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Contemporaneous Loan Stress and Termination Risk in the CMBS pool: how “Ruthless” is Default?

By

Tracey Seslen
Marshall School of Business
University of Southern California
701 Exposition Blvd. HOH 701
Los Angeles, CA 90089
Tel: (301) 569-0151
seslen@marshall.usc.edu

William C. Wheaton*
Department of Economics
MIT
50 Memorial Drive, E52-252b
Cambridge, MA 02139
Tel: (617) 253-1723
wheaton@mit.edu

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Abstract

This study analyzes the impact of contemporaneous loan stress on the termination of loans in the commercial mortgage-backed securities pool using a novel measure, based on changes in net operating incomes and property values at the MSA-property type-year level. Employing a semi-parametric competing risks model for a variety of specifications, we find that the probability of default is extremely low even at very high levels of stress, though the coefficient estimates of greatest interest are very statistically significant. These results suggest the possibility of substantial lender forbearance and reluctance to foreclose, and are consistent with a previous literature which models the incidence of default as “gradual” rather than “ruthless” once “in the money”.

* Corresponding author

Introduction

The last 15 years have seen significant fluctuations in commercial property markets across the country: recession and collapse during the late 1980s and early 1990s, recovery in the late 1990s, and downturn yet again with the events of September 11th. During much of this period, default rates on commercial loans have moved strongly with these market trends: soaring in the late 1980s - early 1990s and then falling steadily with market recovery in the 1990s. Recently, however, they have remained low despite the market stress after September 11th. So how does one go about explaining this phenomenon?

The recent empirical literature on commercial loan termination – default and prepayment - largely has focused on the underwriting stringency applied to the loan at the time of origination and then the subsequent pattern of interest rates, credit spreads, and other characteristics of the broader financial markets. With regard to the ongoing state of the collateral behind the loan, researchers have not used contemporaneous measures of loan stress or else tried rudimentary proxies such as geographical and property-type fixed effects. This omission has undoubtedly led to biased results and leaves unanswered many questions that have been raised in the contingent claims theoretical literature regarding the conditions under which termination options are actually exercised. Without this understanding it is difficult to explain the low default outcomes in recent years as opposed to those much higher rates during the last period of market stress.

In this paper, we hope to remedy some of the shortcomings of the previous literature and answer some key questions that have so far been inadequately addressed. First, are the low levels of recent default due to the fact that the market simply has not been *that* bad, or because of reluctance on the part of borrowers to default when faced with an underwater loan or an inability to make payments? Along similar lines, is default immediate (i.e. “ruthless”) or gradual when a state of stress is reached? And what does this imply about lender “forbearance” and a possible reluctance to foreclose?

To answer these questions, we turn to a commonly used database of commercial loans, and augment it with a novel set of indices representing market conditions at the MSA-property-type-year level. Central to our analysis is the creation of a

contemporaneous measure of estimated loan-to-value (LTV) and debt service coverage ratio (DSCR) that captures the yearly impact of local market and property sector forces on loan collateral. To the extent that market forces drive actual property LTV and DSCR, these measures should strongly impact the termination decision. According to the contingent claims theory of mortgage pricing, the higher the LTV, and (in the presence of liquidity constraints) the lower the DSCR, then the higher should be the probability of default. In a competing risks model, and in the absence of a prepayment lockout, these conditions should lower the probability of prepayment. Inclusion of only initial levels of loan stress should lead to significant omitted variable bias, affecting both the coefficient estimates and the estimated baseline hazard of default.

Another key component of our analysis is the notion that parametric estimation techniques, based in this case on an underlying logistic distribution, may be insufficient for properly modeling the conditional probability of default. We hypothesize that the probability of default rises more rapidly with a $DSCR < 1.0$ than it falls with a $DSCR > 1.0$ (similarly $LTV > 1.0$). We employ a spline specification within the logistic model to test this hypothesis.

We ultimately find that contemporaneous measures of LTV and DSCR have highly significant impacts on the probability of prepayment and default, however, our point estimates of the conditional probability of default show *remarkably small* increases in delinquency as DSCR falls below or LTV rises above one. In addition, the impact of LTV gets washed out when both measures are included simultaneously. Incorporating the spline specification, we find that the probability of default is, indeed, more steeply sloped at levels of DSCR less than one, although the probability is still far less than what so called “ruthless” default models would predict.

