Implications of Stochastic Recovery Rates in Evaluating CDO Tranches

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The binomial expansion technique (BET) originally proposed by Moody's has evolved as a standard technique financial institutions and other market participants use to rate tranches of collateralized bond obligations (CBOs) and collateralized loan obligations (CLOs) (see Cifuentes and O'Connor [1996]). The principal reason for the model's popularity is its simplicity and low implementation cost. The technique is sometimes used to estimate preliminary rating indications prior to developing Monte Carlo simulation models, or for transactions with limited information on the underlying pool of collateral.

BET is reasonably accurate for estimating the ratings of individual tranches if the underlying collateral pools are relatively homogeneous. A multibinomial expansion technique generalizes the original approach, allowing application to non-homogeneous portfolios (see Cifuentes and Wilcox [1998]). Even in the more generalized form, however, the technique relies significantly on the assumption that recovery rates are constant across collateral pools. This assumption is not supported by empirical observation.

Altman and Kishore [1996] show that historical recovery rate density functions for every debt seniority category demonstrate non-zero probabilities across the entire range of recovery rates. The variability of recovery rates should widen the overall distribution of losses for the collateral pool and thus have an impact on expected losses and credit ratings of individual tranches. The impact will vary, depending on the properties of the underlying collateral pool (average rating, debt seniority, time to maturity, and diversity score), as well as on the size of both senior and subordinated tranches.

To analyze the effect of stochastic recoveries on individual ratings, we develop a Monte Carlo simulation model that generates credit events with both constant and stochastic recovery rates. We calibrate the simulation model in constant recovery mode to produce results identical to BET's, and use a random recovery mode to identify the impact of the BET constant recovery assumption.

We analyze a broad spectrum of tranches with different characteristics in order to identify where the impact of varying recovery rates is particularly significant. In addition, we estimate adjustments to constant recovery rates for each case that would bring BET results into agreement with the simulation incorporating non-constant recovery rate assumptions.

I. MOODY'S RATING METHODOLOGY FOR CBO/CLO TRANSACTIONS

Moody's general rating methodology for structured finance transactions is based on the concept of expected loss. An expected loss estimate for each tranche is mapped into the rating using Moody's expected loss table. Depending on the characteristics of the pool of assets, several approaches can be used to produce the portfolio loss distribution. The choice of the appropriate technique is generally driven by the heterogeneity of the portfolio.

A binomial expansion technique (BET) is commonly applied to homogeneous portfolios with a small number of assets (up to approximately 250). For moderately heterogeneous portfolios, an alternative is a multi-binomial expansion technique. The lognormal method is an approach that can be applied to homogeneous portfolios with a large number of assets (generally over 500).

These models are the most popular alternatives to the Monte Carlo simulation methodology, along with the Fourier transform method, which is typically used to analyze portfolios of heterogeneous assets (see Debuysscher [2003]). Monte Carlo simulation is generally superior for analyzing all types of portfolios, but it comes at considerable computational cost. The Monte Carlo simulation methodology can also be used to study properties of other models by reproducing their assumptions and assessing the sensitivity of results. Indeed, it is relatively straightforward to build a simulation model that converges toward BET results for a large number of trials.

BET is based on the derivation of a synthetic portfolio of independent and homogeneous assets with identical size, default probability, and maturity and consistent with the average behavior of the underlying pool of assets. The inputs of BET are the diversity score D (a proxy for the number of independent assets that mimic the original pool), the weighted-average maturity of the pool T, the weighted-average default probability of the pool p, and the weighted-average recovery rate of the pool R. The latter parameter—which varies depending on the debt seniority of the underlying assets in the pool—is assumed to be constant.

Using the assumption of independence, one can easily compute the probability P_j of observing j defaults, where j ranges between zero and D, and therefore describes the overall behavior of the synthetic portfolio that reproduces the behavior of the original portfolio:

$$P_j = \frac{D!}{j!(D-j)!} p^j (1-p)^j \quad (1)$$

where p is the probability of default for a single asset.

