Commercial Mortgage Workout Strategy and Conditional Default Probability: Evidence from Special Serviced CMBS Loans

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February, 2004

Abstract

This study recognizes that commercial mortgage default is not a one-step process and examines a previously unexplored aspect in the whole default process, that is the stage between the initial delinquency and default. We distinguish the servicers' behavior from the borrowers' behavior. A multinomial logit model is applied to analyze the servicers' choice of workout options and a proportional hazard model is applied to analyze the borrower's default decision-making process under time-varying conditions. We find that cash flow condition is the most significant factor in the servicers' decision making process. We also find that borrowers make default decisions based upon both the equity position in the mortgage and the cash flow condition in the space market. Key real estate space market variables, such as market-level vacancy rates, also provide useful information in explaining commercial mortgage defaults. We find that special service seems to be successful in reducing the probability that a troubled loan will default. Finally, sensitivity analysis shows nontrivial economic significance of the impact of explanatory variables, real estate market variables in particular have the most significant impact on the pricing of special-serviced loans.

Introduction

The commercial mortgage-backed security (CMBS) is an important asset class with aggregate outstanding balance of $372 billion as of December 2001.[1] Besides non-financial risks such as regulatory risk and market structure risk, the major risks of CMBS investment are default, prepayment/extension, and liquidity. Contrary to residential MBS where prepayment risk dominates,[2] CMBS is largely protected from this risk by prevailing contractual clauses, such as enforced prepayment penalty, prepayment lockout, yield maintenance and defeasance. This study concentrates on default risk. In particular, we focus on a previously unexplored aspect of this risk, that is the conditional default risk after problematic loans become special serviced. We present both the empirical analysis and the possible application of this study.

The late 1980s to early 1990s saw extremely high commercial mortgage default rates across the country. The life insurance industry reported the highest outstanding foreclosure rate of 7.53% in the second quarter of 1992 (ACLI), and commercial banks reported the delinquent rate of commercial mortgages as 12.57% in the first quarter of 1991 (the Federal Reserve Board). These high default/delinquency rates were certainly a consequence of the devastating commercial real estate market crash and profoundly affected many financial institutions' confidence on the performance of commercial mortgages. Anecdotal evidences indicate that lenders and investors have become much more cautious in recent years. They have tightened underwriting standards and stepped up servicing effort to prevent the reoccurrence of enormous commercial mortgage default losses. As commercial mortgages have been increasingly securitized, investors in the CMBS market also monitor the default risk of collaterals and require various measures to be taken to mitigate the default probabilities and potential loan losses. One of these measures is to have a problem loan specially serviced, which is to transfer the problem loan to a special servicer that has more expertise in handling problem loans than regular servicers.

Three types of servicers are involved in CMBS deals. The *master servicer* reports to Trustee and communicates with investors and rating agencies. It oversees the deal and monitors the timely collection and distribution of principal and interest payments at the deal level. The *master servicer* also oversees *subservicers* (i.e. *primary servicers*) and makes servicing advances. The *subservicer* reports to the *master servicer*. It deals with borrowers directly and performs regular servicing routines such as collecting payments and bookkeeping, etc.. The *special servicer* starts to take over the servicing responsibility when a loan goes into serious trouble that constitutes a transfer event. Transfer events include delinquency and triggers such as imminent default, borrower bankruptcy, litigation, and borrower forbearance requests, etc.. Special servicers are often granted the power to decide the most effective workout strategy (e.g., decide whether to modify the loan term, to cure the delinquency, or to foreclose the property, among other options) based on the best interest of the entire trust. In the absence of potential moral hazard problem to be discussed below[3], this ultimate goal is to maximize the expected net present value of the loans in problem. Because special servicers usually possess more expertise and devote more resources in managing delinquent loans, they charge a much higher fee than the regular servicers. In addition to the higher cost, a potential moral hazard problem may also arise as the special servicer may act in their self-interest rather than in the interest of CMBS investors (Fathe-Aazam 1995 and Riddiough 2000). The effectiveness of special servicers in managing delinquent loans has significant impact on the collateral performance and consequently on the pricing of CMBS tranches, especially the lower-rated first-loss pieces.

This study concerns the performance of the loans that are special serviced. Because the outcome of loan servicing comes from the interaction between the borrowers and the servicers and the distinction between the servicers' behavior and the borrowers' behavior is important, we seek to clarify this distinction in this paper. As a natural extension from this understanding, we first study the decision making process from the servicers' perspective, and then study the factors influencing loan defaults when they are special serviced. We consider the later as largely the borrowers decision because few servicers would favor defaults. The link between the servicers' behavior and the borrowers' behavior is also established through a two-stage Hechman style estimation approach. Simulations of our empirically-derived model show how it can be applied in the valuation and pricing of special serviced loans.

The rest of the paper is organized as follows: the next section provides an overview of the literature; section 3 discusses the default process in commercial mortgage lending; section 4 describes the data used in this study; section 5 discusses the estimations and the empirical results, section 6 presents sensitivity analysis and pricing implications of the empirical model, and the final section concludes.

Literature Review

This paper benefits from many insights from earlier literature. In the first study on default risk assessment of commercial mortgages, Vandell (1984) hypothesizes that default could be due to the occurrence of either adverse cash flow or negative equity in the property. Vandell recognizes both the interactions between cash flow and equity conditions in affecting default risk, and the need to consider the timing of default and to incorporate the time-varying information about the property, market, and economic conditions. Kau, Keenan, Muller and Epperson (1987) and Titman and Torous (1989) were among the first to apply contingent-claims approach to valuing commercial mortgages. Vandell (1992) carries out empirical study using aggregate commercial mortgage foreclosure experience and confirms the equity theory of default. The study also attributes the possible high transaction costs as the cause of the under exercise of the default option. A series of studies by Snyderman (1991, 1994), Esaki, L'Heureux and Snyderman (1999) and Esaki (2002) provide aggregate longitudinal data of actual defaults based on a large sample of commercial mortgages originated by life insurance companies.

Vandell, Barnes, Hartzell, Kraft and Wendt (1993) were the first to use loan-level commercial mortgage data from a large life-insurance company. Empirical results confirm the dominance of loan terms and property value trends in affecting default. Ciochetti, Deng, Gao and Yao (2002) use a similar data set (also from a major life insurer), and apply the competing risk framework developed by Deng, Quigley and Van Order (1996, 2000) in the residential mortgage market to commercial mortgages. Their findings confirm that the put and call options are highly significant in explaining commercial mortgage default and prepayment. Transaction costs are also found to be important in explaining mortgage termination. In particular, solvency conditions reduce default risk, and small borrowers default much more frequently. Goldberg and Capone (2002) incorporate both equity and cash-flow considerations (so called double-trigger) in default models. Their empirical analysis using data of multi-family loans purchased by Fannie Mae and Freddie Mac confirm the importance of double-trigger theory, that is, they find that models relying solely upon property equity may have a tendency to overstate potential default rates, and those relying only on cash flows understate default risk. Archer, Elmer, Harrison and Ling (2002) argue for the endogeneity in commercial mortgage underwriting in terms of LTV ratio, which would imply dampened empirical relationship between default and LTV because lenders would require lower LTVs for high risk mortgages. They examine 495 multifamily mortgages securitized by the Resolution Trust Corporation (RTC) and the Federal Deposit Insurance Corporation (FDIC) and find no evidence of LTV effect on default, while the strongest predictors of default are property characteristics, including property location and initial cash flow. Ambrose and Sanders (2003) are the first to conduct empirical study on CMBS loans.