In the end our results point towards two conclusions. First, there simply could be a reluctance to default at high levels of current loan stress – at least over the study period (1992-2003). This suggests greater forbearance by lenders towards delinquent borrowers or prohibitive penalties for default by borrowers. The probabilities of default estimated from the spline specification also suggest that at low levels of stress, default may be significantly more idiosyncratic in nature, while at higher levels of stress, default may be a result of more systematic, market-related forces. This raises a second conclusion: that

our results may be driven by the fact that actual property measures of loan stress are only weakly correlated with market movements and it is this fact that accounts for our “gradual” relationship between the two. Overall, though, the inclusion of a contemporaneous measure of loan stress based on market changes at the MSA-property-type-year level represents a significant improvement over the previous literature and sets a new benchmark for future work.

The remainder of the paper is organized as follows. We begin with a brief summary of the previous literature relevant to our study, followed by historical review of the commercial default experience and a description of the commercial mortgage-backed securities (CMBS) market. Due to the fairly centralized nature of the CMBS market, and the demands by securities analysts for clean and accurate data, the CMBS market has become an important new source for data on commercial loans. Virtually every piece of empirical literature on commercial loans, prior to the last few years has employed data from the same small handful of insurance companies. Such unsecuritized loans might differ in ways that could influence our conclusions, and in the next section, we discuss these issues as we review the literature. In the following section we introduce the actual data employed in our analysis. We then describe our empirical strategies and present our results. A final section offers up discussion and conclusions.

Commercial Mortgage Research

The literature on commercial mortgages falls into two camps: theoretical and empirical. Contingent claims theoretical models have long recognized since the early 1990s that prepayment and default are competing risks, with prepayment largely driven by interest rate movements and volatility while default is driven in addition by the movements and volatility of collateral value. Using simulation with estimated parameter values for the interest rate and value movements, Kau, Keenan, Muller and Epperson (1990) is one of the earlier examples of such an approach. In most early theoretical papers, the default or prepayment option is exercised as soon as the value of collateral falls below the value of the mortgage using current interest rates by the specified hurdle. In augmented contingent claims models, with liquidity constraints, the hurdle can be influenced by the property’s cash flow (DSCR) as well as collateral value. We can think

of all such models as describing “ruthless” default since the option is exercised deterministically right at the hurdle value.

A few years later, several theoretical papers began to question the notion of “ruthless” default. Schliefer and Vishnay (1992) argued that more general market conditions would affect the default decision by impacting the ability of lenders to liquidate assets. This could make default at the hurdle value less than certain. Kau, Keenan and Kim (1994), Riddiough and Thompson (1993), Riddiough and Wyatt (1994) and Brown, Ciochetti and Riddiough (2005) also present models in which there is negotiation rather than instant foreclosure upon delinquency. In each case the model relies on a different explanation – for example, the cross-collateralization of assets, strategic behavior by lender or borrower, noisy information signals and the market’s ability to absorb assets. The implications, however are similar in each case: that there is not a deterministic hurdle value at which default is exercised. Alternatively, the true calculation of the hurdle involves many factors that might be very difficult to ever measure – with the empirical implication that default would rise gradually as collateral values deteriorates.

Empirical work on commercial mortgages began with Snyderman’s descriptive analysis of life company loan defaults. Snyderman and subsequently Esaki (1999) found a baseline probability of default that is hump-shaped with respect to loan age. However, lacking other covariates and any econometric analysis it is difficult to know whether this represented some true “seasoning” effect or the state of loan stress associated with loans of different ages. Once econometric models were applied to similar private mortgage data pools, researchers found strong evidence of “gradual” defaults. Vandell (1992) and Vandell et al. (1993) demonstrated that default probabilities seem to rise gradually with increases in a very crude estimate of contemporaneous LTV. Lekkas, Quigley and Van Order (1993) showed that loan loss experience is substantially less than would be predicted by “ruthless” default, and Follain and Ondrich (1997) showed that prepayment is also not automatic once “in the money”. Other similar studies examining either prepayment or default using agency-based data on multifamily properties include McConnell and Singh (1994), and Ciochetti and Vandell (1999). In all of this empirical research, defaults or prepayments were modeled as single events and not competing risks.