The total expected loss is then simply described by:

$$E = \sum_{j=1}^{D} P_j Loss_j \quad (2)$$

where $Loss_j$ is the loss realized due to j defaults assuming constant recovery rate R.

The expected loss of each tranche of the capital structure depends on two additional parameters: the size of the tranche, and the extent of the subordination. For a tranche with size T and subordination S, the expected loss should be equal to:

$$E_T = \sum_{j=1}^{D} P_j \max[0, \min(T, Loss_j - S)] \quad (3)$$

The validity of the BET assumptions clearly depends on the properties of the underlying portfolio. Even in the ideal case, when the portfolio is composed of independent and homogeneous assets, additional assumptions may play an important role. These assumptions are related to the stochastic nature of the probabilities of default and recovery rates and to macroeconomic credit cycles. Among these assumptions, the non-variability of recovery rates is the critical one, as the impact of credit cycles may be more or less pronounced, depending on the maturity of a transaction.

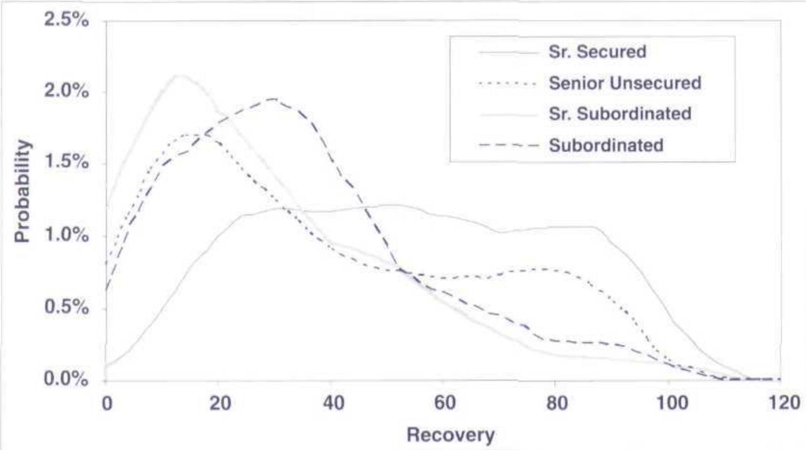
II. DISTRIBUTION OF RECOVERY RATES

We first define the distribution functions of the recovery rates for each class of debt seniority. Recovery rate is defined as the price of a newly defaulted debt instrument, rather than the price upon emergence from bankruptcy, since the timing and relative success of emergence are generally uncertain.

Altman et al. [2003], Friedman and Sandow [2003], Frye [2003], and Hamilton, Cantor, and Ou [2002] note the direct dependence of recovery rates on economic cycles. In fact, economic downturns appear to have a stronger effect on recovery rates than on default rates. Historical analysis also demonstrates that the impact of economic cycles is more pronounced for the most senior debt classes.

In order to eliminate model dependence from our analysis, we choose not to incorporate dependence on economic cycles in our simulation model, but rely on historical recovery rate distributions published by Moody's for an extended observation period. We do not parame-

EXHIBIT 1
Historical Distributions by Debt Seniority



terize the empirical distribution for the same reason.

Market practitioners commonly use the beta distribution to describe recovery rate density functions. Despite its several advantages, beta parameterization of historical data would also introduce model dependence and make the results of our analysis less general.

Exhibit 1 shows empirical distributions of recovery rates for four debt categories based on default data over 1970–2003. As would be expected, the means of these distributions are consistent with their seniorities. The curves also demonstrate substantial bimodality, which is the result of the underlying economic cycles. This bimodality is particularly noticeable for senior debt classes, which is consistent with the observation that economic cycles have more severe impacts on senior debt recovery rates. Therefore, the use of historical recovery rate distributions allows us to at least partially incorporate the impact of economic cycles.