While the aforementioned studies provide excellent theoretical ground and empirical evidence on the determinants of commercial mortgage defaults, all these studies focus on the probabilities of loans moving from performing status to default status. Several studies, Riddiough and Wyatt (1994a, 1994b) and Harding and Sirmans (2002), start to consider theory of workout strategy of troubled debt and its implication on loan defaults and valuation, although none of these studies provide empirical evidence. Our study not only empirically analyzes servicers' workout strategic decisions but also analyzes the performance of troubled loans after they have been turned over to special servicers. Our study shares some similarity with that by Capone (1996) and Ambrose and Capone (1998) on single-family mortgage default resolutions and the workout alternatives to foreclosure in the residential mortgage industry. While both recognize that default is not a one-step process, their study focuses on the step from initial default (90-day delinquency) to final foreclosure, ours focuses on the step from initial delinquent (first enter special service) to default. Another related study is Springer and Waller (1993) who examine lender forbearance and find that the primary factors influencing the timing of the lender's foreclosure decision are the borrower's equity position and the erosion of that position with continuing delinquency.

Default Process

There are several stages for loans in non-performing status. First, the borrower decides to miss a scheduled monthly payment and the loan becomes delinquent. Because default is generally considered as the exercise of the implicit put option embedded in the mortgage contracts[4], the initial delinquency can be considered as the borrower's tentative step to exercise the put option. We say tentative because it is easy to make up one missed monthly payment. The special servicer usually is brought in when the loan is truly in trouble, e.g. when the loan has missed two scheduled payments. The transfer of servicing function from the regular servicer to the special servicer is usually an indication that the borrower is intentionally let the loan becoming non-performing, i.e. the servicers determine that the missed payments are not due to inadvertent mistakes but rather due to the borrower's deliberate action. The special servicer then decides the best workout strategy, while the borrower continues to re-evaluate the financial situation. We define 90 days past due as default because this status shows the borrower's determination to exercise his put option. While there could be jumps between these stages, the general process is summarized in Figure 1.

The process from delinquent to special service to workout outcomes depends on the behavior of both special servicers and borrowers. After examining the financial condition of the collateral, the market condition, the borrower's own financial situation, and other relevant factors, special servicers decide the best workout strategy. We call this as the "expected" outcome. The major categories of "expected" outcome include foreclosure, modification, and return to current. If the servicers expect the borrowers to be delinquent for a prolonged period, foreclosure is usually the best strategy. The "expected" outcome does not necessarily equal the actual outcome because the later is also determined by the borrower's behavior. We expect borrowers would still follow the rules of default put option when they are being special serviced. In fact, the borrowers could be more ruthless in this stage because they have already shown willingness to exercise the put option. Of course, cash flow condition may still play a critical role as found by some other studies. A rational borrower would be hesitant to complete the exercise of put option if there is still positive cash flow from the collateral, while negative equity must be the necessary condition for the borrower's final completion of exercising default put option.

Data

The special service loan data are gathered from Standard & Poor's Conquest CMBS deal library.[5] The data collection date ends in September of 2002, with loan status recorded as of August 2002.

We searched 144 CMBS deals, most of which are conduit deals, and collected the records for 577 loans in the special service status. We found 74 loans that are either cross-collateralized or backed up by the same borrower. Borrowers that have multiple loans were largely hotel, retail, and restaurant chains. We exclude these loans from our analysis because it is not in the scope of this study to analyze business failures. We also excluded 23 loans with missing data, and thus retained a final data set of 480 loans. Although there is still a possibility that we missed cross-connection between some of the loans in our final data set, we believe that the possible error would be insignificant and that the loans in our final data set are mostly independent therefore satisfying the data requirement for the following statistical analysis. In order to perform the Heckman style two-step analysis to study the potential correlation between special servicer's behavior and borrower's behavior, we further collected the data of the performing loans from the same 144 CMBS deals. After excluding the records with missing data and cross-collateralized loans, we retain a total of 13,132 loans for the first stage estimation in the framework of the Heckman approach.

Table 1 shows the breakdown of the final data set of the special serviced loans by property type of the collateral. While mortgages of retail properties register the highest percentage in terms of loan balance (30.5%), hotel, retail and apartment have similar high percentages in terms of loan counts. Office loans have the largest average balance among all property types while apartment loans have the smallest average balance, and warehouse loans rank the second smallest by balance.

Table 2 shows the breakdown of the final data set by servicers' workout strategy. Close to half of the sample loans do not contain information on servicers' workout strategy, which suggests difficulty in collecting complete CMBS data, probably owing to a diverse universe of originators, servicers, trustees, and investors, all of them have different reporting standards and requirements.

Of the loans that have the information of servicers' workout strategy, about half are modified, with the remaining loans falling about equally into three categories: foreclosure, return, and bankrupt (the latter apparently not being a servicer choice).

Real estate market data include occupancy rates for the hotel sector and vacancy rates for the remaining property types.[6] In addition, NCREIF Property Indices are used to proxy for the market-level value indices and NOI indices.

Empirical Analysis

Multinomial Logit Analysis of Lenders' Workout Strategy

Of the 217 special serviced loans with clear identification of servicers' workout strategy, servicers intend to bring 52 loans back to "current" status, to foreclose 47 loans, and to modify the terms of the remaining 118 loans. Remember that servicers' intention does not guarantee the success of each strategy, loans could still fail to perform even though servicers intend to bring them back to "current" or have modified the loan terms. Since in this section we attempt to understand the reasons behind servicers' choice of a particular workout strategy over alternatives, we leave out the ultimate outcome of these strategies, which is a subject we shall return to in the next section concerning proportional hazard analysis. We focus on the effect of the measurable variables at the time loans enter the special service category on servicers' choice of workout strategy. These measurable variables are mainly related to loan characteristics and real estate market conditions. Unfortunately, we do not have enough information on borrower characteristics.

Following option pricing theory and mounting empirical evidence in the mortgage research literature, a loan's current equity share (measured by one minus the current loan-to-value ratio, i.e. LTV) has a dominant effect on the probability of the underlying collateral value dropping below the critical value (the par value of the outstanding principal amount) and hence to default. We expect servicers would more likely foreclose high LTV loans because these loans are more likely to eventually have their collateral value fall below loan value. To cut the carrying cost and interest payment advance, the sooner the loans are foreclosed, the lower loss severity would be. For the loans with middle-tier LTVs (that is, LTV is not high enough to justify immediate foreclosure and LTV is not low enough where there is no need for servicers to modify loan term[7]), we expect servicers would be more willing to modify the loan terms in order for them to stay "current". For this type of loans, a small payment reduction could be enough for the borrowers to remain solvent. Therefore we expect LTVs should be positively related to servicers' choice of foreclosure strategy and to a lesser extent to servicers' choice of loan term modification strategy.

When borrowers are insolvent and run into trouble (that's the likely reason why they enter the special service category), net operating cash flows are critical because they affect the immediate financial stress to the borrowers of commercial mortgages. Because commercial properties are very illiquid and involve substantial transaction costs (both tangible and intangible), borrowers are very unlikely to dispose their properties quickly to meet the cash payment requirements even if the market value of collateral is higher than the mortgage principal amount. We expect the net operating cash flows (proxied by debt-service-coverage-ratio, i.e. DSCR) to have a negative relationship with foreclosure.

