005)
Subordination level * issuance year ≥ 2004	0.012**	0.008*
	(0.004)	(0.005)
N	292	223
Adjusted R-Square	0.0342	0.0077

Standard errors are in parentheses. * for p<10 %, ** for p<1 % and *** for p<0.1 %

in the regression some tranche characteristics such as the log amount of the tranche and the expected life of the tranche. The regression takes the following form:

$$\begin{aligned} b_i = \alpha &+ y_1 NumProps_i + y_2 WLTV_i + y_3 Off_i + y_4 Hotel_i + y_5 Apt_i + y_6 Nurs_i \\ &+ y_7 Retail_i + y_8 Top5Loan_i + y_9 Lockout_i + y_{10} Penalty_i + y_{11} Yldmain_i \\ &+ y_{12} Defeas_i + y_{13} LogAmt_i + y_{14} Life_i + \eta_i \end{aligned} \tag{6}$$

We present the regression results in Table 10, model 4. Conforming to the common wisdom, subordination level is significantly related to the weighted LTV of the CMBS deal, which is usually seen as the most important credit risk factor. The expected life of the tranche has a significant and negative impact on subordination level. The share of the largest 5 loans generally has a negative impact on subordination level, which contradicts with the view that concentration is a risk. It is possible that there are offsetting factors considered by the CRAs that are correlated with the aforementioned two factors.

Estimates of other variables are generally conforming to the common wisdom. For example, the percentages of office, hotel and nursing/retirement properties have significant and positive impact on subordination levels, as office, hotel and nursing/retirement loans usually have higher default risk. Lockout and yield maintenance have positive impact on subordination level, which is also reasonable given that existing literatures find that prepayment constraint increases commercial mortgage loan default risk because borrowers can use default as a strategy to exit the mortgage obligation (see, e.g., Riddiough 2004; An et al. 2013). Prepayment penalty and defeasance are believed to give CMBS borrowers reasonable ways to prepay their loans and thus are

Table 10 OLS estimates of the subordination level regression, dependent variable: CMBS tranche subordination level

	AAA		BBB	
	Model 4	Model 5	Model 4	Model 5
Intercept	20.275***	−72.099	5.379***	17.198**
	(0.28)	(50.628)	(0.170)	(6.194)
Number of underlying properties	−1.391***	−1.154***	−0.661***	−0.678***
	(0.307)	(0.252)	(0.188)	(0.168)
Deal weighted average LTV	2.894***	2.453***	2.001***	1.833***
	(0.411)	(0.341)	(0.239)	(0.218)
% of office mortgages	1.615***	0.688*	0.064	−0.512**
	(0.336)	(0.273)	(0.203)	(0.181)
% of hotel mortgages	2.648***	2.397***	0.042	−0.545**
	(0.38)	(0.305)	(0.236)	(0.209)
% of multifamily mortgages	1.023**	−0.157	0.572**	−0.33
	(0.312)	(0.267)	(0.183)	(0.184)
% of nursing/retirement mortgages	0.539	0.188	0.460**	0.238
	(0.294)	(0.231)	(0.177)	(0.153)
% of retail mortgages	2.058***	0.012	−0.491*	−1.553***
	(0.345)	(0.303)	(0.208)	(0.200)
Share of the largest 5 loans	−0.280	−0.106	−0.823***	−0.734***
	(0.394)	(0.319)	(0.246)	(0.215)
Lock out coverage	2.579***	0.561	0.681**	−0.277
	(0.346)	(0.298)	(0.208)	(0.198)
Yield maintenance coverage	3.354**	1.926*	0.770	0.240
	(1.05)	(0.836)	(0.587)	(0.510)
Prepayment penalty coverage	−3.133***	−1.639*	−1.006*	−0.550
	(0.937)	(0.743)	(0.512)	(0.445)
Defeasance coverage	−3.505***	−0.646	−1.105**	0.206
	(0.566)	(0.468)	(0.345)	(0.308)
Log of tranche amount	0.122	−0.444	−0.584**	−0.301
	(0.295)	(0.244)	(0.192)	(0.186)
Expected life of the tranche	−5.058***	−4.471***	−1.096***	−1.002***
	(0.4)	(0.333)	(0.229)	(0.201)
More than one book runners		0.116		−0.295*
		(0.236)		(0.156)
Special servicer=servicer		0.161		−0.087
		(0.272)		(0.178)
Securitization program as beneficiary		−2.842***		−1.574***
		(0.287)		(0.197)
Rating shopping		−0.052		0.192
		(0.253)		(0.164)
Lagged credit spread slope		−1.107***		−0.924***