Deng, Quigley, and Van Order (2000) made a significant advancement in the literature by presenting a unified empirical model in which prepayment and default are competing risks. Their residential study shows that the simultaneity of the two outcomes is important in explaining termination behavior. Initial LTV is found to play a significant role in both prepayment and default when incorporated nonlinearly. Ambrose and Sanders (2003) are the first to utilize this competing risk (prepayment-default) empirical model to study a broad group of commercial mortgages. They are also the first to apply such analysis to CMBS loans. With a multinomial logit model their study finds no effect of initial LTV (incorporated linearly), but the authors argue that this could be due to endogeneity – loans that are more intrinsically more risky are underwritten more stringently.

In the current study, we combine all of the best features of this previous work as well as several improvements. Our contributions are as follows:

1. We use a full competing risk model of both prepayment and default that incorporates full fixed effects for loan age to uncover any true seasoning effect.
2. We advance the Vandell et al. (1993) use of contemporaneous LTV by developing yearly contemporaneous estimates of both LTV and DSCR that are both property-type and MSA specific – rather than using a single regional index.
3. We explore for the first time the exact detailed relationship between contemporaneous loan stress and default with several parametric and “flexibly”-parametric specifications – finding overwhelming evidence of very gradual default.

The Commercial Property Market and Mortgage Defaults

Generally speaking, the commercial real estate market has been through two “cycles” or shocks during the last 25 years. Figure 1 illustrates this in the case of office properties. After a tight market in the late 1970s, rents (in constant \$) were high and vacancy low throughout the early 1980s. Then as vacancy rose and leveled off, rents

dropped continuously, reaching a bottom in 1992. From then on there was a market recovery, until September 11th created another spike in vacancy and downturn in rents. The market is expected to gradually recover going forward.

Figure 2 shows that during this time frame, real estate pricing has been generally backward rather than forward looking. Low cap rates throughout the 1980s reflected unmitigated optimism rather than anticipating the downturn around 1990, and high cap rates in the early 1990's failed to reflect the subsequent recovery. It is sometimes argued that the low cap rates (high prices) in recent years may be due to record low interest rates rather than reflecting a change in investor expectations – in this case anticipating the forecast recovery.

Defaults among commercial loans as a whole have tended to follow these market movements. Figure 3 compares the valuation of properties in the NCREIF pooled portfolio with two default experiences: that of the American Council of Life Insurers (ACLI, who have the largest private pool of commercial mortgages) and that of a particular pool within the ACLI monitored by Esaki, et.al. Rising asset prices in the early 1980s kept defaults low, just as stagnant or falling asset prices from 1987-1995 generated defaults not seen since the Great Depression (Esaki, et al.). From 1996 on, a recovering market and falling cap rates (Figure 2) generated asset appreciation again – and with very low defaults.

It is interesting that despite the sharp market downturn after September 11th (Figure 1), there was only a brief period of asset depreciation. With the relatively short recovery in rents, net operating incomes did not have a chance to rise much between 1996 and 2001 and as a result property income fell only moderately thereafter. Equally important, interest rates continued to fall after 9/11 and this was a major contribution to the return of asset appreciation. Rising prices with only slight growth in income has kept cap rates declining over much of the last decade (Figure 2). This contrasts with 1987-1995 where tight monetary policy kept interest rates high and asset prices declined along with property income. Hence defaults from 2001-2005 have barely risen at all – in contrast to the late 1980s.

The CMBS Market

The CMBS market is one of the younger and less-developed securities markets in the U.S., but has become a rapidly growing source of capital to commercial lenders. The CMBS market currently has around 200 pools comprised almost exclusively of new loans that were originated since the market decline of the late 1980s and early 1990s. The default rate of these loans has been quite low – generally less than 2% lifetime. Loans originated since 1992 tend to have been very conservatively underwritten and have behaved very differently than older loans, originated at the market peak a decade prior. These older loans are a small portion of the CMBS pools.

Before being placed in the pool, the loans are carefully examined under a number of risk-based criteria and the securities that will back the pool itself are rated by one of the major agencies. The pool's income, which constitutes the payout to investors, is divided into risk "pieces," (i.e. "A", "B", etc.) which represent positions on the payout ladder. The lower down the ladder the piece is, the riskier the investment. Presently, there is an active market for trading in shares of pieces among investors, and yields vary widely between the most secure and riskiest pieces. In terms of operating mechanics, a "regular" loan servicer is responsible for breaking down pool funds and sending them to investors.