Rational servicers would look forward to determine whether the performance of particular collateral will get better or worse and whether the properties will be eventually sold at a higher or lower price. Because all these property market conditions ultimately affect the possibility of the borrowers' regaining financial solvency through either improved cash flows and/or profitable sales of the properties, we expect that higher rental growth rates in the real estate space market (proxied by the market-level NOI growth rates) and higher value appreciation rates in the property asset market (proxied by the market-level value appreciation rates) would have a negative relationship with servicers' choice of foreclosure[8]. Also, in an improving commercial real estate market, servicers are less likely to modify the loan terms so that the NOI growth rates and property value appreciation rates should have a negative relationship with servicers' choice of loan term modification.

We use the change of market-level vacancy rates as another variable proxying for real estate market conditions. It is well known by commercial real estate participants that vacancy rates (or the occupancy rates) serve as an excellent leading indicator of the future cash flows and property value growth potential[9]. If the vacancy rates in a market are falling, the servicers would expect improving cash flow and would be less likely to foreclose the property. We therefore expect a positive relationship between the change in vacancy rates and foreclosure.

Empirical mortgage research literature has also identified the seasoning effect in loan default probability. That refers to the default seasoning pattern that default probabilities steadily increase in the initial years after loan origination and then level off between the third and the seventh year and then gradually decline (see Goldberg and Capone 2002 for recent evidence). We expect servicers would consider the seasoning of troubled loans in their decision making process. However, no theoretical consensus has been reach regarding whether the seasoning will be a positive or negative factor in servicers' decision. For both financial and psychological reasons, we expect servicers are more likely to tolerate payment delay and more likely to workout a modification strategy after the loans are in good standing for a long time period. We therefore expect a positive relationship between loan age and modification. On the other hand, Riddiough (2000) argues that borrower's bargaining power in renegotiating the loan may be reduced in the CMBS market because the special servicer may view financial distress as an isolated occurrence instead of an ongoing business relationship. This impersonal relationship between the borrower and the special servicer may restrict the ability to arrive at a mutually agreeable outcome. We empirically test this hypothesis in our statistical analysis.

Studies by Clauretie (1987), Ciochetti (1997) and Ambrose, Capone and Deng (2001) also documented the importance of state foreclosure laws on the probabilities of default. We separate states by two categories: judicial foreclosure and power-of-sale, the assignment of each state to these categories follows Ciochetti (1997).

In all, we have identified seven variables that represent the various dimensions rational servicers are likely to take into consideration in making workout strategic decisions. These are listed and their simple correlations are reported in Table 3. No correlation is above 0.31 and most are not different than zero at 95% confidence level. This suggests that the independent variables we choose indeed represent different dimensions that are likely to be orthogonal.

Once the potential explanatory variables are identified, we further assume a loss severity function where lenders maximize a linear utility function U_j over j workout strategies[10]:

$$U_j = \alpha_j + \beta_j X + \gamma_j Z + \varepsilon_j, \qquad j = 1, 2, 3. \tag{1}$$

where X is a vector of loan and property characteristics (LTV, DSCR, and loan age), Z is a vector of real estate market variables (growth rates in value and NOI and change in vacancy rates). The possible workout strategies in our case are: (1) foreclosure, (2) modification, and (3) return to "current", which are all conditional on the mortgage being specially serviced. The workout strategy j is chosen whenever the servicers expect the lowest future loss severity conditional upon that strategy. For example, if the servicer finds that the real estate market is dramatically improving, he would neither foreclose the loan nor modify its terms. Instead, he would simply push the borrower to make timely payments so that he wouldn't realize any loss. Although the expected loss severity function is unobservable, we do observe the choices servicers made under varying conditions, and these choices directly reflect the least loss severity expectations for the servicers. We therefore model the probability of each workout strategy P_j as a multinomial logit function[11]:

$$\Pr(P_j = 1) = \frac{e^{\alpha_j + \beta_j X + \gamma_j Z}}{\sum_{k=1}^{3} e^{\alpha_k + \beta_k X + \gamma_k Z}}, \qquad j = 1, 2, 3. \tag{2}$$

The expected sign of the coefficients are explained earlier in the section. The multinomial logit analysis is performed using SAS CATMOD procedure. Table 4 shows the results from the maximum likelihood estimation with "return to current" as the base case.

The empirical results indicates strong negative association between market NOI growth rates and foreclosure strategy. The order of choices impacted by market NOI growth rates on servicers' workout strategy is also confirmed. Everything else being equal, in a real estate market where rents are increasing (NOI growth rate is positive), servicers prefer to bring the loans back to "current" and are least likely to foreclose on that property. The coefficient of market value growth rates is negative as expected but is insignificant. Possibly servicers pay more attention to cash flow variables (NOI growth rates) than to property value variables (value growth rates), possibly because cash flow is tangible and easily measurable at the time of decision making while property value is subject to error-prone value appraisals and less accurate in practice. Another real estate market proxy, the change of market occupancy rates, has the wrong sign and is insignificant. The possible reason is that the market vacancy rates (occupancy rates) exert indirect influence on loan performance through affecting the cash flows of underlying collateral, servicers have no immediate need to understand the more complex real estate market if they have property cash flow information at hand.

The empirical results also indicates significant positive association between loan age and servicers' choice of loan term modification strategy. Servicers do seem to be more tolerable to borrowers who have been performing for a long period.

Two loan-specific financial variables, LTV and DSCR are not significant, with LTV having the correct sign and DSCR has the incorrect sign. This is possibly attribute to some errors in variable problem. Since both variables are largely estimated from market-level indices, they may not reflect the true financial conditions for these properties (for example, some of the properties could encounter certain idiosyncratic trigger events before they enter the special service category). In other words, both LTV and DSCR in our model are imperfect (noisy) measure of financial characteristics of individual property. Another possibility could be that, even if we precisely estimated LTV and DSCR, servicers might still pay more attention to general market conditions rather than focusing on individual property performance. Because rational lenders would focus more on the possibility of curing the problem in the future, which is mostly dependent upon the general market condition, rather than on backward looking at the past financial situation that brought the loans into special service.

We find significant positive impact of judicial foreclosure law on servicers' choice of foreclosure strategy. This seems puzzling at the first look, because judicial foreclosure is more costly than power-of-sale, one might expect the servicers not to prefer foreclosure in the states where judicial foreclosure is required. However, as suggested by Riddiough and Wyatt (1994b), servicers may not want to reveal their unwillingness to foreclose in these states because doing that would encourage more defaults. Actually, as shown from the statistical results, servicers may purposely become tougher in states with judicial foreclosure laws in order to discourage future defaults.

The significant coefficients of both intercepts suggest that, either our model misses some explanatory variables, or servicers prefer foreclosure the least and prefer the “return to current” strategy the most. We think both are equally likely reasons. The later explanation seems to corroborate with the lenders’ rationale as we examined earlier.

In summary, the results of multinomial logit analysis appear to suggest that special servicers make workout strategic decisions based largely upon the real estate space market condition – proxied by market-level NOI growth rates. This is understandable since space market condition (rental growth and NOI growth rates) are easily observable and measurable. The forward-looking component of current space market condition is also helpful in the decision-marking process. We also find that servicers are more willing to modify loan term for more seasoned commercial mortgages and are more likely to foreclose loans in states where judicial foreclosure is required.

Proportional Hazard Analysis of Default Probability of Special Serviced Loans

Before we turn to the proportional hazard analysis of default outcomes of special serviced loans, recall we define loans being “bad” as the “90 days late” in mortgage payment or worse. Thus “bad” includes “foreclosure” or “REO”[12]. Since loans enter special service due to various payment problems, we consider “30 days late” and “60 days late” as “good” in our sample. Hence “good” loans in our sample include “current” loans and those loans in minor delinquency. Among the 480 special serviced loans in our data sample, 179 are identified as “bad” since they became “90 days late” or worse by the end of the data collection date, and 301 still remain in “good” standing by the end of the data collection date. We stamp these 301 loans as censored observations. Because special-serviced loans are counted as non-performing status in many industry reports, it is important to realize that not all special-serviced loans end up in default and the percentage of non-defaults is actually not trivial[13].