III. ANALYSIS AND RESULTS

To analyze the impact of stochastic recovery rates, we implement a Monte Carlo (MC) simulation model constructed around the same assumptions used in BET. The constant recovery rates used by both BET and MC are based on historical averages calculated for each seniority type (e.g., senior debt, subordinated debt).

As expected, the MC simulation, generated with enough trials, accurately replicates BET results for all cases analyzed. The MC model is then modified to incorporate stochastic recovery rates generated according to empirical distributions for each seniority type. Finally, observed differences in expected losses and ratings are analyzed as a function of capital structure and the underlying pool's characteristics to see where there are significant biases produced by the constant recovery rate assumption.

To categorize the characteristics of the pool and the underlying capital structure, we identify parameters including average rating of the underlying pool, seniority of the underlying assets, and size of the tranche and its subordination. In all cases analyzed, time to maturity is fixed at five years, and the diversity score is chosen to equal 25 in order to limit the set of parameters to those that dominate the impact.*

A series of tests are developed to cover a wide range of values for the four parameters. The size of the tranche can range from 5% to 85% and subordination from 5% to 50%. Combining these parameters for the capital structure with four asset seniority types and with ratings ranging from Aa2 to Caa, we construct 134 sample sets of results. When there are rating inconsistencies between the MC and BET models, we estimate the adjustment to the constant recovery rate that would reproduce the ratings based on stochastic recovery rates.

Exhibit 2 demonstrates the results for a set with B2-rated subordinated assets and an 80%/10%/10% capital structure. The results of the MC simulation for each tranche—in terms of expected loss (EL), probability of

EXHIBIT 2
Sample Test Results

		Senior Tranche(s)	Analyzed Tranche	Junior Tranche(s)
	Size	80%	10%	10%
Monte Carlo Simulation	EL	0.002%	3.1%	51%
	ProbLoss	0.1%	12%	89%
	LGD	1.9%	26%	58%
	Rating	Aa1	Ba2	C
Initial BET	EL	0.001%	2.6%	52%
	ProbLoss	0.1%	15%	89%
	LGD	1.7%	17%	59%
	Rating	Aaa	Ba1	C
Adjusted BET	EL	0.002%	3.1%	53%
	ProbLoss	0.1%	15%	89%
	LGD	2.5%	20%	60%
	Rating	Aa1	Ba2	C

EL is expected loss. ProbLoss is probability of experiencing a loss. LGD is expected loss, given non-zero loss.

