A Series of Essays on Commercial Mortgage-Backed Securities

by

Stephen Lyon Buschbom

(Under the Direction of James B. Kau)

Abstract

This dissertation is comprised of two essays where the unifying theme is the use of hazard models in the study of commercial mortgage-backed securities (CMBS). The first essay constructs a model of mortgage delinquency which tests the extent to which borrowers anticipate a loan modification resulting from such a delinquency. Using a sample of modified loans from CMBS pools, we estimate the present value of modified cash flows and project modification benefits each month for all CMBS loans which are weighted by each loan's survival probability up to the time of modification to proxy for a borrower's anticipation of a beneficial modification. Our results confirm a borrower's anticipation of a modification increases the delinquency hazard, and supports theory that borrower delinquency is strategically endogenous.

The second essay examines the investment decisions of regulated financial institutions. Specifically, an empirical model is developed to examine the selling behavior of insurers following a rating downgrade of a commercial mortgage-backed security (CMBS). The regulatory environment in the insurance industry creates a setting where firms must consider not only the regulatory impact of selling a security, but also the price of the security. By modeling the selling decision using a hazard model, it is possible to capture a dynamic characterization of the firm- and bond-specific attributes which affect the selling decision. Similar to prior studies, the model controls for an insurer's aggregate portfolio risk exposure but introduces an important variable: price. Estimating each security's price allows for creation of a proxy for an insurer's unrealized gain or loss. The results provide evidence that insurers are not primarily motivated by regulatory capital, but instead are influenced by aggregate portfolio risk exposure as well as the size of an unrealized gain or loss, which is found to be asymmetric between high- and low-risk exposure insurers, when evaluating a prospective sale transaction for a downgraded holding.

Index words: Default, Modification, CMBS, Mortgage-Backed Securities, Regulation, Liquidity, Insurance Companies, Ratings Agencies

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Chapter 1

Delinquencies, Default, and Borrowers' Strategic Behavior toward the Modification of Commercial Mortgages

1.1 Introduction

Many models and empirical studies of commercial mortgage delinquency and default depend upon the predictive power of the ratio of property cash flow to debt service (debt service coverage or DSCR) and the current loan-to-value ratio (LTV) to measure a borrower's financial position (Deng et al., 2004; Seslen and Wheaton, 2010; Black et al., 2012; Chen and Deng, 2013; Ambrose et al., 2016).[1] While these two variables are direct measures of a borrower's financial position for a given property and should therefore help predict execution of the default option, debt restructuring via a loan modification is an alternative outcome to default where a successful loan modification depends on, in part, DSCR and LTV. To the extent borrowers anticipate both the likelihood and benefit of a loan modification, the present value of probability weighted benefits is then the option value of modification and should therefore help explain a borrower's delinquency decision. This paper seeks to show that a borrower's estimate of the modification option significantly affects the likelihood of delinquency and is consistent with the notion that borrower delinquency is strategically endogenous.[2]

[1]In this paper, delinquency is defined as 60+ days of non-payment and permanent default, abbreviated as simply default, is defined as the terminal point of delinquency so that default in the current context is synonymous with foreclosure or loan liquidation. Default is defined as the terminal point since there are two groups of 60+ delinquent loans in the current study where one group is known to have exercised the default/put option but this is not the case for the second group as the delinquency is either temporary or the delinquency outcome is censored.

[2]A borrower's anticipation of modification benefits through mortgage contract renegotiation is analogous to studies of asset price and bargaining power by Benmelech and Bergman (2008) in the context of the airline industry and Roberts and Sufi (2009) who examine corporate debt.

CMBS delinquency rates increased steadily throughout the 2008 financial crisis, peaking at around 10% in May to July of 2012 (CREFC, May 2016). This period of time provides a unique opportunity to study commercial mortgage performance and modification outcomes. Past research on commercial mortgages often faced a limited number of observed delinquency events, as well as limitations on sample size, when the data source was non-securitized mortgages. The dataset used in this paper comes from Trepp, LLC, who is a well-known data and analytics service provider for securitized commercial real estate. This paper uses a sample of 65,072 loans from 593 non-agency CMBS pools issued in the U.S. between 2000 and 2014, with 6,344,167 loan-month observations.

The outline of the paper is as follows. The "Review of Literature" provides an overview of theoretical and empirical studies regarding commercial mortgage delinquency, foreclosure/liquidation, and modification. "Modeling Modification and Delinquency Outcomes" presents the reduced form model of modification and its incorporation into the model of delinquency. The "Results" section then discusses the empirical results of the comprehensive model. The paper's summary of results and direction for future research is presented in the "Conclusion".

1.2 Review of Literature

Most empirical studies within the commercial mortgage literature employ a duration model when estimating termination patterns. The proportional hazard framework is a particularly popular duration setup, one which assumes that a fixed baseline hazard is shifted up or down by time-varying covariates. Ciochetti et al. (2002), Deng et al. (2004), Seslen and Wheaton (2010), Black et al. (2012), Chen and Deng (2013), and Ambrose et al. (2016) are just some of the many papers using duration models to estimate termination. DSCR and LTV are two factors found to be of particular importance in predicting default of commercial properties, the usual explanation for the first being that owners may be unable or unwilling to cover a cash flow shortfall, whereas for the second, it is argued that diminished or negative equity will render it more difficult to obtain the requisite refinancing, in the absence of additional equity being pledged.[3] Other factors found to influence commercial mortgage default risk include the prepayment option which includes lockout constraints (Deng et al., 2004; Christopoulos et al., 2008; Ambrose et al., 2016), property type and condition (Archer et al., 2002; Harding and Sirmans, 2002), yield-curve slope (Seslen and Wheaton, 2010), interest rate and equity market volatility (Seslen and Wheaton, 2010), local market conditions (Deng et al., 2004; Chen and Deng, 2013), originator type (Titman and Tsyplakov, 2010; Black et al., 2012), and finally, special servicers (Gan and Mayer, 2007; Liu and Quan, 2013; Mooradian and Pichler, 2014).

While the theoretical and empirical literature on commercial mortgage default is considerable, much less work has been done on the modification of commercial mortgages. Chen and Deng (2013) and Ambrose et al. (2016) are two recent empirical studies focusing on CMBS servicers, where Chen and Deng (2013) examine the determinants of modification strategy as well as the extent to which special servicers influence future loan performance, while Ambrose et al. (2016) study potential conflicts of interest when servicing rights are split between two firms and how these conflicts diminish when servicing rights are concentrated in one firm. The empirical modelling strategy of Ambrose et al. (2016) is somewhat similar to the current paper. Ambrose et al. (2016) fit a two-stage model where the predicted likelihood of servicing rights being concentrated in one firm is used as an explanatory variable in a hazard model that estimates the likelihood of permanent default and foreclosure conditional on the subset of loans which became 90+ days delinquent in their sample. Theoretical studies by Riddiough and Wyatt (1994a,b), Harding and Sirmans (2002), and Brown et al. (2006) develop models explaining why a modification might occur and the implications for the borrower's incentive to default, together with the resulting consequences for loan

[3] Mortgage termination literature typically defines default as 60+ or 90+ days delinquent.

valuation. A common theme in this theoretical literature is that a borrower's decision to default ought to be affected by the extent to which they anticipate a beneficial modification outcome, particularly since borrowers of commercial loans are generally considered well informed and quite rational, at least in comparison to borrowers of residential loans that are less often modified. As servicers for conventional residential loans do not require a borrower to regularly disclose income so long as that borrower is current, residential servicers are subject to greater information asymmetry relative to servicers of commercial property loans and a residential borrower thus incurs information disclosure costs to minimize asymmetry in order to increase the likelihood of modification. An additional friction to modification for residential borrowers is potential servicer bias favoring foreclosure when residential loans are securitized rather than held in a lender's investment portfolio (Piskorski et al., 2010; Agarwal et al., 2011; Ghent, 2011). As foreclosure costs for CMBS loans are widely available through rating agencies and industry research reports, borrowers are likely to be cognizant of the opportunity costs, and so can well predict the threshold at which it makes financial sense to go delinquent and seek a modification.[4] The conclusions of the aforementioned studies of commercial mortgage modification are analogous to studies of corporate debt renegotiation which find it is optimal for debtors and creditors to renegotiate debt obligations in situations where such action can align interests to maximize firm value in an attempt to avoid a costly liquidation (Gilson et al., 1990; Mella-Barral, 1999; Noe and Wang, 2000).

Our study contributes to the literature on commercial mortgage default and modification by empirically modeling the dynamic process of a loan becoming delinquent, where borrowers may then obtain a modification, though, if not, face the alternative possibility of permanent default and foreclosure. By estimating the time series of the probability-weighted net present value benefit of obtaining modification after becoming delinquent, and entering this variable

[4]Mayer et al. (2014) study a unique situation where residential borrowers are well informed with respect to lender/servicer modification preference following a Countrywide legal settlement in 2008 and provide evidence of strategic behavior by residential borrowers.

into the model of a borrower's decision to then become delinquent, we can correct the bias introduced in estimating the effect of other correlated variables on delinquency, which would arise were one to ignore this additional influence coming from the anticipation of a subsequent modification benefit. Our results show that the anticipated benefit of a modification is indeed positively related to a borrower becoming delinquent.

1.3 Modeling Modification, Default and Delinquency Outcomes

1.3.1 Data

The primary data source used in this study comes from Trepp, LLC, where we focus on non-agency CMBS pools issued in the U.S.[5] After filtering the Trepp data based on only the pool type restriction, there are 117,649 loans in the sample. The largest two additional filters we apply to the sample are eliminating floating rate loans and pools issued prior to 2000, which drops just under 45,000 loans from the sample. The aforementioned vintage restriction is necessary as the CoStar property value index by region and property type is not available prior to 2000. Lastly, we omit loans with missing information for critical variables, cross-collateralized/cross-defaulted loans, and left-censored observations (approximately 8,300 loans in total). Our final sample consists of 65,072 loans from 593 non-agency CMBS pools issued in the U.S. between 2000 and 2014, yielding 6,344,167 loan-month observations. The data contains detailed information on loan and property characteristics and performance, including loan origination date, loan originator, original balance, underwritten DSCR and LTV, property type and location, current delinquency status, cumulative pay-

[5] We choose to exclude agency CMBS loans as a vast majority of these loans would get excluded from our sample, due to missing values for many of the variables we use in this study. In addition, we exclude CMBS pools classified as CBO, CDO, Canada, credit tenant, franchise loan, health care, Re-REMIC, short term, and pools with more than one unique classification type code. To ensure deal classifications are correct, we cross-validate Trepp data with securitization data from Commercial Alert (CMA) in a fashion similar to An et al. (2015) and manually inspect instances where classifications differ between the two sources to determine the correct pool classification.

ment history, term to maturity, amortization terms, and detailed information on modification or liquidation outcomes. In addition to loan data, Trepp also tracks aggregate pool level information, including the securitization underwriter(s), the special servicer, the weighted average term to maturity for all loans in the pool (weighted by outstanding balance), and the percent of the pool in special servicing in a given month.[6]

The detailed data regarding the nature of a loan modification is crucial to our study, as it allows us to measure the financial benefit realized to the borrower. The nature of the modification includes a temporary or permanent reduction in loan coupon, a change in the amortization terms, such as allowing for interest-only payments or extension of the amortization term, maturity extension, principal forgiveness, bifurcation of the loan into a senior-subordinate structure (hope notes), or some combination of the aforementioned modification strategies. After determining the nature of the modification, the discounted present value of the resulting modified payment schedule is calculated in order to measure the magnitude of financial benefit to the borrower.[7] We incorporate a risk premium into the risk-free term structure to account for market specific risk of CMBS, using the monthly average spread-to-treasury of the Bank of America fixed-rate CMBS sub-indices segmented by weighted average life (WAL) which we interpolate across the term structure using the month-end WAL for each sub-index.[8,9]

[6]The percent of a pool in special servicing at a given pool-month observation is the total outstanding balance of loans specially serviced in a pool divided by the aggregate outstanding balance of all loans in that same pool.

[7]The present value calculation includes any partial principal paydown(s) post-modification, since we treat such reductions as if they were contractually required as part of the modification agreement. We use the modification terms as of the last observation date to construct the future payment schedule for right-censored loans. We choose to exclude senior-subordinate structure modifications after evaluation of the raw data for a sample of such modifications given concerns about reporting accuracy for pro-rata financial information and resulting aggregation bias as these bifurcated loans would need to be combined for modeling purposes.

[8]An overview of the BoA CMBS index series is available at `http://www.mlindex.ml.com/GISpublic/bin/getDoc.asp?fn=IndexRules/Archives/launch/Sep-05IntroCMBSIndex.pdf`.

[9]The incorporation of a term structure dependent risk premium is motivated by the structural model of Titman et al. (2004) and our process is similar to Ciochetti et al. (2003) who model mortgage contract spreads using ACLI data.

We supplement the Trepp data with variables related to the state of the U.S., regional and local economies. Treasury rates used are obtained from `Treasury.gov`. In addition to their use in discounting, we also use the aforementioned treasury series to find a loan's spread versus interpolated treasury rates of equal maturity.[10] In addition to the Bank of America CMBS spread data used for discounting, we use CMBS spread data from the Cleveland Financial Stress Index, defined as the difference between the effective yield on CMBS securities and the 5-yr treasury (available from the St. Louis Federal Reserve), for hazard regressions. We use a quarterly time series of weighted average LTV (weighted by loan balance) for commercial mortgage commitments of U.S. life insurance companies, as reported by the American Council of Life Insurers (ACLI). The quarterly CoStar Commercial Repeat Sales Index provides a measure of aggregate commercial real estate appreciation by property type and census region, and is used to estimate property values in our sample. We interpolate this index on a monthly basis, where the value of each property in the sample is then indexed through time using the most recently appraised value. These estimated property values are subsequently utilized for calculations of LTV and the net present value of a modification.[11] Details regarding the calculation of indexed property values are shown in Appendix A.

Table 1.1 provides descriptive statistics for the loans in our sample as of the first observation month for each loan. The average loan balance (*CurrBal ($MM)*) is approximately $11.5 million dollars with an average LTV of 67.13% and NOI (*NOI ($MM)*) of $1.37 million dollars. The average loan interest rate (*Coupon*) for our sample is 6.04% with a spread to treasury as of a loan's origination date (*OrigSprdToTsy*) of 171 basis points. The remaining number of months until maturity (*remTerm (mths)*) for loans in our sample is just under

[10] For loans with an original term greater than 20 years, we use a given loan's WAL for matching rather than original term.

[11] Loans that become delinquent and are transferred to the special servicer must be re-appraised (typically after the loan is 90+ days delinquent). After the first re-appraisal event, most PSA agreements require the property be re-appraised each subsequent year until the loan is either liquidated from the trust or again becomes current and is again in good standing with the master servicer.

10 years. Loans in our sample appear to have approximately 2% higher leverage than those under commitment by life insurers for a given quarter ($ACLI\_LTV$) . Approximately 37% of loans in our sample are collateralized by properties located in a judicial foreclosure state (*JudState*). The majority of loans in our sample are collateralized by retail, apartment and office properties (34%, 27% and 20% respectively).