Once the problem loans are transferred to the special servicer, the special servicer must decide the most effective (least cost) solution to the problems. The decision must be made repeatedly until the loans terminate or drop out of the special service category. The loans may remain in special service for varying length of time. If the loans remain current while they are special serviced, that would imply the effectiveness of special service. While the results certainly depend upon various conditions, the ideal goal of special service is to cure the problems of the loans and make them current, which maximizes the present value for the lenders/investors. The special servicer also makes decisions regarding whether modifying loan term would be the least-cost alternative. The survival probability of special serviced loans is a function of various characteristics, observable at the time when loans became special serviced and during the special service period.

We apply the Cox proportional hazards model to analyze the probability of loans becoming "bad" once they enter the special service category. The Cox model has recently become the most popular technique in mortgage performance studies (Green and Shoven [1986], Schwartz and Torous [1989] are among the first to apply hazard model to mortgage termination risk analysis, and Deng, Quigley and Van Order [2000] presents more recent applications with increased realism and sophistication). The model was primarily developed and extensively used in the biomedical sciences to predict survival of patients (e.g., patients who have had heart transplants or cancer diagnoses) based on patient and treatment characteristics. Because mortgage default (becoming "bad") can also be considered as a survival failure, the model has been conveniently borrowed by mortgage researchers to estimate the effects of explanatory variables on the commercial mortgage's time to default. In particular, the model estimates the probability that a mortgage with certain characteristics will default in a given period given the fact the mortgage is still alive at the beginning of the period, which is also called the conditional probability of default. Cumulative default probability can then be easily computed from the conditional default rate (CDR).

Assuming the probability density function of duration of the loan to first default at t is $f(t)$, and the cumulative probability distribution is $F(t)$, the hazard function is defined as the probability density of default at time t, conditional on its being active before time t:

$$h(t) = \lim_{\Delta \to 0} \frac{\Pr(t < T < t + \Delta \mid T \geq t)}{\Delta} = \frac{f(t)}{1 - F(t)}. \tag{3}$$

This hazard function, $h(t)$, represents the conditional default probability in the next period given that loan was current at time t. The proportional hazard assumption of Cox (1972) assumes a vector of covariates, $z_i(t)$, either time-invariant or time-varying, affect the baseline hazard function, $h_0(t)$ proportionally in exponential form. Thus the hazard function for subject i at time t can be specified as:

$$h\left(t_i; z\left(t_i\right)\right) = h_0(t_i)\exp\left(z\left(t_i\right)'\beta\right), \tag{4}$$

where β is the vector of constant coefficients. Note that the baseline hazard function reveals the pattern of default hazard rates over the time for the average loan in the sample (one can view baseline hazard function as 100 percent PSA in prepayment risk analysis or 100 percent SDA in default risk analysis). The proportional risk factors, vector $z\ (t_i\ )$, include time-varying or time-invariant trigger events, such as LTV or DSCR. The estimated β coefficients reflect the default risks increase/decrease proportionally to the baseline pattern of default in response to change in risk factors.

A popular estimation approach is *Cox's Partial Likelihood* specification, which only requires the existence of a common stationary baseline hazard function, h_0, for all subjects. This approach estimates the coefficients for the proportional factors based on rank and order statistics (hence called *Partial Likelihood*). So β can be identified without parametric restrictions on the baseline function since $h_0(t)$ is concentrated out as a nuisance number. Note the proportional hazard model is parametric in the specifications of proportional change while the baseline hazard function can be either parametric or non-parametric.

Before proceeding to the Cox hazard model, we first examine the empirical survivor functions from the unadjusted sample by property type. Figure 2 shows that survival probabilities vary substantially by property type. The graph clearly suggests that hotel loans are the most likely to default, followed by retail loans. Only about 37% of the hotel loans are still alive 12 months after they are special serviced. Retail loans also have high default rates. The performance of apartment, office and warehouse loans looks similar considering the sample size. This observation seems to reflect the recent property market conditions, that is, during the recent economic slowdown, the hotel sector was hit the hardest due to reduced traveling, and the retail sector was also hit very badly due to heightened competition and increased bankruptcies of many retailers.

We also examine the summary statistics both at the time loans first enter the special service status and at the time loans either become "bad" or censored at the end of the data collection date. Table 5 shows the aggregate statistics. There appear to be big differences between "bad" loans and "good" loans in terms of average LTV and the market-level occupancy rates. There is also slight difference in the initial coupon rates, "bad" loans have relatively higher coupon rates, yet the difference is not that big. The differences of year-to-year value appreciation, DSCR, the NOI (year-to-year) growth rate, and property-level cutoff occupancy rates are also as expected, but the differences do not appear to be as pronounced as in LTV. We did not find meaningful differences between the two categories in terms of loan age and annual loan payment, which we use as a proxy for the financial obligation of the borrowers.

Table 6 reports the summary statistics by property type. It is striking to notice that the big differences of LTV come mainly from retail, hotel and apartment sectors. The difference of LTV does not appear to be significant in both office and warehouse sectors. The major difference of DSCR comes from apartment and office sectors. The differences of NOI and value growth rates are not significant in all the sectors. Closer observation of Table 6 also suggests that the marked performance differences between property types could be explained by more fundamental variables, for example, the whole hotel sector appears to have suffered the greatest cash flow drain (the biggest negative NOI growth) and largest value decline (more than 10% value decline on annual basis). We also notice that "bad" retail loans have exceedingly high LTVs based on our estimation. These observations lead us to suspect that more fundamental variables rather than property type determine the default probabilities.

The biggest advantage of proportional hazard model over the multinomial logit model is that we can examine the dynamic of the time-varying decision making process. In so doing, we should incorporate time-varying explanatory variables in the proportional hazard model to capture the time-dependent financial conditions of the commercial mortgages and real estate market conditions. This is a very nice feature because we know that borrowers constantly evaluate their financial situation and monitor the market condition before they make the decision to either continue or withhold the mortgage payments. We incorporate the following time-varying covariates: *PeriodicLTV*, which is calculated based on the estimated property value and the calculated unpaid mortgage principal balance at each point in time before they either become "bad" or are censored. The property value is estimated by first taking the initial appraised property value in the loan file and then applying the market-level value growth rates moving forward period to period. In cases where the loan file contains a recent property value, we compare that value to the initial value, if the recorded recent value is different from the initial value, we then assume either lenders or property owners re-appraised the property and we take that value as the new value at the current value recording date, if two values are the same, we assume that the recent value is simply a carry-over from the initial value and is disregarded[14]. We then continue to apply market-level value growth rates to this new value going forward period to period. The variable, *ValueGrowthMkt* is the market-level year-to-year value appreciation rates. Because the market-level value indices we used are NCREIF indices that are known to be sticky and affected by the infrequent appraisals, we feel it is the best choice to use year-to-year change as a proxy for the market property value change. Since most properties in the NCREIF index are re-appraised at least once a year, the year-to-year market value change should have overcome some of the weakness in this market value index. The variable, *NOIGrowthMkt* is also the market-level year-to-year NOI growth rates. We use the variable, *VacancyChangeMkt* to represent to leading indicator of the space market condition, which is also measured as the year-to-year vacancy change. Because we saw from Table 6 that hotel sector experienced the largest value and NOI decline while the other property sector performed relatively better, we test an alternative model including a dummy variable *HotelFlag* that takes value 1 if the collateral is hotel and takes value 0 if otherwise. As in the previous section, we use a dummy variable *JudicialForeclosure* to indicate the states that have judicial foreclosure laws.

