SECONDARY MARKETING EXECUTIVE®

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Credit Risk Becoming Increasingly Relevant To Mortgage Investors

As nonagency mortgage assets assume a greater share of the secondary market pie, investors are growing more concerned with measuring and understanding credit risk.

By Kyle G. Lundstedt

There is an enormous amount of credit risk in the mortgage sector. Government statistics show that over $3.8 trillion in single-family residential mortgages were originated in 2003. Even a very small percentage of credit loss on such an enormous asset class would have serious repercussions for the U.S. economy.

For many years, however, credit risk has been of little concern to investors in mortgage securities. Historically, the housing government-sponsored enterprises - Fannie Mae, Freddie Mac and Ginnie Mae - have provided significant, if not total, protection from credit risk for well over half of the mortgages originated in the U.S. each year. The remaining credit risk traditionally was held in portfolio as whole loans by financial institutions such as banks and thrifts.

Nonetheless, in the last 10 years, mortgage investors have seen the emergence of a significant secondary market for non-agency mortgage-backed securities (MBS), mortgage-related asset-backed securities (ABS), and the collateralized mortgage obligations derived from them. As a result, fixed-income investors now must concern themselves with measuring and understanding credit risk, in addition to the traditional market and prepayment risks for mortgages.

This article describes some commonly used tools for measuring credit risk. We discuss the pros and cons of these tools and describe a methodology called "competing risks" models. We discuss how prepayment and default constitute competing risks in the context of mortgages, and give some examples of why mortgage investors might consider this methodology for use in evaluating nonagency MBS and ABS.

Types of default models

There is a long history of attempts to quantify the amount of credit risk in mortgages. One might categorize these attempts (K.G. Lundstedt, "Credit Models in Banking: Past, Present, and Future," 2004) into four types of methodology:

- scoring models,
- roll rate or migration models,
- life-of-loan loss/actuarial models, and
- option-based structural models.

"An Introduction to Credit Scoring" (E.M. Lewis, Athena Press, 1992) provides an excellent history of consumer scoring for retail lending as a whole. Scoring models tend to use single-period classification (logit and variations) techniques to assess the probability of default for a loan. These techniques have been commercially developed in Fair Isaac's FICO score and Fannie Mae's Desktop Underwriter. Historically, such "origination" or "behavior" scores predict default likelihoods over 12 to 18 months.

"Migration Patterns of the Delinquent Home Equity Loan" (R. Dubitsky, et al., 2003) is a good example of so-called "roll rate" or "rating migration" type models.

Roll rate or rating migration type tools historically have looked at delinquency status and default or, alternatively, bond ratings as states in a multi-state time-constant Markov model. Banks and thrifts have applied roll rate models to mortgages, credit cards, personal loans and other products. Ratings migration models are popular with secondary market participants in the MBS and ABS sectors, as well.

For a description of the life-of-loan loss or actuarial approach,

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"Credit Scoring for Risk Managers" (E. Mays, South-Western Educational Publishing, 2003) is an authoritative reference. This methodology generates estimates of lifetime defaults based on origination characteristics. Often, ratings agencies and large banks use this methodology, along with an assumed timing curve, to project loss behavior for pools or portfolios of loans over time.

The final method used to measure credit risk is applying option-based structural models. "The Pricing of Adjustable Rate Mortgages" (J. Kau, et al., Journal of the American Real Estate and Urban Economics Association, 1985) and "The Conditional Probability of Default" (D. Capozza, et al., Real Estate Economics, 1998) are good examples of this model from the academic literature on mortgages. Such models look upon default as an American option on underlying value of the collateral. While this approach has proven successful in the corporate sector, such as Moody's KMV, consumer lending tends to be characterized by "inefficient exercise" of the default option.

Data-driven approaches

For consumer lending, in general, academic and practitioner research confirms that data-driven approaches outperform pure option-based models such as Kau (Merton-like option model). Most banks utilize internally developed models rather than externally developed vendor models. In particular, "data-driven" approaches tend to dominate mortgage default modeling.

However, these traditional consumer default methods tend to have significant drawbacks. Scoring and life-of-loan loss models ignore timing of default and the effect of prepayment, and they fail to account for covariates changing over time. Roll rate models do not incorporate predictive variables, and assume that "history repeats itself" with respect to macroeconomic risk factors. Finally, option-based structural models insist that the default option be ruthlessly exercised.