Table 1.2 provides the securitization-year distribution of the 593 CMBS pools in our final sample of 65,072 loans. A majority of the pools in our sample date from 2004 to 2007 (256 pools or ∼43% of the total). Note that only 20 pools are securitized between 2008 and 2010, which is not an artifact of our sample, but instead, representative of the general state of the CMBS market. Table 1.3 shows the distribution of loan origination dates in our sample, which follows a pattern similar to that of pools, with 2004 to 2007 representing the peak years of origination volume (38,765 loans or ∼60% of the total).

Table 1.4 provides a summary of delinquency, modification and default events in our final sample, by year of occurrence. As one would expect, the majority of events in our sample occur between 2009 and 2013, which corresponds to the period in which property values and cash flow were declining for most commercial properties, nationwide. Delinquency, which we define as the point at which a loan becomes 60+ days past due, is transferred to the special servicer prior to a future delinquency event or is coded as a non-performing matured loan, appears to be a leading predictor of modification and default events, as one would expect. The average number of months from delinquency to modification or default is the length of time loans for a given event year were delinquent or specially serviced before a modification or default event occurred. On average, loans which are modified appear to spend approximately 10 months less in a delinquent state than loans which ultimately default. The additional time spent in delinquency for defaulting loans is consistent with the notion that the borrower and special servicer typically exhaust workout negotiations in an attempt to minimize deadweight costs of default and liquidation, so that if negotiations end up failing, one would expect the delinquency duration until default to be at least as long as the duration until modification, if not longer, which is what we find in the data.

The CoStar regional commercial property value indexes by property type are shown in 1.1, where the aforementioned decrease in property values is quite visible, with property values reaching a trough between 2011 and 2013. The most noticeable exception is the index for multifamily properties in the northeast, which is heavily influenced by Manhattan and Boston, where there was considerably more investment demand than in most other U.S. metropolitan areas over the same time period. While there is likely some measurement error between a given MSA and its regional property type index, CMBS geographic concentrations are generally in the major MSA's which contribute heavily to the regional indices, so that we should be capturing the general trend for the major MSA's.

1.4 Formulation of the Problem

In going delinquent, a borrower knows that there will be consequences arising from his decision to stop making payments on a regular basis: either a modification will be negotiated or eventually foreclosure will ensue. The main point is that the potential modification is not something that arrives as a serendipitous surprise: the borrower foresees that this might happen and so ought to strategically take this into account when deciding whether to go delinquent. The goal here is to find whether there is empirical evidence that this presumption of rationality on the part of the borrower is supported empirically. We might foresee such strategic behavior even were it a residential loan, but we particularly foresee such incentives being revealed in the case of these commercial loans, where the borrowers are presumably making more careful financial determinations than might a homeowner.

Loans in our sample often have complicated patterns of entry into and exit from delinquency, patterns that we associate with episodes of temporary financial difficulties. Since our goal is instead to discuss purposeful and definitive delinquency, we separate out these temporary delinquencies, which might seriously confound an attempt to estimate deliberate delinquency. It is of course not entirely clear when a delinquency is temporary and when it is definitive, but as an operational matter we include only those entries into delinquency that are never then again followed by a return to being current, short of a modification.[12]

We want to enter into the estimation of the hazard of delinquency a generated covariate which will represent the anticipated benefits of potentially receiving a modification if one goes delinquent in month t. For "simplicity," we write this term as

$$\sum_{i=1}^{n-1}\left(\prod_{j=1}^{i-1}(1-p_1(t+j)-p_2(t+j))\right)(p_1(t+i)(V(t+i)-B(t+i))\prod_{j=1}^{i}(1+r_{t+j})^{-1} \quad (1.1)$$

where $p_1(t+i)$ is the probability of receiving a mod in period $t+i$ if delinquency commenced in period t, while $p_2(t+i)$ is the probability, instead, of default ensuing in that period, so that the first product in the expression is the probability of the state of delinquency having "survived" up to time $t+i$. The property, whose current value we denote by $V(t+i)$, will no longer remain in the borrower's possession if a modification is not obtained, so the reward to reaching a modification is that the borrower retains clear ownership of the property at the discretion of the special servicer who acts on behalf of the pool investors, at the cost of having to agree to a new stream of payments, whose present value at the tentative time $t+i$ of modification we denote by $B(t+i)$. The complexity of the entire expression (1) arises from the fact that the borrower in going delinquent does not know when and if he will receive a modification, and so must consider the various alternatives, all of which must be valued and discounted back to the present, as represented by the last product, which is of course just a

[12] Loans in temporary delinquency are not considered at risk of going into permanent delinquency, since by construction this does not happen. The most problematic cases are those loans in delinquency whose fate is uncertain by the end of observation. We tried apportioning them but they were so few and the effect on the estimations so small that in the end we simply did not include any of them in the set of mortgages at risk of going into default or receiving a modification, which is then effectively considering that they went into temporary delinquency.

discount factor applied to a possible modification at time $t + i$, brought back to the time t of potential delinquency.[13]

Nothing in the way we wrote (1) shows that these various terms are unknowns, since the expression already appears complicated enough, but of course they are unknowns, since they are all in the future and thus undecided at time t, where the evaluation occurs. Since they are not objectively knowable at that time, they clearly cannot be known to the borrower either. Ideally, he would know, and we would know as well, the objective joint distribution of everything affecting (1), and so he, and we, could evaluate the expectation of this entire expression at time t. However, we lack such distributional knowledge and, moreover, seriously doubt that the borrower possesses such knowledge either. Instead, following the tradition of decision-making under uncertainty, we assume that the borrower does know the objective functional forms of the various relations that go into determining (1), lacking only knowledge of the relevant state variables. He thus evaluates (1) using his knowledge of these functional forms, but replacing the future actual values of the state variable by his expectations of these variables at time t. This, then, is what we do as well, though not really knowing the true functional forms, we have to estimate them using the actual data.

We have, though, developed no elaborate theory of how the borrower forecasts the various relevant state variables, and so, except for those directly referring to the term structure, we assume that the borrower has completely static expectations emanating from time t. While, for at least some of the unknown state variables, this is presumably not the case, the times involved are not so very long, given that the resolution of whether one is going to receive a mod or not cannot drag on forever, so that the error in assuming that the borrower uses

[13]Note that we expect the term $V(t+i) - B(t+i)$ to be positive, not just on average, but in each instance, since the borrower is already in delinquency and we would not expect him to accept a disadvantageous modification. One could turn the argument around and say why should the special servicer ever allow such an advantageous loan when they could have the property instead, but it would be unusual if the property were worth quite so much to the servicing side as to the borrowing side, given that it was the borrower and not the special servicer who chose to own it in the first place, and also in view of the fact that the property and its ability to generate income are liable to seriously degrade as the result of a foreclosure process.

simple static expectations would appear to be minimal. On the other hand, the current term structure is something knowable to all and of considerable consequence, and so here we assume that the borrower evaluates purely interest-rate determined variables using the forward rates implicit in the term structure at time t. We then, of course, do the same. As will be seen, this involves replacing the discount factor for time $t+i$ in (1) by the price of a zero coupon bond sold at time t but maturing at time $t+i$. In addition, though, there needs to be a substitution into the calculation of $B(t+i)$, where the actual ten-year yield at time $t+i$ is replaced by the corresponding ten-year yield at time t but i months forward, since it is the anticipation at time t of what this yield will be that is then relevant.

To get the value $B(t+i)$ at time $t+i$, we perform a regression, where the dependent variable is the present value, discounted using the same zero coupon bonds just described plus a risk premium which varies across the term structure to account for the market specific risk of CMBS, of the new flow of promised payments for each delinquent loan in our sample that experiences a modification.[14] The independent variables actually used will be elaborated in describing the results, but prominently include the ten-year discount rate that we just discussed. Since the coupon and other terms of the promised payments are the outcome of complex negotiations between the borrower and the servicer, who represents the entire lending side, we include, to the extent that it seems reasonable, both those variables representing the conditions of the borrower and those reflecting the lending side, all considered at the time that the modification is obtained. The fact that there are so many different dimensions to modification needing to be anticipated explains why we have collapsed everything into what is presumably the only relevant thing to the borrower looking forward, the cost to him of the new modification.

[14] The discount bonds used are of course those at the time of the modification with each maturity being at the time of the particular promised payment being discounted. The risk premium comes from the interpolated term structure of the average monthly fixed rate CMBS spread-to-treasury of the Bank of America CMBS sub-indices segmented by WAL.

However, as noted, the time of this modification is not known before the fact by the borrower, nor indeed is it even clear that there will be a modification: in our data, modifications occur at many different times after going into delinquency, while many loans do not end up being modified at all, terminating in default instead. To account for all of this, we need to estimate a competing hazard model, where the two possible resolutions are, then, obtaining a modification or going into final default. Like the terms of a modification, these hazards also represent the outcome of the unmodelled "negotiation" process, and so are also presumably explained by both features of the borrower and of the lending side, as well of course as by the state of the economy and of the loan. Another useful feature of entering lending-side covariates is that they can be presumed to not otherwise appear in the delinquency decision, and so are useful for identifying the covariate that we are to generate from (1), and which needs to be placed into the delinquency hazard. As an aside, note that it might appear that the default part of the competing hazard is of no immediate concern, since we are trying to account for anticipation of the modification event, but modification and final default are substitute events, as the name "competing hazards" suggests, and so the probability $p_2(t+i)$ does appear in the survival probabilities that enter into (1).

Once we have the above, we are able to assemble the parts to form (1), remembering that actual variables at any time $t+i$ must be replaced by their expectations at time t, whenever an effective distinction between them is being made. The resulting generated covariate can be then be entered, along with other covariates describing the borrower, the state of the economy, and the loan, into a hazard estimation of the time of a final delinquency. By comparing the results to the same sort of hazard estimation, but with the generated covariate not present, we should be able to reach conclusions about whether, other things equal, borrowers indeed let the prospect of a modification influence their proclivity to enter a final delinquency. Our hypothesis, of course, is that it will serve to encourage such delinquency.

We must note an inevitable empirical problem arises, however, if one uses the model shown in (1), as the parameter estimates which generate fitted values of p_1 have been produced by a sample of loans in financial distress. Extending the projection onto loans not in financial distress then results in a distortive comparison as the contemporaneous property value is, in part, attributing to the level of financial stress. To alleviate this problem, we replace the property value $V(t+i)$, in (1) with the outstanding mortgage balance $M(t+i)$, resulting in

$$\sum_{i=1}^{n-1}\left(\prod_{j=1}^{i-1}(1-p_1(t+j)-p_2(t+j))\right)(p_1(t+i)(M(t+i)-B(t+i))\prod_{j=1}^{i}(1+r_{t+j})^{-1} \quad (1.2)$$

which then allows us to measure the change in a borrower's equity position resulting from a modification. The term $M(t+i)-B(t+i)$ remains positive consistent with (1) and now allows for the possibility that the value $B(t+i)$ for a loan not in financial distress is higher than the current debt level where we force the term $M(t+i)-B(t+i)$ to be zero in this instance since, as noted earlier, we would not expect a borrower to accept a disadvantageous modification.

As the covariate used is a generated one, we note that in addition to it having to be identified, the standard errors will need to be adjusted in the typical fashion as a result of the use of the generated covariate. This is done through use of standard bootstrap methods discussed in the next section. The actual results follow.

1.5 Results

1.5.1 Competing Hazards of Modification and Default

The results for the Cox proportional hazard estimates of modification and permanent default for the 6,000 loans in our sample in delinquency, and so eligible to experience such an event, are shown in Tables 1.5 and 1.6, respectively. The period of time used to model each hazard is limited to the time each of the 6,000 loans was delinquent prior to a modification, or instead, permanent default and a liquidation event, with the averages of these delinquency durations by event year shown in 1.4. The ratio of a loan's current outstanding balance to its original balance (*RemBalToOrig*) captures the degree of amortization, and is found to have an insignificant effect upon the likelihood of a modification. *ln_LTV* is found to have a decreasing, inverse effect on the modification likelihood, this being consistent with the theory that a borrower with sufficiently high negative equity will exercise his put option. *ln_NOI* has a positive effect on modification likelihood, in accordance with Chen and Deng (2013). The cumulative number of months a special servicer has indicated a definitive workout strategy (*noOfWkOuts*) is positively associated with modification likelihood, indicating special servicers in our sample are providing a useful information signal regarding which loans, and the associated borrowers, are increasingly likely to obtain a successful modification outcome. The percent of a given pool specially serviced (*SSPctDeal*) within a given month is found to increase the likelihood of modification at a decreasing rate.[15] Our specification is motivated by the model developed by Liu and Quan (2013), who show the time-to-foreclosure for a delinquent loan is potentially extended when special servicers have ownership interest in the first-loss bonds of the same mortgage pool they service. We choose to utilize the special servicing variable in the modification hazard rather than the default and liquidation hazard, since special servicers could offer a temporary modification as a means to delay foreclosure. Our results are weak evidence showing that special servicers attempt to protect their ownership interest and/or servicing rights when faced with increasing potential losses from specially serviced loans.[16] Only one of the four fixed effect variables for property condition (*PropCond*) is significant relative to the reference category of "Fair", indicating

[15] The specially serviced percent for a given pool-month observation is matched to all loans within the pool. If a loan is specially serviced during a given month, the pool-month specially serviced percentage is adjusted to be net of a loan's own contribution to the percentage.

[16] We deem the results as "weak" evidence as we are unable to observe what, if any, ownership interest the special servicer retains for a given mortgage pool.

properties categorized as being in “Excellent” condition are more likely to be modified, which is supportive of the theory put forth by Harding and Sirmans (2002). The argument is that borrowers who anticipate a modification to the loan term (rather than principal forgiveness) are less likely to under-invest in the property through curtailment of the ongoing expenses and capital improvements required to maintain or improve the property's condition. The fixed effect variables controlling for the largest mortgage pool underwriters (UW) of modified and defaulted loans in our sample are insignificant relative to the base category, which is the group of all other underwriters.

The hazard of permanent default and liquidation shown in Table 1.6 is a competing risk to the hazard of modification. The natural log of the outstanding loan balance (*ln_Bal*) is found to have a negative effect upon the likelihood of default, which is consistent with the idea that the largest loans within a CMBS pool receive the most scrutiny by investors and rating agencies, so that these loans are likely to be among the more conservative ones, and so less prone to default. The degree of amortization (*RemBalToOrig*) has a negative effect on default likelihood, implying that borrowers who have accumulated little or no equity though amortization or unscheduled principal paydowns, spend less time in permanent delinquency. Similar to the specification for the modification hazard, we allow LTV to have a non-linear impact on the default likelihood, to account for the possibility that a special servicer's decision to foreclose is not monotonically affected by the magnitude of potential losses faced upon liquidation. We find the first- through fourth-order effects of LTV to be significant, which we interpret as a preference by the special servicer to foreclose as the loan-to-value increases up to a sufficiently high inflection point where the default likelihood begins to increase as a special servicer attempts to minimize potential losses, equivalent to a stop-loss order in equity trading. The one-month lag of a loan's contract rate (*lag_ContRate*) negatively affects the default likelihood, possibly due to fact that borrowers with the highest contract rates in our sample may have sought a modification outcome for payment relief.