Finally, we follow Lekkas, Quigley and Van Order (1993) and Ambrose, Capone and Deng (2001) by including an inverse Mills ratio as an additional explanatory variable in the hazard model to correct the sample selection bias. This Heckman-style approach consists of two steps. The first step is to estimate a simple binary probit model of commercial mortgages falling into the special serviced pool using the full sample that consists of the event history of both performing and non-performing loans, and the second step is to add the inverse Mills ratio from the first-stage probit model as a covariate into the second stage hazard model. The Mills ratio is calculated as $f/(1-F)$, where *f* is the probability density function and *F* is the cumulative density function. Heckman (1976) shows that including the inverse Mills ratio in the second-stage estimation corrects the sample selection bias and provides more consistent estimates of the behavioral parameters. The Heckman two-stage approach is the appropriate estimation when dealing with truncated samples (in our case, non-special serviced loans are truncated).

Amemiya (1985) pointed out that the inverse Mills ratio can be explained as hazard rate. Therefore by adding the inverse Mills ratios in the second-stage estimation, the model also explores possible correlation between the efforts of special service screening process and the default risk of the special serviced loans.

Tables 7A and 7B show the results of Cox proportional hazard model using SAS PHREG procedure. Model 1 in Table 7A shows the estimation without *inverse Mills ratio*. The coefficients behave mostly as we expected, and the significance level is much higher than that from the multinomial logit model. The most significant variable is *PeriodicLTV*, suggesting that the equity effect is dominant in affecting borrowers' decision to continue or withhold the payments. Higher LTV leads to more defaults, which is exactly as option pricing theory would suggest, and appears to conform with what we have observed in other mortgage default studies, both residential and commercial. Two other variables, *NOIGrowthMkt* and *VacancyChangeMkt*are are significant at the 10% and 5% level respectively, suggesting that market-wide cash flow increase makes default less likely, and that the market-wide decline in vacancy rates has a positive effect on the borrowers' willingness to continue the mortgage payment and therefore reduce the default probability. *JudicialForeclosure* does not show up as significant, suggesting that borrowers do not consider foreclosure laws in their default decision. In other words, our results do not provide support for the hypothesis that states "judicial" states should have higher default incidence, reflecting a tendency for mortgagors to risk default more readily if foreclosure is more difficult to effect (Archer, Elmer, Harrison and Ling 2002). *HotelFlag* is significant at the 10% level, probably because the hotel sector experienced the largest value decline in the last few years therefore captures a large chunk of the variation in *ValueGrowthMkt*, which does not appear to be significant at all.

Model 2 in Table 7B reports the estimated proportional hazard model including *inverse Mills ratio*. The inclusion of *inverse Mills ratio* increases the significance and the magnitude of the coefficients of *PeriodicLTV*, *NOIGrowthMkt*, *VacancyChangeMkt* and *HotelFlag*. This indicates that model 2 yields more efficient estimates by inclusion of *inverse Mills ratio*. The robustness of the variables representing a loan's LTV, the market-level NOI growth rates and market-level vacancy change is very encouraging, as these variables make perfect theoretical sense.

Tables 8A and 8B present two alternative models. Model 3 in Table 8A shows that includes *LoanAge*,*PeriodicDSCR* and *LTVJudicial* in addition to the variables included in Model 2. *LoanAge* is measured as the months that a loans remains outstanding since the first payment due date. *PeriodicDSCR* is the current DSCR based on the estimated current property NOI and mortgage payments. The methodology in estimating current property NOI using market-level NOI indices is similar to that in estimating *PeriodicLTV*, as we explained earlier. Following Ambrose, Capone and Deng (2001), we also include *LTVJudicial*, the interaction term of *PeriodLTV* and *JudicialForeclosure*. The results show that both *LoanAge* and *PeriodicDSCR* are not significant. The big change of the coefficient of *ValueGrowthMkt* also confirms that this variable does not possess explanatory power. The interaction term *LTVJudicial* is not significant, confirming our earlier conclusion that state foreclosure law is not a significant factor in the borrower's default decision making process.

Model 4 in Table 8B extends Model 3 by including the *inverse Mills ratio* variable. The inclusion of *inverse Mills ratio* not only increases the significance and the magnitude of the coefficients of the key variables, such as of *PeriodicLTV*, *NOIGrowthMkt* and *LoanAge*, the *inverse Mills ratio* itself is significant at the 10% level. This suggests that the more likely a loan is special serviced, the less likely the loan will end up in default. In other words, sending a problem loan to the special servicers does have a positive impact on the performance of the problem loan, and the special servicers appear to be functioning in its expected role.

In summary, a borrower is very likely to make his payment decision based largely upon his equity position in the mortgage and the potential cash flow condition as indicated by the current space market movement. The borrower also looks at the space market vacancy (occupancy) movement to aid his estimation of potential cash flows from the collateral. State foreclosure laws do not seem to have significant impact on the borrower's default process. In addition, the result from the fully-specified model seems to confirm the positive role of special service.

The two hypothesis regarding residential defaults: negative equity hypothesis and ability to pay (cash flow) hypothesis, seem to co-exist in commercial mortgage defaults. The proportional hazard model appears to validate the importance of both negative equity effect and cash flow effect. The results also highlight the significance of real estate market-wide variables, such as market-wide vacancy movement, as excellent proxies for the default determinants.

Sensitivity Analysis of Survival Probabilities and Pricing Implications

In this section, we conduct sensitivity analysis of survival probabilities by changing the independent variables that are found to be significant in the above statistical analysis. We also examine the pricing implications by applying different loss severities. To implement the sensitivity analysis, we first calculate the means and standard deviations of all independent variables. We then estimate the base case survival probability by applying the means of each independent variable to the baseline hazard function. The next step is to estimate the economic significance of each independent variable. This is done through changing each independent variable by one standard deviation while holding constant the remaining variables. Table 9 shows both inputs and results of the sensitivity analysis. For example, in Case 9-1, we change the PeriodicLTV to 79.2% instead of the base case 63.5% while all other variables are held constant. The results show that the survival probability will decrease by 4.7% to 44.5%. This change of survival probability will then affect the pricing of such a mortgage. The price of the mortgage[15] in Case 9-1 will decrease by 1.65 to 80.58 assuming a loss severity of 35%, and will decrease by 2.13 assuming a loss severity of 45%. The economic significance of the other variables are also examined and shown in Case 9-2 through Case 9-8. It is interesting to notice that the Hotel dummy is actually the most economically-significant variable among all variables and the market vacancy change is the most significant continuous variable, economically speaking. This suggests that real estate variables dominate loan characteristics, supporting the notion that commercial real estate relies on income stream to pay off the debt therefore real estate market conditions are indeed more critical than loan characteristics.

Because real estate market variables are the most economically-significant variables, we further perform sensitivity analysis under assumptions of two opposite real estate market scenarios. Table 10 shows those assumptions and results. Case 10-1 assumes that three real estate market variables are all improving by one standard deviation while Case 10-2 assumes that three real estate market variables are all deteriorating by one standard deviations. Both cases assume the same loan characteristics such as LTV and DSCR. The results show significant differences in survival probabilities and loan prices. In an improving real estate market, the survival probability increases to 74.1% while it decreases to 23.4% in a deteriorating real estate market in two years. This significant difference in survival probability also leads to significant difference in loan prices between the two scenarios. A price difference of 17.74 is shown under the assumption of 35% loss severity.