EXHIBIT 3

Maximum Discrepancy by Debt Seniority

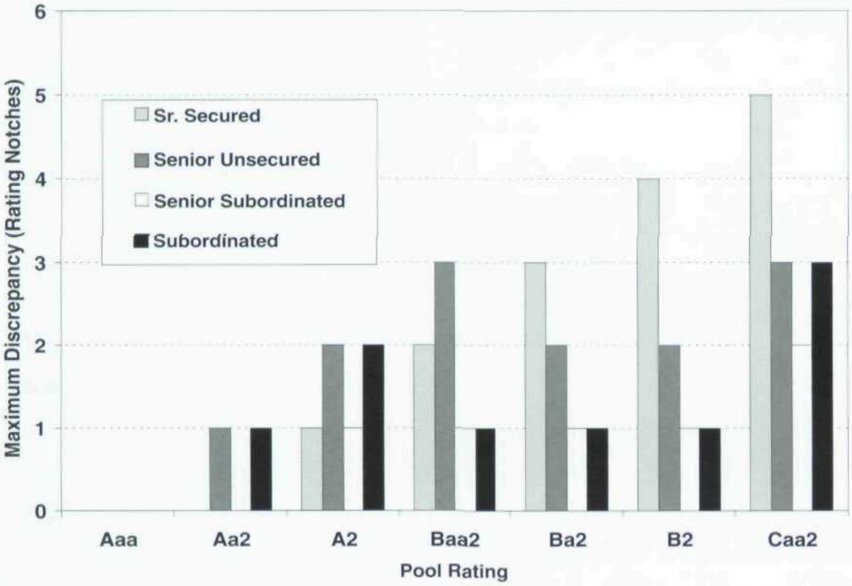


EXHIBIT 4

Average Recovery Adjustment by Average Underlying Rating

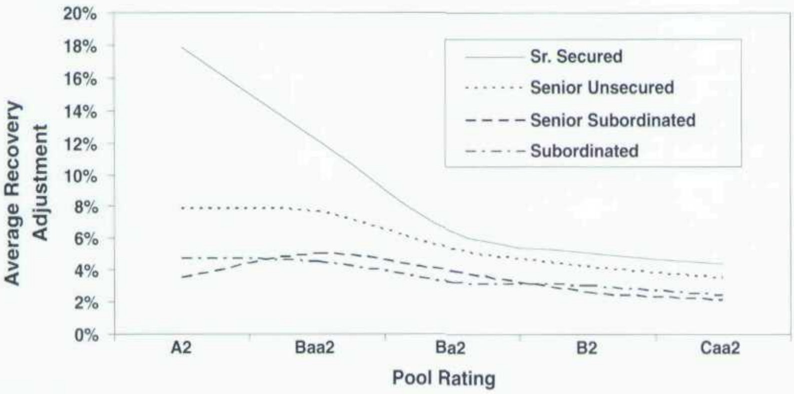
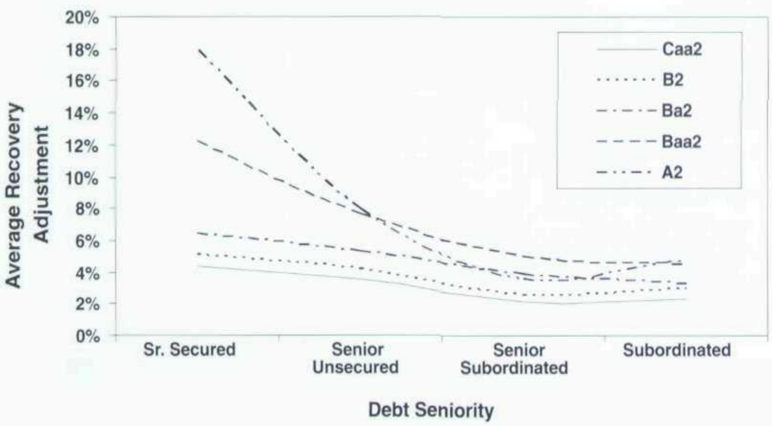


EXHIBIT 5

Average Recovery Adjustment by Debt Seniority



experiencing a loss (ProbLoss), expected loss, given non-zero loss (LGD), and the corresponding rating—are compared to similar results for BET (Initial BET) based on average recovery rates. In this example, we see a one-notch difference for the senior and intermediate tranches.

The last panel displays the results of BET with an adjusted constant recovery rate that would produce the same expected loss for the intermediate tranche. The adjusted constant recovery rate is 32.8% versus the average of 34.9% for subordinated bonds. In this case, the adjusted recovery rate replicates the ratings of both the senior tranche and the intermediate tranche.

Exhibit 3 shows the greatest discrepancies in ratings among analyzed capital structures for a prespecified average credit rating of the pool and debt seniority. The impact of stochastic recovery rates appears to be minimal for high-credit quality pools. For an Aaa pool, observed differences between ratings based on stochastic and constant recovery assumptions are not found to be significant. For non-investment-grade pools, however, the impact is much more pronounced—as much as one to three rating notch differences in ratings for typical capital structures.

Exhibits 4 and 5 display the average recovery adjustments when we see rating discrepancies. The adjustment is defined as the difference between the average recovery for a given type of debt seniority and a modified recovery rate that replicates the expected loss from Monte Carlo simulation.