The natural log of the weighted average number of months until maturity for all outstanding loans in a given pool (*ln_MthToMaturity*) is found to have a negative effect on the default likelihood, which is in line with most other empirical studies, these generally showing that the hazard of default is low early in a loan's life and grows steadily thereafter, before peaking at around years 5 to 7. The cumulative number of missed payments over the life of a loan (*Dlq <3*) is found to have a negative effect upon the default likelihood, consistent with most findings that a loan progressing to 90+ days delinquent will probably remain in that state. The five securitization year fixed effects of interest are the ones associated with pools issued after 2003 (*Vint =2004* through *Vint >=2008*), where we find loans in these pools to have a lower likelihood of default relative to pools issued in 2000, indicating that a higher proportion of loans from these vintages were modified. Lastly, we find that loans collateralized by a property located in a judicial foreclosure state (*JudState*) are less likely to default. This is opposite to what is found in Chen and Deng (2013), and more closely aligns with the theory that because foreclosure cost is likely to be lower for special servicers (and borrowers) in non-judicial states, this lower financial hurdle encourages foreclosure by the special servicer.

1.5.2 Prediction of Modification Outcome

The results for the cross-sectional regression of the 867 modification outcomes in our sample are shown in Table 1.7, where the dependent variable is the natural log of the sum of actual payments after modification, discounted at the interpolated yield for a treasury bond whose maturity corresponds to the length of a loan's modification period plus a risk premium which is also interpolated across the term structure to account for the market specific risk of CMBS.[17] The natural log of the outstanding loan balance (*ln_Bal*) and natural log of LTV as of the beginning of a given loan month (*ln_LTV*) have significant, opposing effects on the magnitude of the present value of modification. The present value of modified cash

[17] The risk premium is the spread-to-treasury of the Bank of America fixed-rate CMBS sub-indices segmented by WAL described in the data section.

flows is increasing at a decreasing rate over loan balance, while LTV decreases the present value of modified cash flows at an increasing rate, indicating that the special servicer does reduce the borrower's payment liability when the LTV is sufficiently high, with a decreasing marginal benefit as LTV increases. The natural log of a loan's remaining term in months (*ln_remTerm*) increases a borrower's liability after modification at a decreasing rate which is, at least in part, a natural result of discounting the payment liability. The 10-yr treasury yield in natural log form (*ln_Treas10Y*) is negatively associated with a borrower's liability after modification, which is of little surprise given the inverse relationship between the 10-yr treasury and property values in our sample period. The natural log of net operating income of a property (*ln_NOI*) is not significant at the 5% level. The natural log of the weighted average LTV for ACLI commercial mortgage commitments of U.S. life insurance companies within a given quarter (weighted by loan balance) increases a borrower's payment liability at a decreasing rate. As this variable reflects lender expectations regarding the future macroeconomic environment, it is more natural to interpret the effect in the opposite direction such that a lender expecting property values to decline will require more equity (lower LTV), which increases debt. An appraisal reduction event (*AppReduc*) is a signal by the special servicer that a loss on the loan would be likely were the property to be liquidated in the near term, and is found to be insignificant at the 5% level. Only one of the originator fixed effects (*Orig* =*JPM*) is significant at the 5% level. While possibly an artifact of our particular sample, we find loans managed by certain special servicers (*SS* =*Midland* and *SS* =*OtherSpServ*) obtain a lower payment liability after modification relative to trusts where the special servicer is CW Capital. Lastly, we control for property type and find hotels as well as industrial properties (*Hotel* and *Indstr*) incur higher payment liabilities after modification relative to the base category of retail properties.

1.5.3 The Duration till Delinquency

The estimated parameters from the first three regressions shown in Tables 1.5, 1.6 and 1.7 are used to construct the primary variable of interest for our final regression, which is the predicted net present value benefit of a modification. This variable serves as proxy for the degree to which borrowers anticipate a modification outcome and its expected benefit. First, the present value of modified cash flows is estimated for all 65,072 loans in the sample (4,965,101 loan-month observations), using the results from Table 1.7, along with implied forward spot rates for the 10-yr treasury at each loan-month observation for 24 future months, which produces 119,162,424 observations .[18] We then take the difference between the current loan balance as of a given loan-month and each of the future 24 modification values in order to derive the net modification benefit, which, as discussed earlier, is constrained to be greater than or equal to zero since we would not expect a borrower to accept a disadvantageous modification. Next, the net modification benefit is weighted by the product of a loan's predicted likelihood of modification and survival for each future period, where the likelihood of survival is the residual likelihood net of the previously predicted modification and default hazards. Finally, the discounted sum of these weighted net modification benefits is computed for all loan-months, where the summation includes 24 future periods up to the point where a loan is modified or defaults and is liquidated, to account for the potential time in delinquency before receiving a modification.[19] We correct standard errors to account for the generated regressor problem, using 1001 bootstrap replications where we employ a pairs bootstrap for the two hazard regression and a wild bootstrap for the OLS regression.

An important issue we have delayed discussing up to this point is identification. In order to properly identify the delinquency hazard, we must ensure each of the three regressions in

[18] The 4,965,101 loan-month observations excludes those loan-month observations used for estimation of the modification and default hazards. We also censor loan-month observations after a loan matures, is prepaid or defeased in full, and observations after the first instance of delinquency.

[19] The choice of 24 months is based on the average time spent in delinquency for modification and default outcomes in our sample so that the predicted survival likelihood beyond 24 months is close to zero.

Tables 1.5, 1.6 and 1.7 used to construct the primary variable of interest include instruments which affect the modification or default outcomes but can be excluded in our specification of the delinquency hazard. We make use of pool-level variables for this purpose where we attempt to choose variables which influence a special servicer's propensity to liquidate or modify a loan but which a borrower excludes from their own delinquency decision. The modification hazard in Table 1.5 uses the percent of a given pool specially serviced (*SSPctDeal*) within a given month for this purpose, as special servicers are likely influenced by the amount of prospective losses for a given mortgage pool.[20] The permanent default and liquidation hazard in Table 1.6 uses the natural log of the weighted average number of months until maturity for all outstanding loans in a given pool (*ln_MthToMaturity*) as an instrument, given that mortgage pools contain loans with maturities typically ranging from 5 to 10 years but may be as long as 15 to 20 years. Pools with higher relative concentrations in 5 year maturities would then have a higher likelihood of permanent default and liquidation, all things equal, while the reverse is true of pools with higher relative concentrations in 10 year maturities. The important identifying element here is that a given loan in a mortgage pool typically represents at most 10% of a mortgage pool but on average is usually less than 1%, so that the variable *ln_MthToMaturity* will not be perfectly correlated with a given loan's own maturity term. Finally, the special servicer fixed effects in the modification outcome regression in Table 1.7 control for the discount or premium a special servicer may offer relative to their peers, which we would not expect a borrower to know given that the exact modification terms of any one loan are not common public knowledge.

The final regression, then, is the hazard of a loan becoming delinquent, where we first model the hazard without accounting for the endogenous nature of a borrower's decision (Table 1.8 *a*) and then include the predicted net present value benefit of a modification

[20] Two possibilities noted earlier are that special servicers may attempt to protect their ownership interest and they also have some interest in protecting servicing rights when faced with increasing potential losses from specially serviced loans.

in natural log form (Table 1.8 b).[21] In model (a), the partial effects of the natural log of a loan's outstanding balance (ln_Bal) is insignificant at the 5% level. The effects for ln_LTV and $DSCR$ are consistent with expectations, where we also find LTV to increase the delinquency hazard at a decreasing rate, while DSCR works in the opposite direction, these being the anticipated effects of both the borrower's equity and property cash flow with regard to the delinquency decision. The log dollar amount of any current appraisal subordination entitlement reduction or ASER (ln_AserMm) is the amount of a loan's balance on which the special servicer is no longer advancing principal and interest, signaling that the special servicer expects a loss were the property securing the loan to be liquidated in the near term. We find that ASER negatively impacts the delinquency hazard, which may seem counterintuitive, but the result is likely due to the fact that non-delinquent loans typically do not have ASER's, unless they have returned to being current after a modification (we censor these observations), or as a result of the borrower becoming current upon resolution of a temporary difficulty (less than 1 month delinquent). Such a resolution then indicates that the loan is likely to remain current, at least for the near term. The difference between a loan's coupon and the interpolated constant maturity treasury of equal maturity at the time of origination ($OrigSprdToTsy$) is positively associated with the likelihood of delinquency, indicating that originators may have priced some of the potential delinquency risk, but given the endogenous nature of the amount of debt that a borrower chooses after accounting for the price of said debt versus that borrower's cost of equity, we hesitate to interpret these results given we lack detailed knowledge on borrowers and loan pricing, leaving this topic for future research. The property type fixed effects for hotel and office properties ($PropType = Hotel$ and $PropType = Office$) are positive and significant relative to the omitted category

[21] p-Values for Model (a) are cluster-robust (clustered at the loan level) and Model (b) p-values are derived from 1001 bootstrap replications where ln_PVMod uses a one-sided test consistent with our strategic behavior hypothesis (variable is constrained to be greater than or equal to zero) while the remainder of p-values in Model (b) are two-sided tests.

of retail. The CMBS yield spread versus the 5-yr treasury (*CMBSIdxSprd*) is positively related to delinquency likelihood. Borrowers presumably recognize when credit spreads are increasing, which then decreases the present value of their holdings, so that they become more likely to exercise their put option. Securitization year fixed effects (*Vint*) are significant only for 2000 and 2002 through 2004, where the omitted category is *Vint >=2008*. The fixed effect for payment history (*Dlq <3*) is significant, meaning that a history of missed payments (*Dlq >=3*) increases the likelihood of delinquency, while few or no missed payments over the life of the loan (*Dlq <3*) has the opposite effect. The only significant fixed effect for property condition is for properties reported in "Good" condition ($prCondt = G$) relative to the reference category of "Fair". Lastly, the fixed effect for a loan being within six months of its scheduled maturity date (*le6MoToMat*) has a positive effect upon delinquency likelihood, confirming that borrowers in our sample seem to have then faced reduced equity and/or tougher credit constraints relative to when their loan was originated, so that refinancing their current debt becomes difficult in the absence of additional equity being pledged.

Table 1.8 Model (b) augments Model (a) with the inclusion of the predicted net present value benefit of a modification in natural log form (ln_PVMod). This variable is found to be statistically significant, such that a borrower's anticipation of a modification event increases the delinquency hazard. This result is supportive of the notion that borrower delinquency is strategically endogenous, as originally hypothesized. The one variable change we wish to highlight is for the natural log of a borrower's outstanding balance (ln_Bal) which becomes significant in Model (b) after correcting for omitted variable bias present in Model (a). The result here is consistent with the results of Table 1.6 in that the largest loans within a CMBS pool receive the most scrutiny by investors and rating agencies, so that these loans are likely to be among the more conservative ones, and so less likely to default.

1.6 Conclusion

Empirical literature on commercial mortgage performance often seeks to explain delinquency using only past or current values of covariates given that it is rare, if not impossible, for researchers to have knowledge of a borrower's expectations regarding the future outcomes which affect their decision to become delinquent. While theoretical models of delinquency acknowledge that borrower's anticipate the best response of the special servicer and act accordingly, precious little research has attempted to explicitly model such anticipation. Our paper seeks to contribute to this void by explicitly modeling the net benefit of a modification and entering its expectation as a predictor of delinquency. We find the anticipated net benefit of a modification to be a significant predictor of delinquency and is supportive of the notion that a borrower's delinquency decision is strategically endogenous.

Our results also support the findings of other literature concerned with commercial mortgage performance, where we confirm both cash flow and property value affect the delinquency likelihood in the appropriate manner, a proxy for foreclosure cost (judicial vs. non-judicial) affects a special servicer's decision to foreclose and liquidate a defaulted loan, and borrowers facing a balloon maturity in periods of constrained credit availability are more likely to become delinquent. The model presented in this paper may be useful for secondary pricing of CMBS bonds given that we address two problems which tend to frustrate sophisticated models or elude more simplistic ones: credit and convexity risk. By accounting for the likelihood a loan may terminate through a default liquidation or have its terms altered via a modification, our model and potential extensions of it could consolidate bond valuation efforts or augment current methods.

Topics of interest for future research on commercial mortgage delinquency and modification outcomes may include but are not limited to testing for anticipation and performance impacts by the exact type of modification granted (rate change, extension, hope note, etc.), more explicit tests of special servicer biases which account for ownership interest, and incorporation of MSA or sub-market default and modification experience to account for the process by which investors may form expectations about the potential outcomes they face should they become delinquent.

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Table 1.1: Descriptive Statistics of CMBS Loans in the Sample

Variable	Mean	Std Dev
CurrBal ($MM)	11.45	28.48
LTV	67.13	18.58
NOI ($MM)	1.37	5.34
Coupon	6.04	0.98
Tsy10yr	4.39	0.81
OrigSprdToTsy	1.71	0.74
remTerm (mths)	113.41	24.55
ACLI_LTV	65.37	2.40
JudState	0.37	0.48
Apts	0.27	0.44
Hotel	0.06	0.23
Indstr	0.13	0.34
Office	0.20	0.40
Retail	0.34	0.47

Statistics are as of the first observation month for each loan in our sample. *CurrBal ($MM)* is the loan balance as of the beginning of the month in millions of dollars. *LTV* is the loan-to-value ratio multiplied by 100. *NOI ($MM)* is the net operating income in millions of dollars. *Coupon* is the loan interest rate as of the beginning of a month multiplied by 100. *Tsy10yr* is the yield of 10yr constant maturity treasury for a given month multiplied by 100. *OrigSprdToTsy* is the difference between a loan's interest rate and the interpolated constant maturity treasury corresponding to a loan's original weighted average life as of a loan's origination date multiplied by 100. *remTerm (mths)* is the current remaining months until maturity for a given loan. *ACLI_LTV* is the weighted average loan-to-value ratio reported by the ACLI for all commercial mortgage loan commitments for a given quarter (weighted by loan balance). *JudState* is a binary variable equal to 1 if the property securing a loan is located in a judicial foreclosure state and is equal to zero otherwise. *Apts*, *Hotel*, *Indstr*, *Office*, *Retail* are binary variables equal to 1 if the property securing a loan is classified as apartments, hotel, industrial, office or retail respectively and zero otherwise.

Table 1.2: Securitization Year of CMBS Pools in the Sample

Pool Year	Frequency	Percent	Cumulative Frequency	Cumulative Percent
2000	36	6.07	36	6.07
2001	49	8.26	85	14.33
2002	43	7.25	128	21.59
2003	50	8.43	178	30.02
2004	60	10.12	238	40.13
2005	66	11.13	304	51.26
2006	65	10.96	369	62.23
2007	65	10.96	434	73.19
2008	7	1.18	441	74.37
2009	2	0.34	443	74.70
2010	11	1.85	454	76.56
2011	23	3.88	477	80.44
2012	45	7.59	522	88.03
2013	70	11.80	592	99.83
2014	1	0.17	593	100.00

Pool year is the defined as the year of the collateral cutoff date for a given pool. The cutoff date represents the date at which a pool is finalized for purposes of the prospectus and is the representative date for any data described as being "at issuance".