The results of the sensitivity analysis confirm the economic significance of the proportional risk factors in the empirical model. The economic implication in fact can be quite significant therefore the findings of this study can and should be used by market participants to correctly evaluate and price special-serviced loans.

Conclusions

The existing literature in commercial mortgage defaults studies the process for loans in the current status to the default status where default is either defined as foreclosure (e.g. Vandell et al. 1993 and Ciochetti et al. 2002) or as 90-days-late or worse (e.g. Archer et al. 2002). This study recognizes that commercial mortgage default is not a one-step process and examines a previously unexplored aspect in the whole default process, which is the stage between the initial delinquency and default, which we define as 90-days-late or worse. We also distinguish the servicers' behavior from the borrowers' behavior in the default process, where the servicers mainly make the initial workout strategic decisions that are expected to minimize the potential losses meanwhile the borrowers make the repeated decisions on the default put option exercise during the course of being special serviced. Because most problem loans become special serviced in the

CMBS market, we empirically study (a) the probability of special servicers' choosing one workout strategy versus others and (b) the conditional probability of borrower defaulting after problem loans become special serviced.

We find that special servicers make initial workout strategic decisions based largely upon the real estate space market condition – proxied by market-level NOI growth rates. In other words, cash flow condition is the most significant factor in the servicers' decision making process. We also find that borrowers are likely to make default decisions based upon both the equity position in the mortgage as suggested by the option theory and the cash flow condition as indicated by the space market movement, therefore negative equity hypothesis and ability to pay hypothesis appear to co-exist in the default process of commercial mortgages. In addition, key real estate space market variables, such as market-level vacancy rates, provide very useful information in explaining commercial mortgage defaults. State foreclosure laws do not have empirically significant relationship with the borrowers' default process. Finally, sensitivity analysis shows nontrivial economic significance of the explanatory variables, real estate market variables in particular have the most significant impact on the pricing of special-serviced loans.

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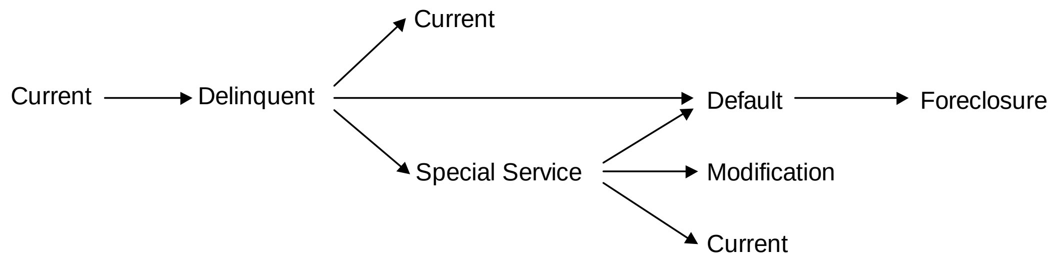

Figure 1. The Default Process

Figure 2: Survival Functions by Property Type

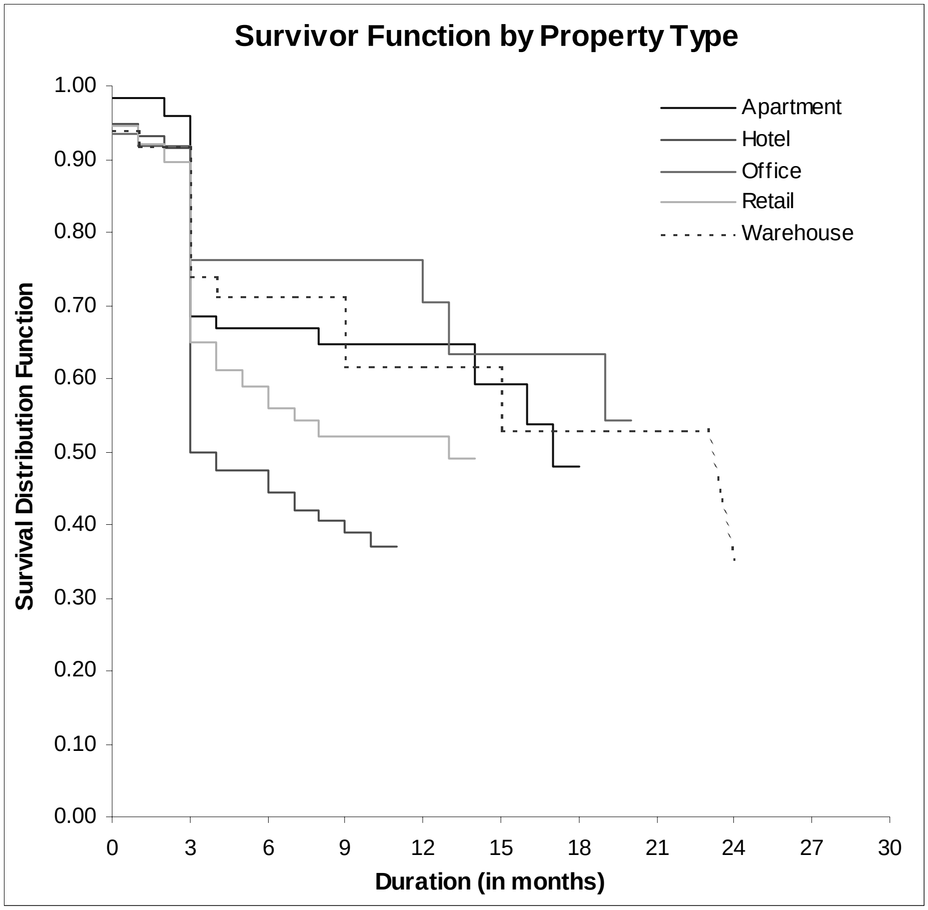

Table 1. Sample Loan Statistics by Property Type

Property Type	No. of Loans	Sum of Cutoff Balance	Average Cutoff Balance	% by No. of Loans	% by Cutoff Balance
Apartment	114	$354,017,961	$3,105,421	23.8%	13.3%
Hotel	130	$686,821,483	$5,283,242	27.1%	25.8%
Office	60	$594,216,586	$9,903,610	12.5%	22.3%
Retail	127	$813,171,306	$6,402,924	26.5%	30.5%
Warehouse	49	$216,304,498	$4,414,378	10.2%	8.1%
Total	480	$2,664,531,833	$5,551,108	100.0%	100.0%

Table 2. Sample Loan Statistics by Workout Strategy

Workout Strategy	No. of Loans	Sum of Cutoff Balance	Average Cutoff Balance	% by No. of Loans	% by Cutoff Balance
Foreclosure	47	$255,970,914	$5,446,190	9.8%	9.6%
Modified	118	$740,438,098	$6,274,899	24.6%	27.8%
Return	52	$289,681,795	$5,570,804	10.8%	10.9%
Bankrupt	36	$186,395,154	$5,177,643	7.5%	7.0%
Unidentified	227	$1,192,045,872	$5,251,303	47.3%	44.7%
Total	480	$2,664,531,833	$5,551,108	100.0%	100.0%