Exhibit 4 shows that more senior debt requires greater recovery adjustments. Adjustments for pools with senior secured debt as the underlying collateral dominate adjustments for pools with unsecured debt as collateral because of the shape of the distribution curve of recovery rates for senior secured debt. The impact is more pronounced since the senior secured debt recovery rate distribution has almost equal probability weight in the range from 20% to 90%, while unsecured debt has significantly lower averages and narrower distributions that are shifted to the left, with high probability mass around the mean.

Similarly, Exhibit 5 shows that higher-credit quality portfolios require greater adjustments. The steep slope of the A2-rated curve is inconsistent with other curves due to limited underlying statistics, since the adjustment is computed only to match the expected loss for cases with mismatched ratings. For the A2 curve, there are only 2 observations among 134 cases (1.5% of the total) with a difference in ratings. Compare this to 7.5% with differences in ratings for Baa2 and 15% for B2 arrived at using BET.

Exhibits 6 through 10 present differences in ratings and the corresponding adjusted recoveries implied by the use of historical recovery rate distributions for each debt seniority. In the case of a typical capital structure, differences in ratings between standard BET and Monte Carlo simulation range between one and three notches.

IV. CONCLUSION

We have shown that non-constant recovery rates can have a significant impact on BET ratings, particularly for mezzanine tranches of CDOs with non-investment-grade underlying collateral pools. In these cases, more accurate estimates of ratings can be produced by Monte Carlo simulations or by correcting for varying recovery rates.

Similar analysis of other BET assumptions—constant probabilities of default—shows even greater differences in ratings estimated by BET and Monte Carlo simulation when we incorporate changes in the probabilities of default due to macroeconomic and credit cycles. The negative correlation between changes in recovery and default rates may have even greater impact.

Similar adjustments will be required for any other model that relies on a constant recovery rate assumption. Modified constant recovery rates are likely reasonable adjustment proxies for other models.

EXHIBIT 6
A2 Pool Discrepancy and Adjusted Recovery Rates

		Size of Tranche								
Debt Type	Subordination	5%	15%	25%	35%	45%	55%	65%	75%	85%
Sr. Secured (54%)	5%	1 (37%)	1 (36%)	1 (37%)	1 (37%)	1 (37%)	1 (37%)	1 (36%)	-	-
	10%	-	-	-	-	-	-	-	-	-
	15%	-	-	-	-	-	-	-	-	
	20%	-	-	-	-	-	-	-	-	
	25%	-	-	-	-	-	-	-		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				
Senior Unsecured (39%)	5%	2 (32%)	1 (32%)	-	1 (32%)	1 (32%)	1 (32%)	1 (32%)	1 (32%)	1 (32%)
	10%	-	-	-	-	-	-	-	-	-
	15%	-	-	-	-	-	-	-	-	
	20%	-	-	-	-	-	-	-	-	
	25%	-	-	-	-	-	-	-		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				
Senior Subordinated (29%)	5%	-	1 (27%)	-	1 (26%)	-	-	-	-	-
	10%	-	-	-	-	-	-	-	-	-
	15%	-	-	-	-	-	-	-	-	
	20%	-	-	-	-	-	-	-	-	
	25%	-	-	-	-	-	-	-		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				
Subordinated (34%)	5%	2 (30%)	1 (30%)	-	-	-	-	-	-	-
	10%	-	-	-	-	-	-	-	-	-
	15%	-	-	-	-	-	-	-	-	
	20%	-	-	-	-	-	-	-	-	
	25%	-	-	-	-	-	-	-		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				