Table 1.3: Origination Year of CMBS Loans in the Sample

Origination Year	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1999	1,641	2.52	1,641	2.52
2000	4,108	6.31	5,749	8.83
2001	4,649	7.14	10,398	15.98
2002	4,113	6.32	14,511	22.30
2003	5,833	8.96	20,344	31.26
2004	6,661	10.24	27,005	41.50
2005	10,770	16.55	37,775	58.05
2006	11,867	18.24	49,642	76.29
2007	9,467	14.55	59,109	90.84
2008	77	0.12	59,186	90.95
2009	9	0.01	59,195	90.97
2010	357	0.55	59,552	91.52
2011	1,038	1.60	60,590	93.11
2012	1,842	2.83	62,432	95.94
2013	2,623	4.03	65,055	99.97
2014	17	0.03	65,072	100.00

Table 1.4: Delinquency, Modification and Foreclosure/Liquidation Events by Year

	Delinquencies		Modifications			Foreclosures/Liquidations		
Year	Count	Percent	Count	Percent	Avg. Mths. DQ to Mod.	Count	Percent	Avg. Mths. DQ to Dflt.
2000	4	0.04	0	0.00	NA	0	0.00	NA
2001	42	0.44	1	0.12	4.00	0	0.00	NA
2002	89	0.94	2	0.23	10.00	7	0.14	11.14
2003	165	1.74	3	0.35	8.00	28	0.55	15.25
2004	163	1.72	9	1.04	7.89	71	1.38	17.75
2005	171	1.81	8	0.92	13.38	117	2.28	16.61
2006	135	1.43	3	0.35	16.67	105	2.05	18.25
2007	217	2.29	0	0.00	NA	121	2.36	15.69
2008	617	6.52	10	1.15	6.30	87	1.69	13.09
2009	2,201	23.25	112	12.92	5.88	181	3.53	13.39
2010	2,255	23.82	268	30.91	8.21	926	18.04	13.35
2011	1,594	16.84	231	26.64	9.31	1,198	23.34	16.79
2012	1,052	11.11	149	17.19	9.53	1,233	24.02	20.32
2013	751	7.93	71	8.19	10.30	991	19.31	23.65
2014	9	0.10	0	0.00	NA	68	1.32	31.50
Total	9,465	100.00	867	100.00	8.65	5,133	100.00	18.35

Delinquency, Modification, an default/liquidation event distribution for the full sample. Delinquency is defined as the point at which a loan becomes 60+ days delinquent, is transferred to the special servicer or is coded as a non-performing matured loan, and is inclusive of the 867 modification and 5,133 foreclosure/liquidation events. The year totals for modification and default events represents the year in which the modification or foreclosure/liquidation event occurred. The average number of months from delinquency to modification or foreclosure/liquidation is the length of time loans for a given year were in delinquent or specially serviced before a modification or foreclosure/liquidation event occurred.

Table 1.5: Cox Proportional Hazard Estimate of Modification

	Dependent variable:		
	Likelihood of Modification		
	Parameter Estimate	p-Value	Hazard Ratio
RemBalToOrig	0.2238	0.6264	1.251
ln_LTV	−0.6564	<.0001	0.519
ln_NOI	0.4041	<.0001	1.498
noOfWkOuts	0.0390	0.0001	1.040
SSPctDeal	2.6031	<.0001	.
SSPctDeal^2	−2.6246	0.0024	.
PropCond =*N*	0.0046	0.9711	1.005
PropCond =*E*	0.3791	0.0476	1.461
PropCond =*G*	0.1586	0.0904	1.172
PropCond =*P*	−0.2156	0.6360	0.806
UW =*CS*	−0.0156	0.8937	0.985
UW =*JPM*	0.0441	0.6695	1.045
UW =*Leh*	−0.0022	0.9881	0.998
UW =*ML*	0.0962	0.4705	1.101
UW =*MS*	0.1595	0.1488	1.173

Estimates obtained from Cox proportional hazard estimate of the likelihood of modification for the 6,000 loans from the sample which are foreclosed/liquidated (5,133 loans) or are modified (867 loans). *RemBalToOrig* is the ratio of a loan's current balance as of the beginning of a given month relative to its balance at origination. *ln_LTV* is the natural log of the estimated loan-to-value ratio where property value is estimated using the most recent appraised value of the property and the CoStar property value index and the loan balance is as of the beginning of a given month (scaled by 100). *ln_NOI* is the most recently reported net operating income for the property in natural log form (aggregated to the loan level if there is more than one property securing the loan). *noOfWkOuts* is the cumulative number of months the special servicer has indicated a definitive workout strategy. *SSPctDeal* is the percent of a given pool specially serviced for a given month exclusive of a given loan's contribution to percentage if that loan is specially serviced (*SSPctDeal*^{2} is the second order effect). *PropCond* is a fixed effect for the property condition from the most recent inspection (N-Missing; E-Excellent; G-Good; P-Poor; F-Fair is the reference category). *UW* is a fixed effect for the mortgage pool lead underwriter (CS-Credit Suisse; JPM-JP Morgan; Leh-Lehman Brothers; ML-Merill Lynch; MS-Morgan Stanley; reference category is a group for all other underwriters).

Table 1.6: Cox Proportional Hazard Estimate of Foreclosure/Liquidation

	Dependent variable:		
	Likelihood of Foreclosure/Liquidation		
	Parameter Estimate	p-Value	Hazard Ratio
ln_Bal	−0.1149	<.0001	0.891
RemBalToOrig	−0.5665	0.0204	0.567
LTV	−0.3775	<.0001	.
LTV^2	0.1401	<.0001	.
LTV^3	−0.0152	0.0004	.
LTV^4	0.0005	0.0013	.
lag_ContRate	−0.0697	0.0281	0.933
ln_MthToMaturity	−0.1515	<.0001	0.859
Dlq <3	−0.1320	0.0223	0.876
Vint =2001	−0.0654	0.3270	0.937
Vint =2002	−0.0715	0.3623	0.931
Vint =2003	−0.1206	0.2574	0.886
Vint =2004	−0.2479	0.0232	0.780
Vint =2005	−0.4016	0.0002	0.669
Vint =2006	−0.3480	0.0002	0.706
Vint =2007	−0.2609	0.0055	0.770
Vint >=2008	−0.3563	0.0173	0.700
JudState	−0.3321	<.0001	0.717

Estimates obtained from Cox proportional hazard estimate of the likelihood of foreclosure/liquidation for the 6,000 loans from the sample which are foreclosed/liquidated (5,133 loans) or are modified (867 loans). *ln_Bal*is the natural log of the outstanding loan balance. *RemBalToOrig* is defined the same as in 1.5. *LTV* is the estimated loan-to-value ratio and is defined the same as in Table 1.5 (LTV^2, LTV^3 and LTV^4 are the second, third and fourth order effects). *lag_ContrRate* is the one month lag of a loan's contract interest rate. *ln_MthToMaturity* is the weighted average number of months until maturity for all outstanding loans in a given mortgage pool-month in natural log form (weighted by outstanding balance). *Dlq* is a fixed effect for the cumulative number of months a loan has been delinquent over its entire life (<3-less than 3 missed payments; reference category is 3 or more missed payment over a loan's life). *Vint* is a fixed effect for the year a given loan was securitized (reference group is 2000). *JudState* is a fixed effect equal to 1 if the property securing a loan is located in a judicial foreclosure state.

Table 1.7: Parameter Estimates for Present Value of Modified Cash Flow

	Dependent variable: Log PV of Modified CF		
	Parameter Estimate	S.E.	p-Value
Intercept	−1.5887	0.6426	0.014
ln_Bal	0.9865	0.0115	<.0001
ln_LTV	−0.0826	0.0219	0.000
ln_remTerm	0.0068	0.0025	0.006
ln_Treas10Y	−0.0525	0.0140	0.000
ln_NOI	0.0103	0.0114	0.365
ln_ACLI_LTV	0.5302	0.1455	0.000
AppReduc	−0.0187	0.0099	0.059
ORIG =BOA	−0.0270	0.0335	0.421
ORIG =Column	−0.0109	0.0298	0.716
ORIG =JPM	−0.0452	0.0228	0.048
ORIG =Lehman	0.0271	0.0266	0.309
ORIG =MorganStanley	−0.0355	0.0310	0.253
ORIG =OtherOrig	−0.0206	0.0191	0.282
ORIG =Wachovia	−0.0009	0.0232	0.970
SS =LNR	−0.0061	0.0139	0.662
SS =Midland	−0.0390	0.0170	0.022
SS =OtherSpServ	−0.0318	0.0104	0.002
Apts	−0.0048	0.0135	0.722
Hotel	0.0460	0.0141	0.001
Indstr	0.0252	0.0126	0.046
Office	0.0071	0.0139	0.609

Estimates obtained from cross-sectional OLS regression for 867 modified loans in the sample where standard errors are adjusted for heteroscedasticity. Values for each variable are taken at the point of modification unless noted otherwise. *ln_Bal* is the natural log of the outstanding loan balance. *ln_LTV* is the estimated loan-to-value ratio in natural log form lagged by one month. *ln_remTerm* is the natural log of the remaining term of the loan measured in months. *ln_Treas10Y* is the natural log of the 10yr constant maturity treasury. *ln_NOI* is the natural log of the most recently reported net operating income for the property (aggregated to the loan level if there is more than one property securing the loan). *ln_ACLI_LTV* is the weighted average loan-to-value ratio reported by the ACLI for all commercial mortgage loan commitments for a given quarter in natural log form (weighted by loan balance). *AppReduc* is a indicator variable equal to 1 if the special servicer is advancing less than 100% of principal and interest due to an appraisal reduction event and equal to zero otherwise. *Orig* is a fixed effect variable for the loan originator (BOA-Bank of America; Column-Column; JPM-JP Morgan; Lehman-Lehman Brothers; MorganStanley-Morgan Stanley; OtherOrig-Other; reference category is missing or unknown originator). *SS* is a fixed effect for the CMBS pool special servicer (LNR-LNR; Midland-Midland; OtherSpServ-Other; reference category is CW Capital). *Apts*, *Hotel*, *Indust* and *Office* are fixed effects for property type (Apts-Apartments; Hotel-Hotel; Indstr-Industrial; Office-Office; reference category is Retail).

Table 1.8: Cox Proportional Hazard Estimate of Delinquency

	Dependent variable: Likelihood of Delinquency					
	(*a*)			(*b*)		
	Parameter Estimate	*p*-Value	Hazard Ratio	Parameter Estimate	*p*-Value	Hazard Ratio
ln_PVMod				0.0387	0.0380	1.039
ln_Bal	−0.0188	0.3629	0.981	−0.0343	0.0440	0.966
ln_LTV	2.3695	<.0001	10.692	2.2137	<.0001	9.150
DSCR	−1.0847	<.0001	0.338	−1.0644	<.0001	0.345
ln_ASER	−0.1078	0.0339	0.898	−0.0894	<.0001	0.915
OrigSprdToTsy	0.3369	<.0001	1.401	0.3256	<.0001	1.385
PropType=Apts	−0.0704	0.1699	0.932	−0.0244	0.1778	0.976
PropType=Hotel	0.4775	<.0001	1.612	0.5487	<.0001	1.731
PropType=Indstr	0.1113	0.0600	1.118	0.1586	<.0001	1.172
PropType=Office	0.1605	0.0064	1.174	0.1891	<.0001	1.208
CMBSIdxSprd	1.0899	<.0001	2.974	1.0606	<.0001	2.888
Vint =2000	0.6950	0.0001	2.004	0.5869	<.0001	1.798
Vint =2001	0.3555	0.0714	1.427	0.2843	<.0001	1.329
Vint =2002	0.4138	0.0007	1.513	0.3704	<.0001	1.448
Vint =2003	0.4686	0.0001	1.598	0.3954	<.0001	1.485
Vint =2004	0.2959	0.0083	1.344	0.2476	<.0001	1.281
Vint =2005	0.1191	0.2735	1.126	0.0899	<.0001	1.094
Vint =2006	0.1206	0.2479	1.128	0.1011	<.0001	1.106
Vint =2007	0.0842	0.4224	1.088	0.0670	<.0001	1.069
Dlq <3	−1.7877	<.0001	0.167	−1.7677	<.0001	0.171
PropCond =N	−0.0419	0.5791	0.959	−0.0361	<.0001	0.965
PropCond =E	−0.0654	0.4139	0.937	−0.0621	<.0001	0.940
PropCond =G	−0.1615	0.0238	0.851	−0.1578	<.0001	0.854
PropCond =P	0.2615	0.3865	1.299	0.2310	<.0001	1.260
le6MoToMat	2.9445	<.0001	19.001	2.8873	<.0001	17.946

Cox proportional hazard estimate of delinquency (60+ days) for the full sample of 65,072 loans. Model (*b*) expands upon (*a*) with the inclusion of *ln_PVMod* which is the estimated log present value modification benefit (Eq. 1.2). *ln_Bal* and *ln_LTV* are the natural log of a loan's outstanding balance and estimated LTV respectively (defined in Table 1.5). *DSCR* is a loan's most recent debt coverage ratio. *ln_ASER* is the natural log of any current ASER (indicative of a potential loss). *OrigSprdToTsy* is the difference between a loan's coupon and the interpolated CMT of equal maturity at origination. *PropType* is a property type fixed effect (reference category is retail). *CMBSsprdIdx* is the monthly Cleveland Financial Stress Index CMBS spread. *Vint*, *Dlq <3* and *prCondt* are defined the same as in Tables 1.5 and 1.6 (reference categories are *Vint>=2008*, *prCondt=F* and *Dlq=0* respectively). *le6MoToMat* is fixed effect equal to 1 if a loan is within 6 months of its scheduled maturity. *p*-Values for Model (*a*) are cluster-robust (clustered at the loan level) and Model (*b*) *p*-values are derived from 1001 bootstrap replications (*ln_PVMod* uses a one-sided test for the hypothesized positive effect while remainder of *p*-values are two-sided tests).