With regard to the composition of the pools themselves, loans may be on virtually any property type, but tend to be smaller in magnitude than loans kept in the institutional portfolios of life insurers or banks. Contrary to popular belief, however, the loans that wind up in the pool to date have experienced no greater risk of default, on average, than the larger un-securitized loans. In fact, the rating agencies for CMBS pools tend to engage in a more rigorous process of due diligence than the originators themselves. This may have helped avoid a potentially troublesome adverse-selection problem that is inherent in the system - if the originators have superior "inside" information about loan risk and keep "better" loans for themselves or private clients.

When a loan does turn sour – a delinquency of 60+ days or outright default - then a "special" servicer takes over all payment collections from the regular servicer. The special servicer is paid with fees, rather than a share of residual value. This would seemingly create an incentive towards more ruthless pursuit of foreclosure than in the

whole loan market. As of yet, however, we have no evidence to support or refute this claim. With the market being so young, there has not been a “hundred year flood” to test this hypothesis.

Data and Empirical Methods

To carry out our analysis, we employ data from two major sources. Loan characteristics and delinquency histories come from the Trepp CMBS data collection service. The raw dataset of loan characteristics is a flat file representing 78,344 securitized commercial loans. Each record contains information on the origination date, the maturity date, the interest rate (and indexing, if variable), the loan amount, the property location and type, the prepayment lockout and yield maintenance provisions (if any), the prepayment date (if applicable), the LTV at origination and the DSCR as of a particular report date. Finally the file contains a field for whether the loan amortizes or not, but does not specify the amortization schedule. The delinquency history contains one record for every “credit event” experienced by any loan in the sample, with the type of event (30 day delinquency, 60 days, 90+ days, foreclosure, bankruptcy, performing/non-performing balloon, or real estate owned) and the date of occurrence. Every month of delinquency is reported as a separate entry.

Our second source of data is a set of indices from Torto Wheaton Research that are specific to each market (MSA), property type (office, retail, etc.) and year. These track changes in property values and net operating incomes for “average” properties and comprise much greater detail than the single index used by Vandell et al. (1993). We use these indices to generate our variables of greatest interest to our study – contemporaneous LTV and DSCR. We use this set of indices to update the static values of LTV and DSCR contained in the Trepp database in the following way:

$$\begin{aligned} LTV_t &= LTV_0 * (Value_0 / Value_t) \\ DSCR_t &= DSCR_0 * (NOI_t / NOI_0) \end{aligned} \tag{1}$$

To account for variation in the month of origination, and the fact that there exists only one index per calendar year, the indices ultimately applied to the reported LTV and

DSCR values are a weighted average of the current and following year's indices. It should be noted that the estimated LTV values do not incorporate any changes in loan balance if there is amortization. Figures 4 and 5 show the trends in estimated NOI and collateral value over our sample period for the four major types of property in the Boston market.

The raw Trepp data were filtered in several ways. First "seasoned" loans with origination dates prior to 1992 were eliminated so that the sample would contain only new loans generated specifically for securitization. There were 4,876 such loans. Then loans with balances at origination of less than \$1,000,000, and those with missing or non-sensible entries for the set of essential of loan characteristics were dropped. The application of these criteria reduced the sample size by about half, to slightly more than 39,000 observations. The final sample was obtained by applying the requirement that the loan's MSA-property type-year combination match those for which TWR property value or NOI indices existed. In the end, the sample size varied with the choice of specification, our definition of delinquency, and the choice of measure representing loan stress. In each of the regressions presented, initial LTV was bounded between 0.1 and 1.5 and initial DSCR bounded between 0.5 and 5. These robustness of these filters is discussed later in the paper^{*}. Given the strong increase in both property values and NOI over the sample period of 1992-2003, the number of actual defaults was very low, so we chose to analyze delinquency at 60 and 90+ days to insure enough variation to generate precise estimates.

The final sample contained approximately 20,000 loans, representing multi-housing (37%), retail (29%), office (22%) and industrial (12%) properties. The average LTV at origination was 0.67 (a decline of only 0.02 from that in the initial sample of 78,000) and the average estimated DSCR at origination was 1.49[†]. The average loan was valued at \$7.2 million with a standard deviation of about \$16 million. The average length of time, or "spell" for which loan was observed for was 4.25 years, taking into account both performing (right-censored) and terminated loans. Loans remained in the sample for

^{*} It is difficult to tell whether initial DSCR values <1 and LTV values >1 represent miscoding of data, or true loan characteristics. Our solution is to examine robustness later.