EXHIBIT 7

Baa2 Pool Discrepancy and Adjusted Recovery Rates

		Size of Tranche								
Debt Type	Subordination	5%	15%	25%	35%	45%	55%	65%	75%	85%
Sr. Secured (54%)	5%	2 (42%)	2 (42%)	1 (42%)	2 (42%)	1 (42%)	1 (42%)	1 (42%)	1 (42%)	1 (42%)
	10%	-	-	-	-	-	-	-	-	-
	15%	-	-	-	-	-	-	-	-	
	20%	-	-	-	-	-	-	-	-	
	25%	-	-	-	-	-	-	-		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				
Senior Unsecured (39%)	5%	3 (32%)	2 (32%)	2 (32%)	1 (32%)	1 (32%)	2 (32%)	1 (32%)	1 (32%)	1 (32%)
	10%	-	1 (32%)	1 (32%)	1 (32%)	-	-	-	-	-
	15%	-	-	-	-	-	-	-	-	
	20%	-	-	-	-	-	-	-	-	
	25%	-	-	-	-	-	-	-		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				
Senior Subordinated (29%)	5%	-	1 (27%)	1 (27%)	-	1 (27%)	-	-	1 (27%)	1 (27%)
	10%	-	-	-	-	-	1 (22%)	1 (22%)	1 (23%)	1 (24%)
	15%	-	-	-	-	-	-	-	-	
	20%	-	-	-	-	-	-	-	-	
	25%	-	-	-	-	-	-	-		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				
Subordinated (34%)	5%	1 (30%)	1 (31%)	1 (31%)	1 (31%)	1 (31%)	1 (31%)	1 (30%)	-	-
	10%	-	-	1 (31%)	1 (30%)	1 (31%)	1 (29%)	-	-	-
	15%	-	-	-	-	-	-	-	-	
	20%	-	-	-	-	-	-	-	-	
	25%	-	-	-	-	-	-	-		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				

EXHIBIT 8

Ba2 Pool Discrepancy and Adjusted Recovery Rates

		Size of Tranche								
Debt Type	Subordination	5%	15%	25%	35%	45%	55%	65%	75%	85%
Sr. Secured (54%)	5%	1 (52%)	1 (51%)	1 (51%)	1 (51%)	-	-	-	1 (51%)	1 (51%)
	10%	2 (48%)	2 (48%)	1 (48%)	2 (48%)	1 (48%)	1 (48%)	2 (48%)	2 (48%)	1 (48%)
	15%	2 (46%)	2 (46%)	1 (46%)	1 (46%)	1 (46%)	1 (46%)	1 (46%)	1 (46%)	
	20%	-	-	-	-	-	-	-	-	
	25%	-	-	-	-	-	-	-		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				
Senior Unsecured (39%)	5%	-	-	-	-	-	-	-	-	1 (36%)
	10%	-	1 (35%)	1 (35%)	1 (35%)	1 (35%)	1 (35%)	1 (35%)	1 (35%)	1 (35%)
	15%	2 (34%)	2 (34%)	2 (34%)	1 (34%)	1 (34%)	2 (34%)	2 (34%)	1 (34%)	
	20%	1 (33%)	-	1 (33%)	1 (33%)	1 (33%)	1 (33%)	1 (32%)	1 (32%)	
	25%	1 (30%)	-	-	-	-	-	-		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				
Senior Subordinated (29%)	5%	-	-	-	-	1 (29%)	-	-	-	-
	10%	-	1 (28%)	1 (28%)	-	-	-	-	-	-
	15%	1 (25%)	1 (25%)	-	1 (25%)	-	1 (25%)	1 (25%)	1 (25%)	
	20%	1 (26%)	1 (26%)	1 (26%)	-	-	-	-	-	
	25%	-	1 (24%)	-	-	-	-	-		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				
Subordinated (34%)	5%	-	1 (33%)	-	-	-	-	-	-	-
	10%	-	-	-	1 (33%)	1 (33%)	-	1 (33%)	1 (33%)	-
	15%	1 (31%)	-	-	1 (32%)	-	-	1 (32%)	1 (32%)	
	20%	1 (31%)	-	-	-	-	-	1 (29%)	1 (29%)	
	25%	1 (28%)	-	-	-	-	-	-		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				