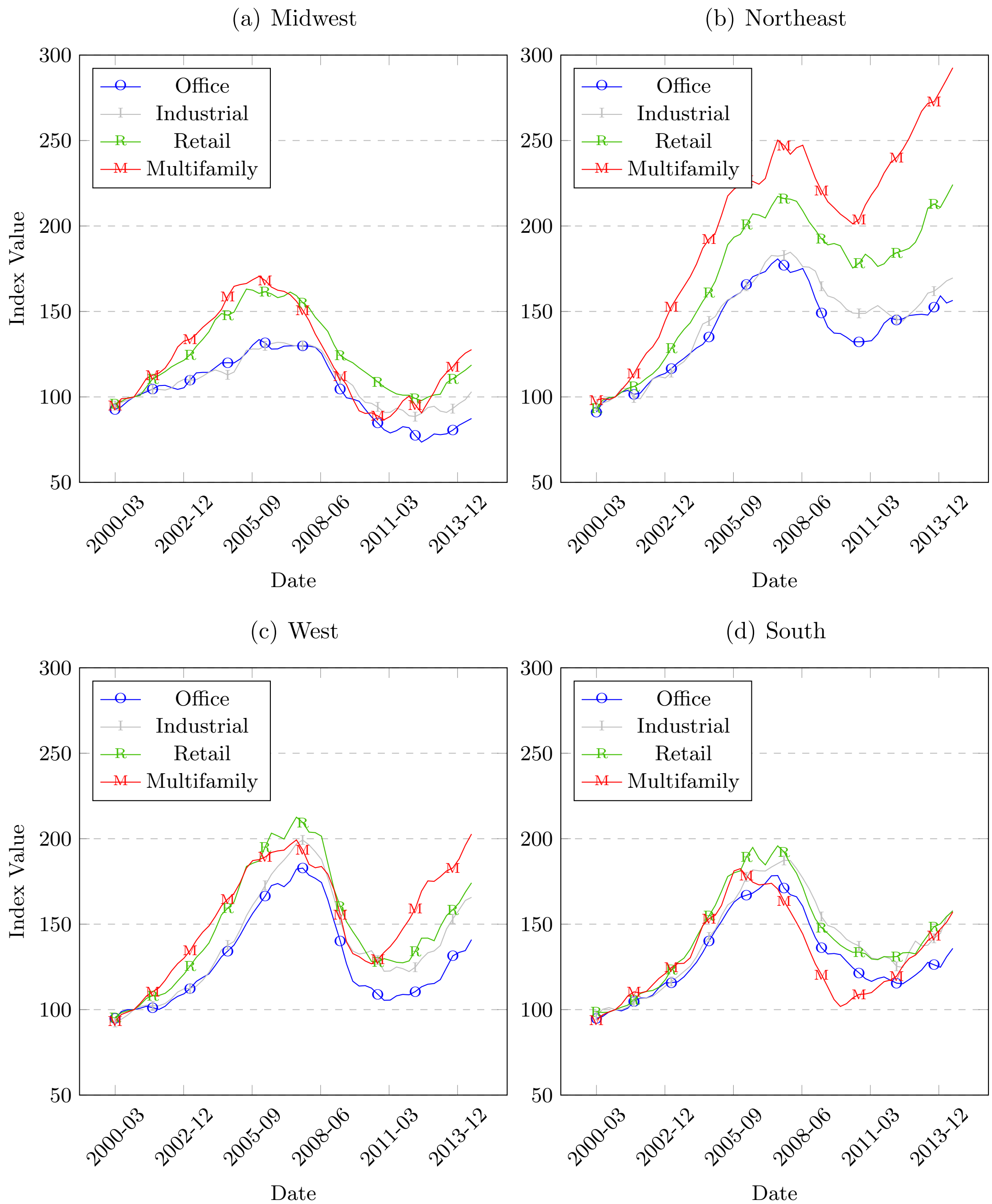

Figure 1.1: CoStar Equal Weighted Property Value Index by Region and Property Type

Notes: Index is created based on a repeat sales approach and is for general commercial property. For more information see http://www.costargroup.com/costar-news/ccrsi.

Chapter 2

Liquidity, Capital Constraints, and Rating Migration in Structured Fixed Income

2.1 Introduction

In this paper, we examine the trading behavior of life and property-casualty (P&C) insurers for their commercial mortgage-backed securities (CMBS) holdings. First, we examine how overall portfolio risk impacts an insurer's decision to sell a downgraded CMBS bond. Prior studies are primarily concerned with an insurer's risk-based capital (RBC), but the majority of firms are not constrained by regulatory capital requirements.[1,2] We instead propose that insurers will be motivated to sell based on the riskiness of their portfolio, where riskier insurers are less likely to sell downgraded securities if such a sale fails to increase capital. Second, we examine the role of unrealized gains and losses in the decision to sell a CMBS bond. We hypothesize that unrealized gains and losses will interact with portfolio risk when deciding whether to sell an asset. Third, we use a hazard model to empirically model the decision to sell a downgraded asset. Prior studies (e.g., Ellul et al., 2011; Hanley and Nikolova, 2015) have generally reported on a single event window when modeling the decision to sell. While shorter windows are potentially appropriate in certain contexts, CMBS bonds are not as liquid as corporate bonds, making short windows less tractable for empirical estimation due to a limited number of sellers. Hazard models have been used by prior studies in finance and have several advantages over static models (Shumway, 2001).

[1] Regulatory intervention occurs when a firm's RBC ratio is less than 2.0. The average RBC ratio reported by Ellul et al. (2011) is 25.63. The average RBC ratio reported by Hanley and Nikolova (2015) is 56.42 for life insurers and 79.61 for P&C insurers.

[2] A number of studies also point out that insurers are generally not bound by regulatory capital requirements (e.g., Cummins and Doherty, 2002; de Haan and Kakes, 2010; Fier et al., 2013).

This topic is of interest not only to researchers, but also to regulators and investors. Acharya and Ryan (2016) call for researchers to exploit the insurance industry as a laboratory to examine the trading behavior of regulated financial institutions. This is exactly the approach we use. Regulators are particularly interested in the investment behavior of insurers. Investment in mortgage-backed securities play an important role in an insurer's RBC ratio (Hanley and Nikolova, 2015). The selling behavior of insurers is also of particular interest due to its potential to contribute to systemic risk (Chiang and Niehaus, 2016). The National Association of Insurance Commissioners (NAIC) recently passed regulation that changes the way MBS are accounted for in RBC calculations (Becker and Opp, 2014; Hanley and Nikolova, 2015), so this issue is of regulatory importance.

Using a hazard model we estimate the duration when a security is downgraded and sold on a set of firm- and bond-specific characteristics theorized to if and when a firm sells a downgraded security. Hazard models have several advantages over static models typically used to model the sell decision with the primary benefit being we can estimate effects for time dependent variables (Shumway, 2001). We are particularly interested in how the riskiness of a firm's portfolio impacts the sell decision, as well as the gain or loss a firm will make from selling a CMBS bond.

Our results indicate that insurers with riskier bond portfolios are less likely to sell downgraded CMBS bonds. The majority of downgrades in our sample occur between 2009 and 2012. The CMBS market was characterized by low liquidity and high price volatility during this time. Accordingly, insurers holding downgraded securities would have to weigh the costs of selling a bond and realizing a loss versus holding the bond and suffering a penalty to regulatory capital. Our results indicate that these riskier firms were more likely to hold than their less risky counterparts. Our results also indicate that the unrealized gain or loss on a bond plays a significant role in determining whether an insurer will sell a downgraded bond. Specifically, we document an asymmetric and non-linear effect where only the riskiest firms sell to harvest unrealized gains, presumably to increase capital, and are also less likely sell and realize a loss relative to lower risk firms.

We make several contributions to the literature. First, we contribute to the evolving literature examining the trading behavior of institutional investors, generally, and financial institutions, specifically. Recent studies have found evidence of fire sales (Ellul et al., 2011), reaching for yield (Becker and Ivashina, 2015), and investment herding (Chiang and Niehaus, 2016). We contribute to this literature by examining different motivations for selling while modeling the decision to sell in a novel way. Second, we contribute to the literature examining systemic risk in the financial sector. Following the 2007-2009 financial crisis there has been a focus on causes and implications of the recent financial crisis (Billio et al., 2012; Berry-Stölzle et al., 2014; Koijen and Yogo, 2015). The trading behavior of financial institutions, specifically insurers, plays a role in systemic risk transmission and we provide evidence that riskiness is related to insurer selling decisions. Finally, we contribute to the literature examining the holdings of mortgage-backed securities. These financial instruments are distinctly different in their structure compared to corporate bonds as well as residential mortgage-backed securities (RMBS) and our study specifically focuses on the motivations of insurers to sell these securities. Prior studies typically focus on other asset classes or pool CMBS bonds with other securities.

The rest of this paper proceeds as follows. In Section 2 we provide background on the trading behavior of financial institutions. In Section 3 we provide an explanation of our research design as well as provide our results. In Section 4 we give a brief conclusion.

2.2 Financial Institution Trading Behavior

Trading behavior of regulated financial firms has received attention from regulators and researchers for a number of reasons. Regulatory capital requirements create an environment where firms must balance capital implications with security prices. Given the recent financial crisis, there has been a particular focus on the role that trading activity among financial institutions plays in contributing to systemic risk (Billio et al., 2012). The insurance industry in particular has received a good deal of focus as a result of having regulatory capital requirements, the industry's role in the recent financial crisis, and the wealth of data on asset transactions.

A number of studies have examined whether financial institutions partake in "fire sales." Fire sales occur when there is a forced sale of an industry-specific asset (Shleifer and Vishny, 1992, 2011). In the context of financial institutions, forced sales are generally attributed to regulatory capital constraints. These forced sales will create price pressures, since all firms in an industry face financial constraints. This limits liquidity and, therefore, results in below-fundamental prices. Ellul et al. (2011) examine fire sales of corporate bonds by both P&C and life insurers. They first find evidence that insurers with lower RBC ratios are more likely to sell downgraded bonds. They next find evidence bond prices deviate from fundamental expectations for bonds with substantial holdings among insurers. They interpret these empirical results as evidence of fire sales in the insurance industry. Ambrose et al. (2012) evaluate returns of corporate bonds following a downgrade which did not appear to reveal new information and find little evidence of price-pressure from forced sales. Merrill et al. (2014) also examine fire sales in the insurance industry, but instead of corporate bonds, as in Ellul et al. (2011), they look for evidence of fire sales in the residential mortgage-backed securities market (RMBS). They find evidence that capital constrained P&C and life insurers were more likely to sell downgraded RMBS bonds during the 2007-2009 financial crisis.

Ellul et al. (2015) examine how financial reporting requirements impacts insurers trading behavior. Specifically, they explore the differing incentives created by historical cost accounting versus fair value accounting. Ellul et al. (2015) contend that the insurance industry provides an ideal setting to examine this question since life and property/casualty insurers are regulated differently (in addition to having different business models) and also because insurance is regulated at the state level.[3] Theoretical studies suggest that fair value accounting requirements can lead to fire sales (Allen and Carletti, 2008; Plantin et al., 2008). Contrary to theory, however, Ellul et al. (2015) find empirical evidence that historical cost accounting is no more effective at dissuading forced sales when regulatory capital implications are taken into account. They find evidence of gains trading for firms subject to historical cost accounting during periods of financial stress (i.e., the 2007-2009 financial crisis).

Becker and Opp (2014) and Hanley and Nikolova (2015) examine the implications of recent changes in capital regulation for the insurance industry. In 2010, the NAIC changed the way CMBS were considered in RBC calculations. Specifically, instead of using credit ratings the NAIC would now require firms to use valuation estimates from BlackRock.[4] Hanley and Nikolova (2015) find empirical evidence that insurers are less likely to sell distressed CMBS and RMBS following this regulatory change.[5] They also find evidence that firms are more likely to hold securities with low ratings, as regulatory capital costs are significantly reduced.

Becker and Ivashina (2015) empirically examine whether insurers "reach for yield" in the corporate bond market. Reaching for yield is the propensity of investors to buy riskier assets in order to achieve higher yields (Cox, 1967). Becker and Ivashina (2015) find evidence that insurers tend to invest in higher yield bonds, after conditioning their holdings on credit ratings. They also find that insurers that reach for yield are more likely to experience large losses and interpret these results as evidence that insurers contribute to systemic risk.

In our present setting, we are focused on the trading behavior of insurers regarding their CMBS bond holdings following rating downgrades where these downgrades increase the amount of regulatory capital required should these insurers continue to hold the bond.

[3]Historically, the insurance industry has been regulated at the state level. While the NAIC serves as a national organization, it has no power to pass legislation, aside from issuing "Model Laws" that states can decide whether or not to pass or not on their own. For a recent discussion of insurance regulation, see Klein (2012).

[4]In 2009 the NAIC also changed the way RMBS were considered, using PIMCO valuation estimates instead of credit ratings.

[5]Hanley and Nikolova (2015) pool CMBS and RMBS sales in their empirical tests.

One main area we focus our study on is the riskiness of an insurer's asset holdings and a second is the impact of CMBS prices.

While prior studies focus on the effect of regulatory constraints on the decision to sell (i.e., fire sales), we instead expect that the riskiness of an insurer's overall asset portfolio is more likely to play a role in determining whether an insurer will sell a CMBS bond. Risk-based capital requirements were instituted in the early 1990s by the NAIC as a way to regulate an insurer's capital and to serve as a mechanism to identify potential insurer insolvencies. The system identifies an insurer's Risk-Based Capital Ratio as follows:

$$\text{RBC Ratio} = \frac{\text{Total Adjusted Capital}}{\text{Total Risk-Based Capital}} \tag{2.1}$$

where Total Adjusted Capital is an insurer's actual capital and surplus.[6] Total Risk-Based Capital is intended to measure an insurer's riskiness. In addition to asset risk (e.g., CMBS investment), the RBC ratio also considers insurance risk, interest rate risk, and business risk. Each risk has an associated "capital charge," where riskier assets, for example, will have higher charges. As long as an insurer's RBC ratio is above 2.0 (i.e., an insurer holds more than $2 of actual capital for every $1 of "risk"), no regulatory action is taken. The intent of the RBC ratio is to provide a measure of whether an insurer holds an adequate amount of capital, but it is is specifically *not* intended to be an overall measure of an insurer's financial strength (Grace et al., 1998).

Accordingly, we expect RBC requirements to play a limited role in determining insurer investment decisions. Instead, we expect their investment risk to be more informative regarding whether an insurer will sell a downgraded bond. These insurers will have considerations beyond their capital requirements such as shareholder pressures or ratings agency consider-

[6] There are some adjustments made to capital and surplus for the purposes of calculating the RBC Ratio. For example the asset valuation reserve is counted in total adjusted capital for life insurance firms.

ations.[7,8] Given these pressures, we expect an insurer's portfolio risk to play a predominant role in the decision to sell.

A specific consideration—in conjunction with overall risk—is the unrealized gain or loss on a given investment. This factor has generally not been explored in aforementioned studies, but is an important factor in the decision to sell. Whether a bond will be sold for a gain or a loss will be influenced by the risks an insurer is taking with its other investments. Specifically, we expect insurers who are overall riskier will be less likely to sell bonds at losses. These insurers will be unable to sell downgraded bonds without, in turn, hurting their capital position. Since the current financial crisis is a time when many of these bonds would have been sold at losses, we expect this to play an important role in our analysis. Finally, we expect insurers unrealized gains and losses enter into the decision to sell conditional upon the amount of portfolio risk an insurer is exposed to relative to their peers.

2.3 Research Design

2.3.1 Data and Sample Construction

Our data are from a number of sources: NAIC, Trepp, Fitch, Moody's, S&P, and Bank of America. We use annual NAIC statutory filings to obtain insurer characteristics as well as year-end investment holdings and quarterly statutory filings for investment transactions between January 2006 and December 2013. We include only Life and P&L insurers.[9] Invest-

[7] A.M. Best is a ratings agency that provides insurer-specific financial strength ratings. These ratings provide an assessment of whether an insurer will be able to pay policyholder claims. Prior research has found evidence that these ratings are an important consideration for insurance firms (Doherty and Phillips, 2002; Epermanis and Harrington, 2006; Doherty et al., 2012).