[†] Since DSCR is only reported once, "as of" a particular date, the DSCR at origination is obtained through our standard adjustment procedure: $DSCR_0 = DSCR_t * (NOI_0 / NOI_t)$

their first performing spell only. If a loan experienced a delinquency indicating “failure” according to our specification, the loan was not put back into the sample even if it actually returned to performing status. Depending on the specification, between 2 and 2.5% of loans fell delinquent and around 8% prepaid. Appendix 1 describes the filtering of the data and what changes occurred in variable values with the filtering.

To analyze the impact of contemporaneous loan stress on the loan termination decision, we employ a “semi-parametric” competing risks estimator, modeled as a panel multinomial logit with loan age fixed effects. We employ this model based on the belief that default/delinquency and prepayment are substitutes for one another, resulting in correlated error terms across outcomes. If we do not take into account this correlation, our analysis will produce biased estimates. We favor the semi-parametric method in particular, given prior evidence that the (conditional) baseline hazard is hump-shaped, as evidenced in Snyderman (1991) and Deng, Quigley, and Van Order (2000). The set of loan age fixed effects serves as a fully flexible representation of the baseline hazard function, measuring the probability of default or prepayment at time t conditional on performance through period $t-1$, all else equal. The underlying error distribution of the logit specification allows us to accommodate the fact that the credit event histories are *not* independently and identically distributed.

Formally, in any given period, t , each loan, i , may experience one of three outcomes, j : it may continue to perform ($j = 0$), it may fall into delinquency ($j = 1$), or it may prepay ($j = 2$). Let N be the set of loans in the sample, and T be the set of periods over which a loan is observed. Additionally, let

$y_{ijt} = 1$ if loan i in period t experiences outcome j and 0 otherwise, and

$p_{ijt} = P(y_{ijt} = 1)$

$j = 0, 1, \dots, J$, $i \in N$, $t \in T_i$.

Under the logit specification, we model the outcome probabilities, conditional on x_{it} and α_i as:

$$p_{ijt} = \frac{\exp(v_{ijt})}{\sum_{k=0}^J \exp(v_{ikt})}, \quad v_{ijt} = \begin{cases} x_{it} \beta_j + \alpha_i, & j = 1, \dots, J \\ 0, & j = 0 \end{cases}, \quad (2)$$

where x_{it} is a row vector of our covariates and β_j is the column vector of coefficients specific to outcome j . α_i is a common, random, loan-specific effect that is normally distributed with mean zero and standard deviation σ_α . By our formulation, we assume that the coefficients are the same for all loans in all periods, that the explanatory variables are the same across outcomes, and that the random heterogeneity, α_i , is specific to loan i , but independent of the outcome that occurs.*

To carry out our analysis, we estimate a variety of specifications, employing initial and contemporaneous loan stress, linear and bracketed measures of each, changes in loan stress, and interactions between initial measures and changes. In our final specification, we carry out a specification check of the “parametric” aspect of our competing risks model through the use of splines on contemporaneous DSCR. Results can be found starting in Table 1a. Common to all specifications are an additional set of explanatory variables representing various loan characteristics and macroeconomic conditions. These variables mirror those in Ambrose and Sanders (2003), where we were able to recreate them. Their definitions can be found in Appendix 1.

Results

We begin our analysis with a basic model, which includes several measures of contemporaneous loan stress in addition to a list of other covariates often found in the existing literature. The results may be found in Table 1a. We can interpret the coefficients of our model as hazard ratios, based on the underlying proportional hazard framework of the multinomial logit model. The likelihood of a termination outcome increases or decreases with a unit change in the variable of interest according to the formula: $e^\beta - 1$.

Beginning with this model, we have moved beyond the metrics employed in the previous literature by employing our constructed measures of contemporaneous loan stress. As expected, an increase in contemporaneous DSCR leads to an increase in the probability of default, while an increase in contemporaneous LTV leads to a decrease in the probability of default. Both coefficients are highly significant. For the prepayment

* See McFadden (1984) for further details on this specification.

outcome, both coefficients have the expected magnitude, but only DSCR is statistically significant. When we include both measures of loan stress simultaneously in a “double trigger” model of sorts the effect of DSCR washes out the effect of the LTV ratio. Given the strong correlation between the two measures, such a result is not surprising. The strength of the DSCR measure again confirms that liquidity is a problem with real estate assets, and that asset prices may not represent a sole sufficient statistic for default analysis.