Table 3. Correlation Matrix of the Variables Used In Multinomial Logit Analysis

	LTV	DSCR	Value Growth (Market)	NOI Growth (Market)	Occupancy Change (Market)	Loan Age
LTV (Loan)	1.00					
DSCR (Loan)	(0.23)	1.00				
Value Growth (Market)	(0.16)	0.30	1.00			
NOI Growth (Market)	(0.14)	0.16	0.31	1.00		
Occupancy Change (Market)	(0.13)	0.26	0.22	0.11	1.00	
Loan Age	(0.17)	(0.05)	(0.15)	(0.02)	(0.05)	1.00
Mean	75.8%	1.28	-2.7%	-6.0%	1.21	40.5
Standard Deviation	38.1%	0.56	6.3%	15.4%	0.32	20.8
No. of Observations	217	217	217	217	217	217

Table 4. Multinomial Logit Analysis of Workout Strategy

	Foreclosure				Modified			
Parameter	**Estimate**	**Standard Error**	**Chi-Square**	**Pr > ChiSq**	**Estimate**	**Standard Error**	**Chi-Square**	**Pr > ChiSq**
Intercept	-3.0108	1.3441	5.02	0.0251	-1.8902	1.0741	3.1	0.0784
LTV (Loan)	1.0368	0.6403	2.62	0.1054	0.4908	0.6053	0.66	0.4175
DSCR (Loan)	0.5506	0.4310	1.63	0.2014	0.4471	0.3383	1.75	0.1863
Value Growth (Market)	-2.4174	4.1440	0.34	0.5596	-3.6360	3.4628	1.1	0.2937
NOI Growth (Market)	-5.1921	1.7572	8.73	0.0031	-1.4455	1.3784	1.1	0.2943
Loan Age	0.0048	0.0124	0.15	0.7017	0.0214	0.0100	4.58	0.0324
Occupancy Change (Market)	0.7282	0.7683	0.9	0.3433	0.6926	0.6174	1.26	0.2619
Foreclosure Law (Judicial)	0.4359	0.2206	3.9	0.0482	0.1063	0.1801	0.35	0.5552
Log Likelihood Value:	-198.80							

Table 5. Descriptive Statistics

Variable	At the Date Loans Were First Transferred To Special Servicer: Loan Status Bad[a]	Good[b]	Total	At the Date Loans either Went "Bad" or Were Censored: Loan Status Bad	Good	Total
Loan Age	42.2	42.9	42.6	45.7	50.9	48.9
	(18.2)	(20.9)	(19.9)	(18.2)	(20.1)	(19.6)
LTV	83.3%	69.1%	74.4%	82.0%	67.9%	73.2%
	(53.9%)	(19.5%)	(37.0%)	(53.6%)	(19.7%)	(36.8%)
DSCR[c]	1.24	1.32	1.29	1.22	1.30	1.27
	(0.72)	(0.61)	(0.65)	(0.71)	(0.59)	(0.64)
Value Change	-5.0%	-2.9%	-3.6%	-5.2%	-3.6%	-4.2%
(year-to-year)	(7.0%)	(7.3%)	(7.2%)	(7.2%)	(6.2%)	(6.6%)
NOI Change	-7.5%	-4.5%	-5.6%	-8.1%	-4.9%	-6.1%
(year-to-year)	(18.9%)	(19.1%)	(19.1%)	(15.4%)	(12.4%)	(13.7%)
Cutoff Occupancy[d]	88.3%	92.3%	90.8%	77.1%	83.6%	81.1%
	(14.6%)	(11.3%)	(12.7%)	(22.7%)	(19.1%)	(20.7%)
Market Occupancy[e]	77.6%	83.5%	81.3%	77.7%	83.3%	81.2%
	(14.7%)	(11.8%)	(13.2%)	(14.1%)	(11.0%)	(12.5%)
Annual Payment	511,059	504,446	506,912			
	(485,046)	(725,296)	(645,685)			
Initial Note Rate	8.52%	8.27%	8.36%			
	(0.86%)	(0.82%)	(0.84%)			
No. of Loans	179	301	480	179	301	480

Note: Standard deviations are in parentheses

[a] "Bad" is defined in this table as having entered "90 days late" or worse condition.

[b] "Good" is defined in this table as having not met the definition of "Bad".

[c] DSCR: Debt-service-coverage ratio.

[d] Cutoff Occupancy is the occupancy data obtained directly from the loan files.

[e] Market Occupancy is the market-level occupancy data supplied by PPR.

Table 6. Descriptive Statistics At the Date Loans either Went "Bad" or Were Censored

Property Type	**Apartment**		**Office**		**Retail**		**Warehouse**		**Hotel**	
Standing	Bad	Good	Bad	Good	Bad	Good	Bad	Good	Bad	Good
Loan Age	38.0	49.2	41.5	45.0	45.0	56.4	41.5	44.7	51.0	53.7
LTV	74.7%	65.6%	62.3%	66.3%	97.9%	69.2%	60.5%	64.3%	83.1%	72.7%
DSCR	1.14	1.33	1.36	1.53	1.44	1.34	1.39	1.44	1.03	0.94
Current Occupancy	89.6%	88.9%	86.7%	85.8%	85.9%	87.0%	96.1%	96.6%	58.9%	62.9%
Market Occupancy	92.6%	91.6%	82.8%	83.7%	87.2%	86.7%	90.8%	89.7%	61.4%	63.0%
Value Change (year-to-year)	1.1%	0.6%	-2.3%	-4.6%	-2.0%	-1.7%	0.9%	-0.9%	-11.8%	-12.8%
NOI Change (year-to-year)	-5.7%	-7.0%	0.5%	3.3%	-3.3%	-1.3%	2.1%	-0.4%	-16.8%	-15.3%
Initial Note Rate	8.31%	8.08%	8.07%	8.31%	8.37%	8.28%	8.24%	8.16%	8.87%	8.54%
Annual Payment	344,912	250,291	524,574	940,387	542,413	614,720	571,392	357,744	535,961	490,375
No. of Loans	27	87	16	44	49	78	16	33	71	59

Note: All the variables are measured at loan level except Market Occupancy.

Table 7. Proportional Hazard Model Analysis Results

Variable	A. Model 1					B. Model 2				
	Parameter Estimate	Standard Error	Chi-Square	Pr > ChiSq	Hazard Ratio	Parameter Estimate	Standard Error	Chi-Square	Pr > ChiSq	Hazard Ratio
PeriodicLTV	0.613	0.20	9.85	0.002	1.85	0.874	0.29	9.12	0.003	2.40
ValueGrowthMkt	0.235	1.86	0.02	0.900	1.26	-0.638	2.56	0.06	0.804	0.53
NOIGrowthMkt	-0.927	0.51	3.30	0.069	0.40	-1.105	0.53	4.38	0.036	0.33
VacancyChangeMkt	0.320	0.16	3.93	0.048	1.38	0.334	0.16	4.16	0.041	1.40
JudicialForeclosure	0.216	0.18	1.52	0.218	1.24	0.249	0.18	1.96	0.161	1.28
HotelFlag	0.427	0.26	2.72	0.099	1.53	0.602	0.27	5.08	0.024	1.83
inverse Mills ratio						-2.968	2.67	1.24	0.266	0.05
Log Likelihood Value:		981.2					957.2			
Schwartz B.I.C.		1012.4					993.4			