[8] A.M. Best specifically takes an insurer's investments into account when providing a rating. For example, in ING USA Annuity and Life Insurance Company's rating rationale in Best's Insurance Report, 2009 edition, Best issues a "Negative" outlook for ING, partially due to Best's belief that "CMBS...will experience elevated defaults given the severe recessionary U.S. economic climate."

[9] There are separate reporting forms for other types of insurers (e.g., health), but these insurers make up relatively small portions of the insurance market. As of year-end 2011, life and P&L insurers accounted for 97 percent of the aggregate insurance industry CMBS exposure based on book value (NAIC Capital Markets Bureau, 2012b).

ment holdings and transaction data is at the individual CUSIP level which allows us to create month-end holdings which includes the prior year-end carry price for a given firm-CUSIP observation so that we can estimate the unrealized gain/loss.[10] Similar to Ellul et al. (2011) and Hanley and Nikolova (2015), we exclude non-arm's length transactions using the broker field in the quarterly transaction filings data.

We match the aforementioned insurer CMBS holdings to bond characteristic data from Trepp, LLC who is a prominent data and analytics service provider for securitized commercial real estate. The Trepp data provides CMBS pool-level and bond-level characteristics at issuance as well as subsequent monthly updates for time-variant characteristics. We include variables commonly used in the literature on asset sales by regulated firms (issue size and age) and utilize variables unique to Trepp (monthly bond factor, credit enhancement, and pool-level delinquency). We utilize bond factors to supplement our non-arm's length transaction exclusion criteria by excluding firm-month-CUSIP observations with a factor not equal to one.[11] We adjust each bond's credit enhancement for a given month using the percentage of loans in that bond's mortgage pool which are in serious delinquency (sum of foreclosure and REO). We preform this adjustment given credit enhancement accounts for past losses while an investment manager's selling decision accounts for expected losses which is likely based on, at least in part, loans in serious delinquency.

We obtain rating information from Fitch, Moody's, and S&P. We merge insurer month-end holdings with rating downgrade events. If a downgrade by any of the three rating agencies triggers an increase regulatory capital, we use the exact downgrade date to measure

[10] An insurer's month-end position for a given CUSIP is calculated using the prior year-end par plus the cumulative net par traded within a given year. We exclude any firm-CUSIP observations if a negative month-end par holding is observed and require the absolute difference between the calculated December month-end par amount held and the reported year-end par amount held be less than or equal to $1,000.

[11] Principal repayment reported in Schedule D Part 4 (bonds sold within a given quarter) often has a broker code indicative of a non-arm's length transaction (call, repayment, amortization, etc.), but is an imperfect identifier of such transactions. A bond which pays principal and interest whose factor is less than one is either being paid back principal or has incurred a loss and choose to exclude these bonds as we are more likely to have measurement error for monthly carry and market price estimates.

the duration until one of the following three events occur for a given firm-CUSIP: 1) the insurer sells the bond, 2) another downgrade occurs within one year which triggers an increase regulatory capital, or 3) one year expires without a sell transaction or downgrade.[12]

To estimate monthly prices for each bond in our sample, we harvest insurer reported fair value prices from the NAIC year-end holding data and observed transaction prices from the NAIC quarterly data. With the exception of December which corresponds to year-end reporting, we calculate the weighted-average price for each CUSIP-month using the aggregate market value bought or sold by all insurers in that month divided by the aggregate par traded. For December observations, we combine the aforementioned transaction data with aggregate year-end fair value and par by CUSIP for all insurers in our sample. While year-end fair values are not ideal, these prices are intended to reflect the most likely selling price for a CUSIP which is generally a broker's bid price if an active market exists and a model generated price otherwise provided by a third party vendor.[13] While mispricing is a concern, we believe year-end prices on average reflect fair value since vendor arbitrage via mispricing cannot exist in an efficient market and a vendor who unintentionally misprices bonds will either correct their model or lose market share to vendors with more accurate pricing information.

The aforementioned CUSIP prices provide us with an incomplete monthly time series but provide a series of price nodes in time from which we can interpolate. We use four CMBS total return indices from Bank of America for interpolation: AAA, AA, A and BBB. We merge monthly CUSIP price nodes with the total return index corresponding to the current

[12]We use the second highest rating in determining whether a downgrade triggers an increase regulatory capital according to Table 2.1.

[13]Third party price vendors often use a "matrix" pricing process where bonds are grouped into similar risk profile bins. The yield from bonds in the bin which transact is used to price bonds in the bin which have not traded recently. See Boudry et al. (2015) for a more detailed description of CMBS matrix pricing.

Moody's rating.[14] The price of bond i at time t is:

$$P_i(t) = P_i(u)\frac{I_k(t)}{I_k(u)} + \frac{t-u}{v-u}\left[P_i(v) - P_i(u)\frac{I_k(v)}{I_k(u)}\right] \tag{2.2}$$

where $P_i(u)$ is the most recent monthly price observed, k is the index rating level to which bond i is assigned, $I_k(u)$ is the total return index level corresponding to month u in which the most recent price is observed, and $P_i(v)$ is the next observed price in month v with a corresponding total return index value of $I_k(v)$.

Table 2.2 provides summary statistics for 781 life and P&C insurers in our sample which includes only those insurers who have exposure to a CMBS bond prior to a downgrade event which triggers an increase regulatory capital. Financial variables are measured using the year preceding a downgrade event.[15] The majority of unique firms in our sample are life insurers (69.5 percent) and these insurers have an even larger exposure to capital increasing downgrade events in our sample relative to P&C insurers (86.6 percent) which is somewhat unsurprising given the difference in total assets between these two types of insurers. Life insurers in our sample appear to be exposed to bonds with a lower average adjusted credit enhancement measured at the point when a downgrade occurs which is consistent with our belief that P&C insurers hold less concentration in the riskiest CMBS tranches as these assets are less well suited to match P&C liabilities (CE less the total percent of a pool in foreclosure or REO). The RBC ratio is commonly used to asses insurer risk where a ratio below 2 signals under-capitalization. Both types of insurers appear to be well capitalized in our sample. The variable risky-to-total is the ratio of bonds classified as SVO 3 through 6 relative to the book value of an insurer's total bond portfolio. RBC did not reveal a noticeable difference in median risk profile between life and P&C insurers, but the risky-to-total ratio

[14] Bonds rated Aaa by Moody's are assigned to the AAA index, Aa1 to Aa3 to the AA index, A1 to A3 to the A index, and bonds rated Baa1 or below by Moody's are assigned to the BBB index.

[15] We use unique firm-year data for financial variables so that an insurer who exposed to more than one downgrade event within a year will have only one firm-year record.

indicates otherwise. P&C insurers have shorter duration liabilities compared to life insurers and the nature of P&C liabilities generally requires greater asset liquidity. The difference in risk profile between these two insurer types is more apparent looking at the risky-to-C&S variable which uses the same numerator as risky-to-total and the denominator is a insurer's total capital and surplus. Later results show pooling these two insurer groups dilutes the marginal effect of portfolio risk on the likelihood of selling a downgraded bond. Figure 2.1 shows the median RBC (Panel A), risky bond percentage (Panel B), and ratio of risk bonds to capital and surplus (Panel C) as well as the median year-over-year change for life and P&C insurers in our sample. The change in levels shows more clearly the information signal difference between RBC and portfolio risk (risky bond percentage) where RBC appears to trend upward from 2008 to 2012 while the portfolio risk measure signals an increase in credit risk not obvious if looking only at RBC. The ratio of risk bonds to capital and surplus in Panel C confirms insurers did not increase capital reserves proportionately to the increase in portfolio risk.

Table 2.3 provides a summary of downgrade events by year for the pooled sample of insurers and Table 2.4 separates life from P&C insurers in Panels A and B, respectively. The majority of downgrade events in our sample occur in 2009 through 2012 corresponding to the peak of financial distress following the 2008 subprime collapse. On average, firms in our sample have exposure to approximately eight CMBS bonds in 2009 and 2010 where a downgrade event triggered an increase in regulatory capital. Life insurers have greater exposure to capital increasing downgrade events in our sample, both in terms of the number of CMBS bonds and par amount. The number of sell events represents only bonds which are sold by an insurer within one year following a downgrade event. While life insurers have the greatest exposure to downgrades in our sample as shown in Panel A of Table 2.4 relative to P&C insurers in Panel B, P&C sell a higher percentage of downgraded bonds relative to life insurers which is consistent with our aforementioned comment regarding differing risk tolerance between life and P&C insurers (32 percent or 199/613 for P&C versus 18 percent or 721/3,967).

2.3.2 Empirical Strategy

The predominant econometric model used to explain an insurer's decision to sell a downgraded bond is a cross-sectional binary outcome model such as a probit similar to Ellul et al. (2011) and Hanley and Nikolova (2015):

$$Pr(Sell_{j,i,t+k} = 1) = \Phi(\alpha_0 + Z_{j,i,Y_t-1}\alpha_Z + X_{i,t}\alpha_X + Q_t\gamma_Q) \tag{2.3}$$

where $\Phi(\cdot)$ is the cumulative standard normal distribution, $Sell_{j,i,t+k}$ is an dummy variable equal to one if insurer j sells their holding of bond i within k days of the bond being downgraded at time t and zero otherwise, Z_{j,i,Y_t-1} is a vector of insurer characteristics as of the previous year-end ($Y_t - 1$) which may include information related to their holding of bond i (e.g., book value, cumulative impairment, cost of capital, etc.) as well time-invariant information (e.g., fixed effects for domicile state), $X_{i,t}$ is a vector of bond characteristics which may include both time-invariant (issue size, original rating, etc.) and time-variant information (bond age, current rating, etc.), and Q_t is a vector of year-quarter time fixed effects.

Our two primary concerns with Equation (2.3) are the arbitrary size of the decision window, k, and the inability to control for changes in insurer and bond characteristics within the decision window. With respect to window size, the choice of a short window of around a month obviates much of our concern regarding time-variant characteristics, but dramatically reduces the sample size depending on the asset class and sample period which potentially increases variance to obfuscate significance for variables which should theoretically be significant.[16] As the window size increases, omission new information becomes an increasing concern which is especially true for CMBS bonds where expected losses, reflected in both credit enhancement adjusted for the percent of loans in serious delinquency and current market price, may change following a downgrade and influence an insurer's sell decision. A more flexible model is needed if one wishes to avoid the aforementioned issues.

One such model is a hazard model which has several econometric advantages over static models (Shumway, 2001). Hazard models allow us to consider time as a factor in the selling decision. Intuitively, consider the cross-sectional probit model used in prior studies. These models only capture how firm or bond characteristics measured on the downgrade date impact the selling decision at some future point in time. There is no consideration of the evolution of firm or bond characteristics over time. We build upon prior studies in finance which use hazard models to estimate various firm outcomes (e.g., Shumway, 2001; Bharath and Shumway, 2008; Pagach and Warr, 2011; Griffin and Tang, 2012) where we use a hazard model to assess the determinants of a firm's decision to sell a CMBS bond.

We make use of a hazards model to relax the window size constraint imposed by a cross-sectional probit model which also allows us to update time dependent variables to model an insurer's decision to sell a downgraded bond. We use a Cox proportional hazard model to evaluate an insurer's sell decision defined as

$$\lambda_{j,i}(\tau; Z_j, V_{j,i}, X_i, Q_t) = \lambda_0(\tau) exp\big[Z_j(Y_{t+\tau}-1)\beta_Z + V_{j,i}(t+\tau)\beta_V + X_i(t+\tau)\beta_X + Q_t\gamma_Q\big] \quad (2.4)$$

where $\lambda_{j,i}(\tau)$ is the likelihood insurer j sells a downgraded bond i on day τ after the bond is downgraded at date t, $Z_{j,i}(Y_{t+\tau}-1)$ is a vector of insurer characteristics similar to Equation (2.3) except that we allow characteristics to change should the insurer hold the bond into the next calendar year following a downgrade represented by $(Y_{t+\tau}-1)$, $V_{j,i}$ is an insurer's

[16]Only 105 of the 920 sell events in our sample (11 percent) occur within 30 days of a capital increasing downgrade event.

unrealized gain or loss on bond i in the month corresponding to t, $X_{i,t}$ is a vector of bond characteristics in the month corresponding to t, and Q_t is identical to its definition in Equation (2.3). While this specification does not impose a strict window per se, Equation (2.4) allows τ to model an infinitely long hold decision up to the point a bond matures or incurs a 100 percent principal loss. We choose to limit τ to 365 days so that we are censored from observing a sell decision if the bond experiences another capital increasing downgrade within one year. The choice of one year is not ad hoc. Looking only at the 5,486 CMBS downgrades by Moody's between 2004 and 2013 which includes bonds not held by insurers in our sample, 1,315 downgrades or roughly 24 percent occur within one year of the previous downgrade. Two or more capital increasing downgrades with one year constitute a censoring event, assuming the bond is held up to that point. As we permit insurer characteristics to change up to one time for a given downgrade event, we believe one year is a sufficient amount of time to estimate sell decision determinants.

2.3.3 Main Results

We begin our analysis by empirically estimating Equation (2.4) to determine if an insurer's bond portfolio risk is a significant factor affecting the decision to sell downgraded CMBS assets. We measure an insurer's portfolio risk as the ratio of bonds classified as SVO 3 through 6 relative to an insurer's total bond portfolio scaled by 100. While we the majority of insurers appear well capitalized in our sample, we still include the natural log of the RBC ratio in the model to ensure against omitted variable bias. As mentioned earlier, studies evaluating insurer leverage decisions show RBC is not a binding constraint and insurers are more sensitive to risk perceptions of rating agencies and shareholders. Table 2.5 contains the results of a Cox proportional hazard model of the likelihood of an insurer selling a CMBS bond following a downgraded which triggers an increase in regulatory capital. The first model, titled *All Insurers*, pools life and P&C insurers together where we use a stratified baseline hazard to distinguish life from P&C insurers along with the new regulatory capital level, SVO 2 through 6, for the the bond resulting in five baselines for life and five for P&C insurers.The last two models in Table 2.5 separate life from P&C insurers and use a stratified baseline hazard according to a bond's new regulatory capital level. Robust standard errors are used in the calculation of p-values for all results.