With regard to the other covariates in the basic model, presence of a prepayment lockout clause has a significant negative impact on the probability of prepayment, but no effect on delinquency. Having the lockout period end in the current year has a substantial positive impact on the probability of both termination outcomes. The presence of a yield maintenance clause does not have a strong influence on either outcome, across most specifications. By way of the variable PPOPTION, we see that loans are more likely to prepay when prepayment is “in the money”, but they’re more likely to default as well. Quite possibly falling rates are picking up some proxy for market or loan stress as well. The steeper the yield curve, the less likely the loan is to prepay, while the higher the credit spread, the more likely the loan is to prepay. Neither of these two covariates has a large or statistically significant impact on the probability of default. The volatility in the 10-year Treasury rate and the credit spread volatility both have very strong, negative impacts on both termination outcomes. If we look to option pricing theory for an explanation, this result appears to make sense. As the volatility in interest rates or credit spreads increases, the hurdle value for exercise should increase – making *current* exercise less likely [Ambrose and Sanders (2003)]. Finally, location of the property in a smaller MSA lowers the likelihood of prepayment, but has an insignificant (positive) impact on the probability of default. These are the expected signs for these coefficients as properties in smaller MSAs are exposed to greater market risk and thus more likely, all things equal, to terminate in default rather than prepayment.

In Figure 6, we graph the conditional and cumulative underlying hazard of delinquency - based upon the set of spell period fixed effects that we estimate in all of our specifications. These baseline impacts of course are estimated completely controlling for all other covariates and thus represent some kind of “intrinsic” loan behavior. We

illustrate a family of baseline hazards – at different contemporaneous DSCR values. Consistent with previous literature, the unconditional baseline hazard is indeed hump-shaped, with a probability of delinquency of nearly zero in the last three years of the sample.* This pattern suggests that it takes a couple of years for problems to swell to a point that an owner will have trouble servicing his property’s debt. Once the most vulnerable years have passed, surviving loans are likely to continue performing without incident.

In Table 1b, we try a slightly more restrictive definition of our LHS measure of default, using 90-day rather than 60-day delinquency. The coefficients are virtually identical, suggesting some robustness to the manner in which we identified default in the primary data base.† We next examine a range of alternative specifications to better understand the exact relationship in our data between default and contemporaneous loan stress.

In Tables 2a and 2b (column 1), we decompose the contemporaneous measure of loan stress into the initial value of the variable and its change since origination - to gain further insight into the impact of changes in local property market conditions. The change is measured, specifically, as the log difference in current DSCR or LTV and its initial value. In effect, we ask whether the manner in which you arrive at a particular level of stress matters, or only the level of stress at which you end up. In mathematical terms, is the risk at time t different for a loan with initial $DSCR = X$ and a change in DSCR since origination of $+Y\%$, versus a loan with initial $DSCR = (1 + Y) * X$ and no market-based change in DSCR? Employing first DSCR as the measure of loan stress, we observe that the effect of market changes is somewhat greater than that of initial underwriting. In other words, the conditional likelihood of delinquency is slightly higher when reached due to a change in DSCR relative to an initial position of low debt service coverage. For LTV (Table 2b, column 1) the effects of the market and initial underwriting components are nearly equal. In both cases, the log likelihood value is only slightly improved using initial and change values suggesting that simply using contemporaneous stress levels is virtually as good.

*The general shape holds under all of our other specifications as well.

† Given the similarity of the results, we report only the 60-day delinquency results in subsequent specifications. Ninety-day delinquency results are available by direct request from the Authors.

In Figures 7 and 8 we use the estimates from our specifications thus far to calculate the probability of loan termination over the range of values for initial loan stress, and then for the change in stress leading to the contemporaneous value. The sample means were employed for all of the other covariates. Even with the low default rates observed in the sample, the estimated probabilities under extreme levels of stress are puzzlingly low. We observe that as initial DSCR values drop to as low as 0.5 (the sample minimum) the annual probability of default rises to only 2.0% from defaults of effectively zero at DSCR values greater than 2.0. These conclusions are similar when we examine changes in DSCR. As DSCR is reduced a whopping 150% the probability of default again rises only from near zero to slightly less than 2%. It again makes little difference whether we use 60 or 90 day delinquency as our measure of default. When we do the analysis for initial LTV and change in LTV the graphs look virtually identical. As initial LTV rises from only a small fraction to 1.5 (the sample maximum), the default rate rises to slightly less than 2%. Changes in LTV (from origination to current levels) of 150% similarly boost defaults to only the 2% annual range. Small as these point estimates are, they are statistically very significant.