Table 8. Proportional Hazard Model Analysis Results

Variable	A. Model 3					B. Model 4				
	Parameter Estimate	**Standard Error**	**Chi-Square**	**Pr > ChiSq**	**Hazard Ratio**	**Parameter Estimate**	**Standard Error**	**Chi-Square**	**Pr > ChiSq**	**Hazard Ratio**
PeriodicLTV	0.715	0.31	5.34	0.021	2.04	1.210	0.40	9.15	0.003	3.35
ValueGrowthMkt	1.251	1.96	0.41	0.523	3.49	-3.302	3.19	1.07	0.301	0.04
NOIGrowthMkt	-1.000	0.52	3.64	0.056	0.37	-1.189	0.54	4.91	0.027	0.30
VacancyChangeMkt	0.347	0.17	4.40	0.036	1.42	0.320	0.17	3.64	0.056	1.38
JudicialForeclosure	0.285	0.36	0.64	0.425	1.33	0.234	0.36	0.42	0.518	1.26
HotelFlag	0.526	0.27	3.88	0.049	1.69	0.614	0.27	5.30	0.021	1.85
PeriodicDSCR	0.048	0.13	0.14	0.709	1.05	-0.227	0.20	1.29	0.256	0.80
LoanAge	0.004	0.00	0.71	0.401	1.00	0.009	0.01	3.04	0.081	1.01
LTVJudicial	-0.052	0.40	0.02	0.896	0.95	0.098	0.41	0.06	0.812	1.10
inverse Mills ratio						-8.102	4.39	3.41	0.065	0.00
-2 Log Likelihood Value:		960.9					954.0			
Schwartz B.I.C.		1007.4					1005.7			

Table 9. Sensitivity Analysis of Each Independent Variable

	Base Case	Case 9-1	Case 9-2	Case 9-3	Case 9-4	Case 9-5	Case 9-6	Case 9-7	Case 9-8
PeriodicLTV	63.5%	**79.2%**	63.5%	63.5%	63.5%	63.5%	63.5%	63.5%	63.5%
ValueGrowthMkt	2.0%	2.0%	**-2.4%**	2.0%	2.0%	2.0%	2.0%	2.0%	2.0%
NOIGrowthMkt	1.0%	1.0%	1.0%	**-9.8%**	1.0%	1.0%	1.0%	1.0%	1.0%
VacancyChangeMkt	0.11	0.11	0.11	0.11	**1.72**	0.11	0.11	0.11	0.11
JudicialForeclosure	0	0	0	0	0	**1**	0	0	0
HotelFlag	0	0	0	0	0	0	**1**	0	0
PeriodicDSCR	1.64	1.64	1.64	1.64	1.64	1.64	1.64	**1.01**	1.64
LoanAge	28.5	28.5	28.5	28.5	28.5	28.5	28.5	28.5	**48.0**
LTVJudicial	63.5%	**79.2%**	63.5%	63.5%	63.5%	63.5%	63.5%	63.5%	63.5%
inverse Mills ratio	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35
Survival Probability in Two Years	49.2%	44.5%	46.7%	47.2%	33.1%	43.4%	29.5%	46.6%	45.2%
Price Assuming:									
Loss Severity of 35%	82.23	80.58	81.33	81.52	76.58	80.20	75.33	81.32	80.83
Loss Severity of 25%	87.31	86.13	86.67	86.80	83.27	85.86	82.38	86.66	86.31
Loss Severity of 45%	77.16	75.03	76.00	76.25	69.89	74.55	68.29	75.99	75.36

Note: The above sensitivity analysis changes the independent variables one by one for each case. The change is made by moving each independent variable by one standard deviation. For example, the standard deviation of Periodic LTV is 15.6% from the historical data so that in case 1 we increase the input LTV to 79.2% meanwhile all other variables are held constant.

Table 10. Sensitivity Analysis for Different Real Estate Markets

	Base Case	Case 10-1: Real Estate Market Improving	Case 10-2: Real Estate Market Deteriorating
PeriodicLTV	63.5%	63.5%	63.5%
ValueGrowthMkt	2.0%	**6.4%**	**-2.4%**
NOIGrowthMkt	1.0%	**11.8%**	**-9.8%**
VacancyChangeMkt	0.11	**-1.51**	**1.72**
JudicialForeclosure	0	0	0
HotelFlag	0	0	0
PeriodicDSCR	1.64	1.64	1.64
LoanAge	28.5	28.5	28.5
LTVJudicial	63.5%	63.5%	63.5%
inverse Mills ratio	0.35	0.35	0.35
Survival Probability in Two Years	49.2%	74.1%	23.4%
Price Assuming:			
Loss Severity of 35%	82.23	90.93	73.19
Loss Severity of 25%	87.31	93.52	80.85
Loss Severity of 45%	77.16	88.34	65.53

Footnotes

[1] Source: Institutional Real Estate Newsline, "Roulac Capital Flows Database."

[2] See, for example, Richard and Roll (1989), Schwartz and Torous (1989), and Quigley and Van Order (1990) for a discussion of prepayment risks in residential mortgage lending, and Downing, Stanton and Wallace (2001) for a more recent development in this field.

[3] We recognize that the moral hazard problem is a serious issue and will be a fruitful area for future research in the field. We leave out in-depth discussions on this subject because it is beyond the manageable scope of the study.

[4] See Hendershott and Van Order (1987), and Ambrose, Capone and Deng (2001) for a discussion of put option theory and mortgage default.

[5] Courtesy access of Standard and Poor's Conquest CMBS deals library is through the University of Southern California.

[6] We are grateful for Property & Portfolio Research, Inc. (PPR), a Boston-based independent commercial real estate research consulting firm, for providing these real estate market data.

[7] Instead of loan term modification that is long term, servicers could offer forbearance, which is short term, to help borrowers overcome temporary cash flow problems for low LTV borrowers. See Capone (1996).

[8] Note we implicitly assume that servicers do not intend to profit by foreclosing a property in a "hot" market in order to sell the property at a higher price than the principal loan amount. We believe this assumption is reasonable given that most servicers have no intention to take advantage of the temporary hardship of borrowers so that foreclosure is always the last and least preferred strategy of lenders facing defaults.

[9] It should be noted that vacancy rates are traditionally used in the commercial real estate studies in the sectors of apartment, office, retail and warehouse, while occupancy rates are preferred measure for hotel properties.

[10] In practice, special servicers are obligated by servicing agreements to make workout decisions that are most beneficial to the entire trust, i.e. the decisions should be made based on the best interest of all bond holders of a deal. This obligation can be analytically expressed as to maximize the NPV to the entire trust, which in principle is also equivalent to our utility function here.

[11] Among many others, similar multinomial logit analysis has been used by Campbell and Detriech (1983) in examining the termination of residential mortgage default, and by Ambrose and Capone (1998) in modeling the conditional foreclosure probability of single-family mortgages.

[12] Defining defaults as 90-days-late or more is consistent with many other studies, e.g. Archer et al. (2002). Loans that are delinquent for 90 days or more are also called "serious delinquency" in the mortgage industry. Foreclosure becomes a viable option only at this stage. See Capone (1996) for details.

[13] We should not conclude from our sample data that the majority of special serviced loans would not default because our data sample is censored.

[14] It is quite common that property owners only appraise the property value once in a long while. Even in the institutional real estate industry, property owners don't re-appraise very often.

[15] There are different ways to calculate the price of mortgages. We opt to use a simple approach to illustrate the main points without complicating the analytics of this study. This approach calculates loan price (Price) through a simple function: Price = Ps*100 + (1-Ps)*(1-LS)*100, where Ps is the probability of survival and LS is the loss severity conditional on default. The formula suggests that the upper limit of loan price is 100 when the probability of survival is 100% and that the lower limit of loan price is 100*(1-LS) when the probability of survival is 0%. In the sensitivity analysis that follows, loss severities are chosen to reflect realistic historical experience. See Snyderman (1991) and Esaki (2002).