Results for the pooled sample in Table 2.5 are consistent with our theoretical prediction that current market conditions and asset specific risk affect an insurer's decision to sell a downgraded CMBS bond. The insignificance of portfolio risk as measured by *Risky-to-Total* highlights our concern about pooling life and P&C insurers together and is consistent with studies showing that estimation of capital constraint and portfolio risk effects in a model of trading decisions should evaluate life insurers separately from P&C insurers given the dissimilarity between underwritten liabilities which in turn influences the optimal level of investment risk for these firms as well as regulatory capital requirements (Ellul et al., 2015; Merrill et al., 2014). The variable *Gain/Loss* is a proxy for an insurer's unrealized gain or loss for a given CMBS bond and is measured using the difference between a bond's estimated market price (see Equation (2.2)) and an insurer's prior year-end carry price. We find insurers are more likely to sell a downgraded bond as losses are decreasing or gains are increasing. We separate gain and loss effects in later results to determine if price effects are linear and symmetric in that price effects are independent of portfolio risk. We find insurer capitalization (*ln(RBC)*) does not affect an insurer's decision to sell a downgraded CMBS bond independent of price and regulatory capital change effects (*Post-2010*) which are also found to be insignificant but will be evaluated further since there is an interaction effect between the regulatory capital regime change in 2010 and subsequent insurer risk capital.[17]

[17] As we lack BlackRock data on intrinsic prices (used for regulatory capital for CMBS from year-end 2010 onward), we cannot determine the exact capital requirement at the individual firm-CUSIP level but believe results should hold with the addition of this data given research from the NAIC indicates lower ratings dispersion between Moody's, S&P, and Fitch for CMBS relative to RMBS so that agency ratings would have resulted in regulatory capital requirements in 2010 and 2011 similar to those actually incurred under the

The variable *Adj.CE* is a CMBS bond's current credit enhancement less the percent of loans in that bond's mortgage pool in foreclosure or REO and is intended to capture credit risk (unadjusted CE) inclusive of future potential losses (foreclosure plus REO). We find insurers are less likely to sell bonds as credit enhancement is increasing. We find a bond's age (*ln(IssueAge)*) to be insignificant, but issue size (*ln(IssueSize)*) positive and significant consistent with studies finding issue size is positively related to liquidity (Edwards et al., 2007; Ellul et al., 2011). Last, we find mutual insurers are less likely to sell a downgraded CMBS bond which is opposite of what is found in other studies noting mutual insurers sell downgraded bonds as they cannot access external capital markets to repair capital. We postulate that mutual companies, at least in our sample, have formed portfolios in such a way to avoid forced selling of downgraded bonds as a substitute for external capital markets.

The second regression in Table 2.5 estimates the hazard of selling a downgraded bond for only life insurers. The estimates are materially similar to estimates using a pooled sample with the notable exception that portfolio risk (*Risky-to-Total*) is negative and significant, indicating that a life insurer is less likely to sell a downgraded CMBS bond as portfolio risk increases. We do not interpret our results as contradictory relative to the findings in other studies where portfolio risk is found to be insignificant or even positively related to the likelihood of selling a downgraded bond, but rather wish to stress that factors affecting a regulated firm's decision to sell a downgraded bond are likely sensitive to the level of aggregation (e.g., combining RMBS and CMBS or life and P&C insurers) as well as bond market conditions (liquidity and credit risk). The majority of downgrade events in our sample occur between 2009 and 2012 which is a period where the CMBS market is generally viewed as having constrained liquidity and higher price volatility. Insurers with higher portfolio risk compared to their peers are likely unable to reduce CMBS risk without incurring losses during our sample period which would in turn decrease capital so that we only expect to see

new regulatory regime using BlackRock modeled intrinsic prices (NAIC Capital Markets Bureau, 2012a).

insurers sell CMBS bonds when the realized loss is less than the net cost of capital to hold the bond.[18]

Figure 2.2 shows the cumulative hazard of selling a downgraded bond within one year for life insurers based upon the second regression in Table 2.5. The hazard is stratified by SVO level (2 through 6) for the cost of capital shown in Table 2.1. The empirical hazards reveal the likelihood of selling a downgraded bond is increasing both in time and the cost of capital required to hold the bond, where bonds which require the most capital, SVO5 (23% RBC) and SVO6 (30% RBC), have a cumulative sale likelihood of approximately 28% and 33% respectively. Even though SVO3 through SVO6 levels correspond to non-investment grade ratings, the regulatory capital required for SVO3 and SVO4 is much lower relative to SVO5 (80% and 57% lower respectively) and the cumulative sale likelihood within one year is lower by almost the same proportion (64% lower for SVO3 and 46% lower for SVO4 relative to SVO5). Figure 2.2 also highlights our concern with respect to small window sizes of one month or even one quarter for cross-sectional studies. The cumulative likelihood of sale within one month is approximately ⅛ of the one year likelihood for all SVO levels and the one quarter cumulative likelihood of sale is approximately ¼ of the one year likelihood. This finding is in line with the concerns of Ambrose et al. (2008) who note that cross-sectional studies where downgraded bond sales represent a small fraction of total sales may falsely reject the reject the null of no fire sales.

The third and last regression in Table 2.5 evaluates only P&C insurers. The variable *Gain/Loss* is insignificant which may be the result of small sample size or an indication that the selling decision of P&C insurers is non-linear over gains and losses. We argue the latter, given that P&C insurers are subject to a different statutory accounting policy than life insurers, where P&C insurers holding bonds with an SVO rating of 3 or below must

[18]The net cost of capital accounts for regulatory capital as well as the net present value of a bond's expected interest payments and principal losses.

carry these assets at the lower of fair market value or amortized cost. This creates inherent gain/loss asymmetries in periods of increased price volatility and rating migration. Portfolio risk (*Risky-to-Total*) is not statistically significant, consistent with our argument that P&C insurers have difference portfolio risk profiles relative to their life counterparts. The effect of a bond's credit risk (*Adj.CE*) is similar to the effect found for the pooled sample of insurers. A bond's age (*ln(IssueAge)*) is not statistically different from zero, but issue size (*ln(IssueSize)*) maintains a positive and significant coefficient supporting the notion that P&C insurers face liabilities requiring them to hold assets of sufficient liquidity. As our sample contains a limited number of P&C insurers, we limit the remainder of our study to life insurers as they have the largest exposure to CMBS bonds in the insurance industry as a whole.

Table 2.6 contains results for life insurer sell hazards where we evaluate the effect of the RBC regime change at year-end 2010 when the NAIC stopped using ratings to determine capital requirements for CMBS bonds and instead used expected loss estimates from BlackRock to determine capital. The first two variables, *Gain/Loss* and *Risky-to-Total*, are remain unchanged from Table 2.5. As suspected, introduction of an interaction term between RBC and a dummy variable variable for observations after year-end 2010 when the RBC regime changed (*Post-2010*) proves significant but the significance of RBC is not as straight forward as Table 2.6 might lead one to initially believe. The hazard ratio for RBC depends upon the dummy variable for the RBC regime and significance is conditional upon the relative value of each of the variables in the interaction. We test for the range of RBC values over which the regime effect is significant. We find the regime change is insignificant for RBC values between 1.5 and 9.95 where insurers with an RBC ratio below 1.5 are less likely to sell downgraded CMBS bonds after the regime change in 2010 while insurers with an RBC ratio of 10 or greater are more likely to sell. As the threshold for regulatory action is 2.0 and Table 2.2 shows the median firm in our sample is well above that level, it is clear that the regime change did not affect the selling decision for the median firm in our sample and may have actually allowed firms with relatively healthy levels of capital de-risk their portfolios by selling downgraded CMBS bonds.

Table 2.7 contains results for life insurer sell hazards where we test for non-linear price effects. Table 2.1 details the capital requirements and accounting treatment for life and P&C insurers for each of the six tiers. The Securities Valuation Office (SVO) is responsible for credit analysis and subsequent risk capital requirements for insurers where SVO tier one assets require the least amount of capital and tier six requires the most capital. For bonds assigned to tiers three through six, which were previously in tiers one or two, P&C insurers are required to carry these bonds at the lower of amortized cost or fair market value which is likely to result in a loss if amortized cost is close to par ahead of a period of declining prices. The first two variables in Table 2.7 separate gain and loss effects, where gain is set to zero if a bond's estimated market price is below an insurer's carry price and represents the difference between market price and carry price otherwise. Loss is defined in the opposite manner of gain such that both gain and loss are strictly greater than or equal to zero. Hazard estimates for life insurers are virtually identical to those in Table 2.5 and a Wald test fails to reject equality of gain and loss effects.

As we have constrained gain/loss effects to be independent of portfolio risk in Table 2.6, we relax this assumption in Table 2.8 where we interact the continuous gain/loss variable with an insurer's relative level of portfolio risk using quartiles for the ratio of the highest risk bonds to total bonds (*Risky-to-Total*) for life insurers in our sample. Testing of significance for hazard ratios of gain/loss effects across quartiles (*Risky1* to *Risky4*) reveals gain/loss is significant only for the third and fourth quartiles which correspond to the highest levels of portfolio risk.

The last estimates presented in Table 2.9 test the conditional linear price effects of Table 2.8 where we interact portfolio risk quartiles with the gain and loss variables used in the hazard regression of Table 2.7. Again, we must test the hazard ratio significance for each quartile separately for conditional gain and loss effects. We find only the highest risk quartile of insurers are motivated to sell downgraded CMBS bonds to harvest gains and, similar to our findings of the model shown in Table 2.8, only insurers in the third and fourth quartiles correspond to the highest levels of portfolio risk are less likely to sell at a loss. The remainder of variables are materially unchanged from prior regressions in terms of size and significance.

2.4 Conclusion

This paper contributes to literature evaluating the effect of regulatory capital constraints on assets sales by isolating the effect in an asset class where a decreased reliance on rating agencies for regulatory capital determination did not appear to signal a change in loss expectations: CMBS. Ex post calculations from the NAIC show the average difference in required capital between the new model based expected loss regime and the prior regime which relied on rating agencies is approximately zero for CMBS over 2010 and 2011 (NAIC Capital Markets Bureau, 2012a). These results are confirmed by Becker and Opp (2014) who show agency ratings and model based expected losses are equally informative with respect to credit risk. In comparison to studies which find capital constrained firms are more likely to sell downgraded assets (Ellul et al., 2011; Merrill et al., 2014; Ellul et al., 2015) or show this effect is insignificant (Hanley and Nikolova, 2015), we document such firms are less likely to sell downgraded CMBS bonds using a portfolio risk measure which is still directly related to regulatory capital but better explains a insurer's motivation to sell downgraded assets. Our results are not inconsistent with findings in these studies, however, as we document the effects which motivate life insurers to sell downgraded bonds are distinct from those for P&C insurers due to differences in accounting policy (Merrill et al., 2014; Ellul et al., 2015).

Our analysis documents the benefits of using a duration model such as the Cox proportional hazard as we are able to account for time variant effects of price and credit enhancement on a firm's sell decision which are not so easily controlled for in a cross-sectional probit model. The price effects are of interest for not only the obvious reason of controlling for unrealized loss but also because we show such effects are dependent upon portfolio risk for gains and non-linear between gains and losses for life insurers with the highest relative portfolio risk. The flexible hazard approach is well suited to model CMBS and RMBS transactions which are believed to be less liquid asset classes where results from cross-sectional models may be sensitive to window size, especially if the timing of an insurer's decisions is related to model factors.

As our study focuses on CMBS, we believe future research on RMBS using techniques similar to this paper may be of interest given regulatory capital changes provided more capital relief to insurers relative to CMBS. The flexibility of a duration approach may also help reveal transaction costs for these less liquid asset classes where early sellers, often classified as distressed sellers, may provide baseline information against which subsequent transactions for bonds within the same pool use to determine fair market value. Accounting for the pricing sequence should then reveal credit adjusted price expectations to determine the approximate discount or premium incurred by these early sellers.

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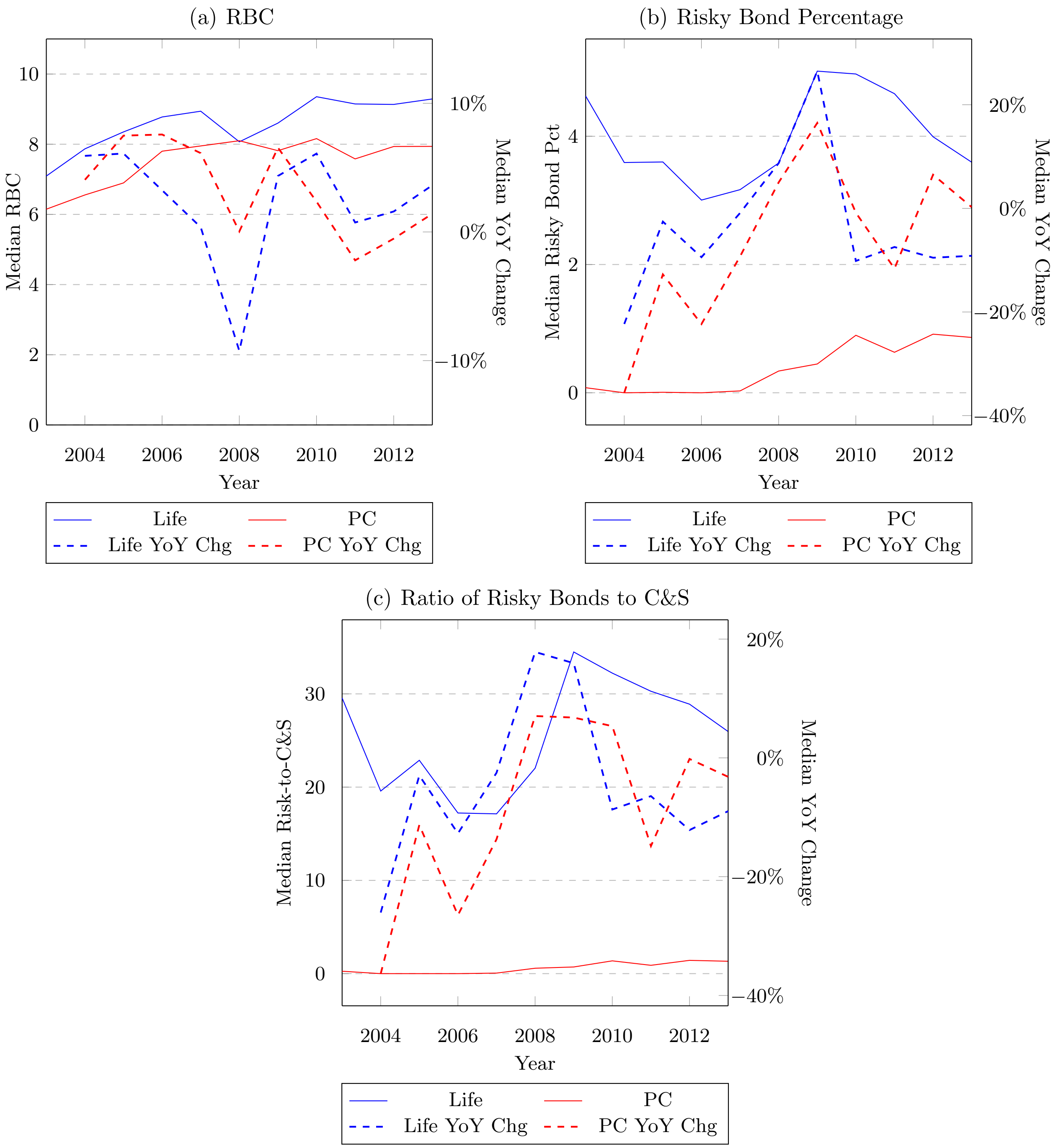