These results are of concern to us, given that no loan *should* be performing with an NOI less than half of debt service, or loan amounts that are 50% greater than the estimated property value. In the second stage of our analysis, we turn to several additional specifications to attempt to shed light on these conclusions. We hypothesize that a specification error could be influencing our results, and that the true impact of loan stress on default is not adequately captured through a pure linear measure of our variables of interest. We test this hypothesis next by incorporating bracketed values of loan stress, interactions, and then using spline terms.

In columns 2 and 3 of Table 2a and 2b, we build upon the specification incorporating both initial values and changes in loan stress to include bracketed measures of initial loan stress and interactions between the bracketed measures and the changes. Where DSCR is our measure of interest, we observe monotonic increases in delinquency with each decreasing bracket of initial DSCR (relative to the default bracket of $DSCR > 1.3$). When the bracketed values are interacted with the change in DSCR, we observe a monotonic decrease in delinquency as the positive change is applied to lower

initial levels of DSCR. For the prepayment outcome, we do not observe as strong of patterns of monotonicity or statistical significance in general. Interacting the change in DSCR with the initial DSCR as a continuous measure (column 5), we do not estimate a statistically significant coefficient for the delinquency outcome. Using LTV as our measure of interest, we observe much, much weaker results: fewer “expected” patterns, and much weaker significance across all specifications.

Another possible explanation for our results is that somehow there are fundamental differences across property types in the relationship between loan stress and default – which again are confounding our results. In Table 3a we try a number of revisions to the model in the first column of Table 2a – incorporating information on property type. In column 1 of Table 3a we use simple fixed effects and in columns 3 and 4 we estimate our models using only multifamily and office properties. In both of these cases, the coefficients for initial DSCR and change in DSCR are little changed from those in Table 2a. Interestingly the fixed effects in Column 1 are insignificant - suggesting that the loan stress measures (which vary considerably between property types) pick up most of the default differences between types of properties.

As a final specification, we incorporate a spline knot, on the assumption that the single, continuously differentiable probability distribution underlying the multinomial logit model is insufficient for capturing the effects of loan stress on the termination outcomes. The spline knot allows us to fit a different probability distribution to values of LTV or DSCR above and below a particular threshold. To be consistent with simple option value theory, we use the threshold of 1.0. At levels of LTV above 1.0 and DSCR below 1.0, default moves “into the money,” so we would expect to see a sharper rise in the probability of delinquency than at values for which default is not in the money. At values of DSCR below 1.0 (or values of LTV above 1.0) the impact of contemporaneous DSCR (or LTV) is “augmented” by the coefficient on the knot. Formally,

$$\Pr(\text{default}_{it}) = \begin{cases} \alpha_i + \beta_{DSCR} DSCR + \beta_{KNOT} (DSCR - 1) + \overline{\beta X}, & \text{if } DSCR < 1.0 \\ \alpha_i + \beta_{DSCR} DSCR + \overline{\beta X}, & \text{otherwise} \end{cases} \quad (3)$$

This formulation creates a continuous probability distribution with a kink at the spline knot threshold. The results indicate that a rethinking of the specifications used to predict default and prepayment in commercial loans may be in order. In Table 4, we observe that at levels of DSCR below 1.0, the probability of delinquency increases more substantially with a decline in DSCR than it does above 1.0. In Figure 9 we plot out the default probability at mean values for other variables and at the lowest levels of DSCR in the sample, the probability of delinquency now rises to almost 8% (as opposed to 2% without the spline). At the higher levels of DSCR, delinquency is low, but also notably it is non-zero (as it tends to be without the spline). The relationship between DSCR and default is dramatically different around the spline knot. The suggestion here is that at higher levels of DSCR, a small but positive delinquency is governed more by idiosyncratic, property-specific forces, while at lower levels of DSCR market generated changes play a stronger role. This notion has been advanced recently by Gibson (2001). For the prepayment outcome, the spline specification performs poorly. At lower levels of DSCR, the probability of prepayment *increases*, which would run counter to our intuition. The spline model performs poorly for both outcomes when LTV is the chosen measure of loan stress.