Table 10 (continued)

	AAA		BBB	
	Model 4	Model 5	Model 4	Model 5
		(0.260)		(0.177)
Lagged tranche price		0.922		−0.120*
		(0.505)		(0.062)
Time trend		−1.768***		−0.578*
		(0.318)		(0.234)
CRE CDO issuance		−1.659***		−0.443*
		(0.311)		(0.208)
Number of tranches in the deal		−1.649***		−1.030***
		(0.328)		(0.229)
N	679	679	657	657
Adjusted R-Square	0.4623	0.6741	0.2907	0.4839

Standard errors are in parentheses. * for p<10 %, ** for p<1 % and *** for p<0.1 %

beneficiary from the default risk perspective. Finally, the size of the tranche has a negative impact on BBB subordination level. The R-Squares are 46 percent and 29 percent for AAA and BBB regressions, respectively. The model fits are decent but there is apparently room for improvement.

Next, we test our alternative hypothesis by exploring the impact of a number of non-credit risk factors on subordination levels. We pay special attention to the factors that relate to the conflict of interest of the CRAs, those related to information asymmetry between issuers and CRAs/investors, and those related to the supply and demand of CMBS bonds. We add the following variables to equation (6).

First, existing literature suggests "rating shopping" in the structured finance market, meaning that issuers choose the CRA that provides favorable ratings (see, e.g., Riddiough and Zhu 2009; Bongaerts et al. 2012, Cohen and Manuszak 2013). To test this hypothesis, we include in our regression a dummy variable for tranches that are rated by more than two of the three major CRAs, Moody's, S&P, and Fitch. The rationale is that regulations require that CMBS be rated by at least two CRAs so if an issuer pays to obtain an additional rating it is likely he/she is not satisfied with the two ratings he/she obtained originally and thus seeks an additional more favorable rating.

Second, we consider the impact of institutional complexity. We include a dummy variable indicating that there are more than one book runners for the CMBS deal. We also include a dummy variable indicating whether the special servicer is the same as the master servicer. Increased institutional complexity can increase the difficulty in the resolution of financial distress while reduced institutional complexity can ease the resolution process and thus reduces default loss.

Third, we include a dummy variable indicating whether the issuer keep some residual pieces of the issuance (securitization program as the beneficiary). Information asymmetry may lead CMBS issuers to avoid being a stakeholder when the credit risk of the issuance if high.

The supply and demand of CMBS bonds may affect the structure of a CMBS issuance. Considering the supply-side effect, we include the credit spread slope in our model. The variable is calculated as the difference between the average AAA CMBS spread and the average single B CMBS spread in each quarter. We speculate that as the credit spread slope becomes steeper issuers would like to issue more senior tranches such as AAA and AA tranches. We lag the variable by one quarter to mitigate endogeneity problem. We also include lagged average tranche price as a regressor. When an issuer sees that the price of a certain tranche (e.g. BBB) was low in the last quarter, indicating that investors are less likely to be interested in such tranche, he/she may choose to issue smaller size of such tranche.

Starting from 2003, the collateralized debt obligations (CDO) market developed rapidly, which might have had an impact on the CMBS market. With the development of the CDO market, CMBS tranches can be re-packaged and sold into CDO pools to make CDOs. From this perspective, the CDO market represents a source of demand on CMBS bonds and can induce more issuance of CMBS bonds through reduced subordination. Therefore, we include CDO issuance as a regressor.

We also test the impact of deal complexity on subordination levels. Recent studies including Furfine (2012); Ghent et al. (2013) suggest that mortgage-backed securities issuers have informational advantage over the investors (and potentially the CRAs) and they use complex deals as a device to disguise investors, e.g. to put bad quality loans into complex deals that are hard for investors to analyze, or to negotiate lower subordination levels to bonds in complex deals. We use the number of tranches in a CMBS deal as a proxy of deal complexity.