Figure 2.1: Insurer Risk Measures

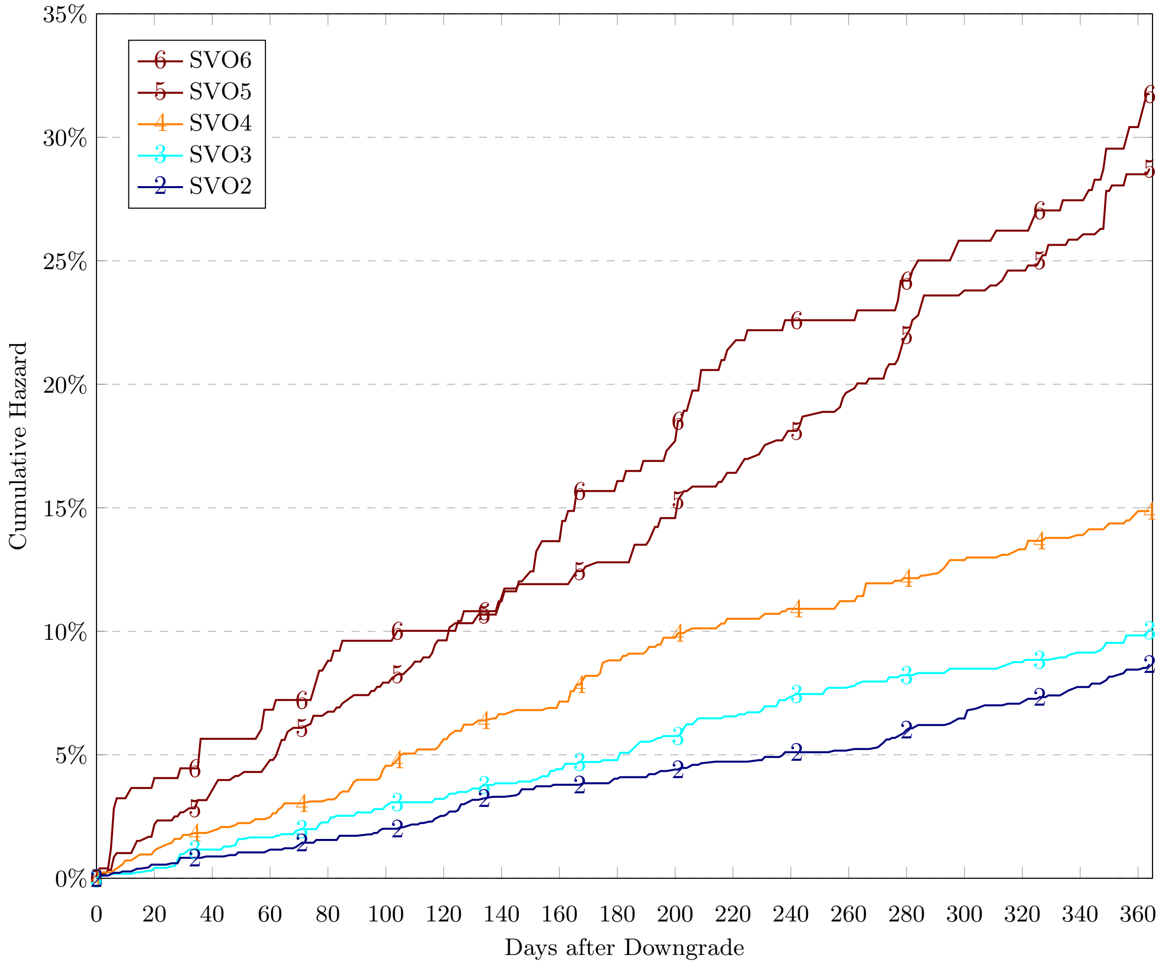

Figure 2.2: Cumulative Hazard of Selling after Downgrade
(by Cost of Capital for Life Insurers)

Table 2.1: Risk-Based Capital for Life and P&C Firms

		RBC Charge		Accounting Treatment	
SVO	Moody's Credit Rating	Life	P&C	Life	P&C
1	A3 and above	0.40%	0.30%	AC	AC
2	Baa 1, 2, 3	1.30%	1.00%	AC	AC
3	Ba 1, 2, 3	4.60%	2.00%	AC	FV
4	B 1, 2, 3	10.00%	4.50%	AC	FV
5	Caa 1, 2, 3	23.00%	10.00%	AC	FV
6	Ca, C	30.00%	30.00%	FV	FV

Table 2.2: Risk Exposure for Life and P&C

	Life		*P&C*	
	Average	Median	Average	Median
Adj. CE at DG	6.87		10.42	
Total Assets	30,739	8,541	3,850	557
Total Bonds (% of Assets)	63.30	68.33	70.73	72.02
RBC	11.00	8.52	16.47	7.00
Risky-to-Total	5.46	5.67	2.02	0.78
Risky-to-C&S	48.28	41.91	4.05	1.40
Num. of Firms	543		238	
Firm-DG Events	3,967		613	

Table 2.3: Insurer Downgrade Events by Year: Life and P&C Combined

Downgrade Year	Firms	Avg. Num. DG Events by Firm	Avg. Par Held($000)	Number of Sell Events
2006	9	1.22	2,194	9
2007	0	NA	NA	0
2008	14	1.50	4,889	2
2009	213	7.88	10,324	270
2010	179	8.07	7,394	335
2011	154	3.98	9,140	97
2012	162	4.58	8,125	190
2013	50	1.38	9,453	17
Total	781	5.86	8,827	920

Table 2.4: Composition of Insurer Downgrade Events by Year and Line of Business

Panel A: Life Insurers

Downgrade Year	Firms	Avg. Num. DG Events by Firm	Avg. Par Held($000)	Number of Sell Events
2006	7	1.29	2,555	7
2007	0	NA	NA	0
2008	13	1.54	4,784	2
2009	141	10.20	11,421	206
2010	121	10.69	7,596	276
2011	98	5.36	9,732	80
2012	118	5.24	9,097	138
2013	45	1.42	10,122	12
Total	543	7.31	9,514	721

Panel B: P&C Insurers

Downgrade Year	Firms	Avg. Num. DG Events by Firm	Avg. Par Held($000)	Number of Sell Events
2006	2	1.00	568	2
2007	0	NA	NA	0
2008	1	1.00	7,000	0
2009	72	3.35	3,783	64
2010	58	2.62	5,671	59
2011	56	1.57	5,609	17
2012	44	2.82	3,280	52
2013	5	1.00	883	5
Total	238	2.58	4,383	199

Table 2.5: Cox Proportional Hazard Estimate of Selling a Downgraded Bond

	All Insurers		*Life Only*		*P&C Only*	
	Parameter Estimate	Hazard Ratio	Parameter Estimate	Hazard Ratio	Parameter Estimate	Hazard Ratio
Gain/Loss	0.0076	1.008	0.0092	1.009	−0.0024	0.998
	(<.0001)		(<.0001)		(0.6055)	
Risky-to-Total	−0.0240	0.976	−0.0667	0.936	0.0126	1.013
	(0.1606)		(0.0015)		(0.2815)	
ln(RBC)	0.0312	1.032	0.0384	1.039	0.1137	1.120
	(0.6720)		(0.7474)		(0.3523)	
Post-2010	0.2091	1.233	0.3950	1.484	−0.5908	0.554
	(0.2858)		(0.0843)		(0.1071)	
Adj.CE	−0.0246	0.976	−0.0128	0.987	−0.0621	0.940
	(<.0001)		(0.0502)		(<.0001)	
ln(IssueAge)	−0.2227	0.800	0.0815	1.085	−1.0495	0.350
	(0.2102)		(0.6658)		(0.0855)	
ln(IssueSize)	0.2755	1.317	0.2778	1.320	0.3657	1.441
	(<.0001)		(<.0001)		(0.0013)	
Mutual	−0.3711	0.690	−0.3635	0.695	−0.3207	0.726
	(0.0154)		(0.0273)		(0.5843)	
Year-Qtr FE	Yes		Yes		Yes	
State FE	Yes		Yes		Yes	
Stratified Baseline	By Type & SVO		By SVO		By SVO	

Cox proportional hazard of selling a downgraded bond. The first model *All Insurers* pools life and P&C together using a stratified baseline hazard by insurer type (Life vs. P&C) and regulatory capital charge level for a given bond (SVO 2-6). The last two models separate life insurers from P&C and stratify the baseline hazard by regulatory capital charge level. *Gain/Loss* is the difference between a bond's estimated market price (see Eq. 2.2) and an insurer's prior year-end carry price. *Risky-to-Total* is the ratio of bonds classified as SVO 3 through 6 relative to an insurer's total bond portfolio scaled by 100. *ln(RBC)* the natural log of a firm's prior year-end RBC ratio. *Post-2010* is an indicator variable equal to 1 for observations after year-end 2010 and 0 otherwise. *Adj.CE* is a bond's credit enhancement as of given month less the % of loans in that bond's mortgage pool in foreclosure or REO. *ln(IssueAge)* is the natural log of a bond's age in years. *ln(IssueSize)* is the natural log of a bond's face value (par amount). *Mutual* is an indicator variable equal to 1 for mutual insurers and 0 otherwise. *Year-Qtr FE* and *State FE* are fixed effects for the year-quarter of a downgrade event and state in which an insurer is domiciled.

Table 2.6: Hazard of Selling a Downgraded Bond — RBC Regime Effect for Life Insurers

	Parameter Estimate	Hazard Ratio	p-Value
Gain/Loss	0.0093	1.009	(<.0001)
Risky-to-Total	−0.0642	0.938	(0.0021)
ln(RBC)	−0.3923	NA	(0.0298)
Post-2010	−1.1317	NA	(0.0260)
*ln(RBC)*Post-2010*	0.6895	NA	(0.0006)
Adj.CE	−0.0120	0.988	(0.0671)
ln(IssueAge)	0.0959	1.101	(0.6108)
ln(IssueSize)	0.2752	1.317	(<.0001)
Mutual	−0.3255	0.722	(0.0466)
Year-Qtr FE		Yes	
State FE		Yes	
Stratified Baseline		By SVO	

The variable *ln(RBC)*Post-2010* is the interaction between the natural log of a firm's prior year-end RBC ratio (*ln(RBC)*) and an indicator variable, *Post-2010*, equal to 1 for observations after year-end 2010 and 0 otherwise. The baseline hazard of selling a downgraded bond is stratified by regulatory capital charge level for a given bond (SVO 2-6). Definitions for all other variables are detailed in Table 2.5.

Table 2.7: Hazard of Selling a Downgraded Bond —
Gain/Loss Effect for Life Insurers

	Parameter Estimate	Hazard Ratio	p-Value
Gain	0.0124	1.012	(0.0120)
Loss	−0.0084	0.992	(0.0006)
Risky-to-Total	−0.0639	0.938	(0.0022)
ln(RBC)	−0.3926	NA	(0.0306)
Post-2010	−1.1193	NA	(0.0282)
*ln(RBC)*Post-2010*	0.6853	NA	(0.0007)
Adj.CE	−0.0123	0.988	(0.0621)
ln(IssueAge)	0.1125	1.119	(0.5529)
ln(IssueSize)	0.2794	1.322	(<.0001)
Mutual	−0.3266	0.721	(0.0457)
Year-Qtr FE		Yes	
State FE		Yes	
Stratified Baseline		By SVO	

Gain and *Loss* are calculated in the same manner as defined in Table 2.5 where *Gain* (*Loss*) is set to zero if market price is lower (higher) than an insurer's carry price and is the absolute difference between market price and an insurer's carry price otherwise. Definitions for all other variables are detailed in Table 2.5.

Table 2.8: Hazard of Selling a Downgraded Bond — Gain/Loss Interaction with Portfolio Risk for Life Insurers

	Parameter Estimate	Hazard Ratio	p-Value
Gain/Loss	0.0040	NA	(0.4225)
Risky2	0.2186	NA	(0.2781)
Risky3	−0.0553	NA	(0.7813)
Risky4	−0.0243	NA	(0.8999)
*G/L*Risky2*	−0.0052	NA	(0.3367)
*G/L*Risky3*	0.0034	NA	(0.5364)
*G/L*Risky4*	0.0153	NA	(0.0064)
ln(RBC)	−0.3655	NA	(0.0439)
Post-2010	−1.2528	NA	(0.0163)
*ln(RBC)*Post-2010*	0.7475	NA	(0.0003)
Adj.CE	−0.0123	0.988	(0.0666)
ln(IssueAge)	0.0959	1.101	(0.6121)
ln(IssueSize)	0.2908	1.337	(<.0001)
Mutual	−0.3222	0.725	(0.0519)
Year-Qtr FE		Yes	
State FE		Yes	
Stratified Baseline		By SVO	

Risky2, *Risky3*, and *Risky4* are dummy variables indicating if an insurer's ratio of risky bonds (SVO 3 through 6) to total bonds is within a given quartile range where the lowest risk quartile (1) is the omitted group. Quartiles are calculated using the full sample period. *G/L*Risky2* through *G/L*Risky4* are interactions between risk quartiles and the continuous gain/loss measure. Definitions for all other variables are detailed in Table 2.5.

Table 2.9: Hazard of Selling a Downgraded Bond —
Gain and Loss Interaction with Portfolio Risk for Life Insurers

	Parameter Estimate	Hazard Ratio	p-Value
Gain	0.0193	NA	(0.0468)
Loss	−0.0011	NA	(0.8600)
Risky2	0.5089	NA	(0.0701)
Risky3	0.1932	NA	(0.4855)
Risky4	0.1385	NA	(0.6065)
*Gain*Risky2*	−0.0390	NA	(0.0693)
*Gain*Risky3*	−0.0179	NA	(0.2261)
*Gain*Risky4*	0.0035	NA	(0.7721)
*Loss*Risky2*	−0.0016	NA	(0.8163)
*Loss*Risky3*	−0.0095	NA	(0.1709)
*Loss*Risky4*	−0.0189	NA	(0.0089)
ln(RBC)	−0.3671	NA	(0.0416)
Post-2010	−1.2730	NA	(0.0155)
*ln(RBC)*Post-2010*	0.7535	NA	(0.0003)
Adj.CE	−0.0122	0.988	(0.0692)
ln(IssueAge)	0.1011	1.106	(0.5968)
ln(IssueSize)	0.2954	1.344	(<.0001)
Mutual	−0.3240	0.723	(0.0503)
Year-Qtr FE		Yes	
State FE		Yes	
Stratified Baseline		By SVO	

Risky2, *Risky3*, and *Risky4* are dummy variables indicating if an insurer's ratio of risky bonds (SVO 3 through 6) to total bonds is within a given quartile range where the lowest risk quartile (1) is the omitted group. Quartiles are calculated using the full sample period. *Gain*Risky2* through *Gain*Risky4* and *Loss*Risky2* through *Loss*Risky4* are interactions between risk quartiles and gain/loss measures described in Table 2.7. Definitions for all other variables are detailed in Table 2.5.

Appendix

Property Value Interpolation

The process by which we calculate property value using the CoStar Commercial Repeat Sales Index for a given month t is

$$V(t) = V(u)\frac{I(t)}{I(u)} + \frac{t-u}{v-u}\left[V(v) - V(u)\frac{I(v)}{I(u)}\right] \tag{A.1}$$

where $V(u)$ is the most recent appraised value and $I(u)$ is the corresponding index value at the prior valuation date u with period v being the point in time of the next appraised value V and corresponding index value I. For properties which are appraised at origination and subsequently never re-appraised (i.e. loans which are never transferred to the special servicer), only the first additive term of Equation A.1 is relevant.