Since the spline results seem more in line with intuition, we examined their robustness more closely – particularly with respect to any issues in the original data. The reader may remember that we initially discarded all loans with initial DSCR that were less than 0.5 or more than 5. In Figure 10 we show the graphed spline results under three additional DSCR filters: we allow loans with initial DSCR of 0.3 and 0.1, and then raise the limit to include only loans with an initial DSCR >1.0. We have not uncovered any explanation for loans with initial DSCR <1.0. Allowing loans with very high initial DSCR yields a spline curve very similar to the base results in Figure 9. On the other hand allowing or discarding loans with unusually low initial DSCR does make some difference. As we include more loans with initial DSCR <1 the probabilities of default at very low DSCR values do fall a bit. This suggests that many such loans are not really “under stress” initially – rather they are the result of data reporting issues.

Discussion and Conclusions

The default and delinquency rates of loans in the CMBS pool have been unusually low over the last decade and with few exceptions have remained low even during the economic turbulence of the last five years. All together since 1992, some of the markets in which CMBS collateral resides have seen periods of significant stress as well as growth. In our sample, loans do end up with an estimated DSCR of below 1.0 due to market declines: Austin apartments (a 35% NOI decline between 1999 and 2002), Atlanta retail (a 25% NOI decline between 1992 and 1996) and New York office properties (a 30% NOI decline between 1992 and 1996), to name just a few. In our analysis, periods of decline like these tend to lower DSCR enough to raise the *annual* default rate from a “baseline” value of 0.5-1.0% into the 5.0-9.0% range. While highly significant statistically, these elevated default rates are much less than occurred in late 1980s and early 1990s. So, how do we explain the low estimated probabilities of delinquency in our analysis? Three possibilities come to mind.

First, the NOI and Value indices used to update the reported measures of loan stress may contain significant “noise” – as measures of actual property NOI and value – since they are based only on the “market” forces driving the changes in a loan’s collateral. Furthermore, the market level considered is the property’s MSA – not a particular submarket or location. Each loan’s collateral is subjected to these market wide shocks only to the extent a “rising tide raises all boats”. In addition, collateral will be subject to property-specific shocks that are not necessarily related to market changes: a major tenant leaves or a building needs significant repairs, etc. If such idiosyncratic shocks are more important than market-based changes in determining default, then the use of a purely market-based adjustment index will introduce a significant amount of measurement error. It may be the case that loans with true DSCR significantly below 1.0 *do* default almost every time – it is simply the case that the properties in our sample have not actually experienced the occasionally severe market-level shocks exhibited by our constructed DSCR (or LTV) indices.

Second, since the broad market bottom in the early 1990s, values have steadily recovered. Even after the 9/11 recession, property rent and incomes declined but values largely held up as investors drove cap rates to new lows (Figure 2). Hence, particularly in

terms of values, the market simply has not been stressed enough to generate significant defaults. The recent strength of real estate values may also explain why, in our analysis, DSCR works better than LTV in explaining the smaller default levels that do occur.

The final (and more behavioral) explanation for our result is that some of the theoretical ideas advanced in favor of “gentle” default are in fact true. Data from the early 1990’s suggest that property values declined dramatically along with income streams. In the case of such a “hundred year flood”, lenders have little option but to foreclose. Borrowers, as well, find that traditional methods of avoiding foreclosure, such as cross-collateralized income, do not work, since all collateral is experiencing stress. Kiyotaki and Moore (1997) have developed such arguments into a full fledged theory of credit cycles. In the CMBS pool, however, the situation over the last decade has been a bit different: stress has been more targeted at specific market and property types. With stress potentially confined to isolated areas of borrowers’ portfolios, lenders (wishing to avoid the considerable costs of termination) may be quite willing to extended considerable leeway, thus enabling borrowers to avoid default. Perhaps default is “ruthless” only when there is a broad market decline where borrowers have no other sources of income and lenders become desperate to recover their assets. This is certainly consistent with the recent arguments by Brown, Ciochetti and Riddiough (2005).

All in all, we believe that the addition of contemporaneous loan stress, even with the shortcomings of the measures used here, represents a significant improvement over previous research. More importantly it provides an important benchmark for future research. If we are to gain a better understanding of lender-borrower *behavior* around termination events, contemporaneous measures of loan stress are absolutely essential.

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