Finally, we add a time trend to the regression. Sanders (1999); Geltner and Miller (2001) document systematic decline in CMBS subordination levels over time. Riddiough (2004) argues that the CRAs follow a "learning by doing" approach in subordination design and they reduce their conservatism when they get familiar with CMBS as the market develops and more and more data become available. Alternatively, the CMBS issuers over time may have gained more and more negotiating power to lower subordination levels in order to carve out more senior tranches out of a deal.

After adding those non-credit risk factors, our subordination regression takes the following form:

$$\begin{aligned} b_i = \alpha &+ y_1 NumProps_i + y_2 WLTV_i + y_3 Off_i + y_4 Hotel_i + y_5 Apt_i + y_6 Nurs_i \\ &+ y_7 Retail_i + y_8 Top5Loan_i + y_9 Lockout_i + y_{10} Penalty_i + y_{11} Yldmain_i \\ &+ y_{12} Defeas_i + y_{13} LogAmt_i + y_{14} Life_i + y_{15} Bookrn2_i + y_{16} Servsame_i \\ &+ y_{17} Secur_i + y_{18} Shopping_i + y_{19} LagCrdslope_i + y_{20} LagPrice \\ &+ y_{21} TimTrend_i + y_{22} CDOIss_i + y_{23} Complexity_i + \eta_i \end{aligned} \tag{7}$$

We report our regression results in Table 10, model 5. Interestingly, we see that securitization program as beneficiary has a significant and negative impact on the subordinations levels of senior AAA, junior AAA and BBB tranches, consistent with the information asymmetry and adverse selection view of issuer's choice in retaining the residual pieces. Lagged credit spread slope has a negative impact on senior CMBS tranches, conforming to our expectation – the steeper the credit spread slope, the more issuance of senior rather than subordinated tranches. Consistent with our conjecture of the impact from the CDO market, commercial real estate CDO issuance has a strong negative impact on AAA and BBB subordination levels – demand on CMBS bonds from the CDO market can drive the issuance of those tranches up. Deal complexity, measured by the number of tranches in a CMBS deal has a significant and negative impact on subordination levels, which echoes the findings by Ghent et al. (2013) in the subprime ABS market and supports the notion that issuers could have used complex deals to disguise investors. Finally, we do observe a significant time trend in AAA and BBB subordination levels. Those AAA and BBB CMBS bonds receive lower and lower subordination levels over time.

By looking at the R-Squares, we do see significant improvement in model fits after we introduce those non-credit risk factors in our subordination models. The impacts are strong in both the AAA and the BBB regressions. This finding, together with the aforementioned coefficient estimates suggest that non-credit risk factors play important roles in determining CMBS subordination levels.

Conclusions

Subordination plays an important role in the senior-subordinated structure of securitized transactions. Typically, the structured finance issuer assembles a pool of loans and passes the information of these loans to credit rating agencies (CRAs). The CRAs then work independently to examine how much subordination is needed for the tranches to reach certain ratings, such as AAA, AA, A, BBB, etc. From this perspective, subordination is about credit risk.

The recent crisis in the securitization markets has made the CRAs the subject of intense scrutiny. The CRAs are alleged of poor subordination design and bond rating that give senior CMBS, ABS and CDO bonds insufficient credit risk protection. In this paper, we reject the null hypothesis that subordination is purely about credit risk and find that a number of non-credit risk factors drive subordination levels. Based on these results, we conclude that subordination level is not just about credit risk as traditionally viewed. It also reflects the market need of a certain deal structure and is influenced by the balance of power among issuers, the CRAs and investors. From this perspective, our study shed new light on the mortgage market crisis that is closely related to securitization (see, e.g., Keys et al. 2010).

The study fills the gap of existing studies and provides important information regarding structured finance vehicles. Rating agencies use their internal models to work with issuers on subordination design. Therefore, little is known to the public (including investors and financial economists) regarding how various credit risk and non-credit risk factors affect subordination. We identify those factors in our analysis. Further, our results show that even within the same credit rating CMBS bonds varies in credit risk. Therefore, investors should pay close attention to how CMBS credit risk impacts different bonds in order to differentiate "good" deals from "bad" deals.

Appendix

Table 11 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

This is based on Moody's study of historical loss ratios of commercial mortgages

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