Mortgages pose a particular challenge for default modelers. As with other types of consumer assets, it would be beneficial to address the timing of the default event, as do roll rate models, and to account for static predictive variables, as do scoring and life-of-loan loss models. However, a mortgage default model also must allow for prepayment and other options, as do roll rate and option-based models, in addition to incorporating time-varying predictive variables (current loan-to-value or asset-to-liability ratios), as do option-based models.

Addresses concerns

The hazard model is a modeling technique that addresses many of these concerns. Moreover, hazard models are heavily used in prepayment modeling (A. Davidson et al., "Securitization: Structuring and Investment Analysis," John Wiley & Sons, 2003; and L. Hayre, "Salomon Smith Barney Guide to Mortgage-Backed and Asset-Backed Securities," Wiley). As a result, though the technique is less commonly applied to defaults, its usage in the prepayment modeling area makes it well understood by investors on Wall Street. In fact, the valuation and market risk measurement of MBS, ABS and other securitization structures most commonly depend upon hazard models of prepayments.

There is an enormous amount of academic and regulatory literature that applies hazard models to both prepayments and defaults. For example, W. Alexander, et al., in "Some Loans Are More Equal Than Others: Third Party Originations and Default in the Subprime Mortgage Industry," published in Real Estate Economics (2002), examines subprime mortgage performance.

The P. Calem and M. LaCour-Little article, "Risk-based Capital Requirements for Mortgage Loans," published in the Journal of Banking and Finance (2002) is the foundation for the current Basel II regulations for mortgages. And the Office of Federal Housing Enforcement Oversight's 2002 risk-based capital rule explains the application of hazard models to mortgages in the context of capital regulation for Fannie Mae and Freddie Mac.

Why are default and prepayment "competing" risks? Since the hazard technique is well understood on Wall Street and in academia, one might expect that a default model for mortgages could simply be estimated and then used with an existing prepayment model. As it turns out, however, prepayments and defaults are competing risks that require simultaneous development and estimation of models.

Consider the fact that two hazards, such as prepayments and defaults, may not be statistically related, but the outcomes may be related in other ways. For each hazard, the probability of transition over longer time intervals will depend on transition probabilities of the other hazard. For example, the lifetime default probability for a mortgage may be lower if monthly prepayment probabilities are higher.

Moreover, some observed predictive variables, such as the current loan-to-value (LTV) or the FICO score, might affect both the hazard of prepayment and the hazard of default. Clearly, increased current LTVs or decreased FICOs likely increase defaults for mortgages; however, the same variables may decrease prepayment likelihood. Separating out the effects of these predictive variables on both hazards simultaneously is best handled by a modeling technique known as competing-risk hazard models.

Understanding the ins and outs of competing-risk models is beyond the scope of this article. However, it is

important to understand how using such a technique can have very significant impacts in real-world situations. Competing-risk hazard models, like traditional prepayment models, have different effects depending upon the projected economic scenario.

In fact, one of their principal benefits is the ability to separate the effect of portfolio composition, static characteristics such as documentation type or original FICO score, from the effect of macro-risk factors, including dynamic effects driven by interest rates or housing prices.

A study by two researchers at Wells Fargo's Home Equity Group (A. Hall and S. Brown, "Modeling Mortgage Default and Prepayment as Competing Risks") included default and prepayment estimates from a competing risk model in a variety of "good" and "bad" future scenarios. The study subjected a hypothetical portfolio to an increase in interest rates and the same portfolio to a decline in interest rates. It showed significantly different prepayment and default rates.

In the falling-rate scenario, fast prepayment rates leave many fewer opportunities for loans to default. Hence, prepayment rates are high, but default rates are low for the same collateral. In the rising-rate scenario, however, the increased duration of the portfolio leaves more opportunity for default. Hence, the default rate is much higher for the same collateral.

The research held collateral quality constant, since the hypothetical portfolios were the same. Imagine, however, two portfolios or underlying collateral pools with different characteristics. A pool with collateral characteristics, such as high LTVs and low rates, will experience low prepayments, while a pool with attributes, including lower LTVs and higher loan rates, will see higher prepayments.

It is obvious that different prepayment rates can lead to enormously different default rates. Consequently, it is critical to use modeling techniques, such as competing risks, that account for the effect of prepayment on default, and vice-versa. SME