EXHIBIT 9

B2 Pool Discrepancy and Adjusted Recovery Rates

		Size of Tranche								
Debt Type	Subordination	5%	15%	25%	35%	45%	55%	65%	75%	85%
Sr. Secured (54%)	5%	-	-	-	-	-	-	-	-	-
	10%	-	1 (52%)	-	-	1 (52%)	-	-	1 (52%)	1 (52%)
	15%	2 (51%)	1 (50%)	2 (50%)	1 (50%)	2 (50%)	2 (50%)	2 (50%)	1 (50%)	
	20%	4 (49%)	2 (49%)	2 (48%)	3 (49%)	2 (49%)	2 (49%)	2 (49%)	2 (49%)	
	25%	2 (47%)	1 (47%)	1 (47%)	1 (47%)	1 (47%)	1 (47%)	1 (47%)		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				
Senior Unsecured (39%)	5%	-	-	-	-	-	-	-	-	-
	10%	-	-	-	-	-	1 (38%)	-	1 (38%)	-
	15%	-	-	1 (37%)	1 (37%)	-	-	1 (37%)	-	
	20%	1 (36%)	1 (36%)	1 (36%)	1 (36%)	2 (36%)	1 (36%)	1 (36%)	1 (36%)	
	25%	2 (35%)	2 (35%)	2 (35%)	1 (35%)	1 (35%)	2 (35%)	1 (35%)		
	30%	2 (34%)	1 (34%)	1 (34%)	-	-	-	-		
	35%	1 (32%)	1 (33%)	1 (32%)	-	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				
Senior Subordinated (29%)	5%	-	-	-	-	-	-	-	-	-
	10%	-	-	-	1 (29%)	-	-	-	-	-
	15%	-	-	1 (29%)	-	-	-	-	1 (29%)	
	20%	-	-	-	1 (28%)	-	-	-	1 (28%)	
	25%	-	1 (27%)	1 (27%)	1 (28%)	1 (28%)	1 (28%)	-		
	30%	1 (27%)	1 (27%)	1 (26%)	-	1 (26%)	1 (26%)	1 (26%)		
	35%	1 (26%)	1 (26%)	-	-	-	-			
	40%	1 (25%)	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				
Subordinated (34%)	5%	-	-	-	-	-	-	-	-	-
	10%	-	-	-	-	-	-	1 (34%)	-	-
	15%	-	-	-	1 (34%)	-	1 (34%)	-	-	
	20%	1 (33%)	-	1 (33%)	-	1 (33%)	-	1 (33%)	-	
	25%	-	1 (32%)	1 (32%)	1 (32%)	1 (32%)	-	1 (32%)		
	30%	1 (31%)	1 (31%)	1 (31%)	1 (31%)	1 (31%)	1 (31%)	-		
	35%	1 (30%)	1 (32%)	1 (31%)	1 (31%)	-	-			
	40%	-	-	-	-	-	-			
	45%	-	-	-	-	-				
	50%	-	-	-	-	-				

EXHIBIT 10

Caa2 Pool Discrepancy and Adjusted Recovery Rates

		Size of Tranche								
Debt Type	Subordination	5%	15%	25%	35%	45%	55%	65%	75%	85%
Sr. Secured (54%)	5%	-	-	-	-	-	-	-	-	-
	10%	-	-	-	-	-	-	-	-	-
	15%	-	-	-	-	-	-	1 (54%)	-	
	20%	-	-	-	-	-	1 (53%)	-	1 (53%)	
	25%	1 (52%)	1 (52%)	1 (52%)	1 (52%)	-	1 (52%)	1 (52%)		
	30%	3 (51%)	3 (50%)	3 (50%)	3 (50%)	3 (50%)	2 (50%)	3 (50%)		
	35%	5 (49%)	4 (49%)	4 (49%)	3 (49%)	3 (49%)	3 (49%)			
	40%	3 (47%)	2 (47%)	1 (47%)	1 (47%)	1 (47%)	1 (47%)			
	45%	1 (46%)	1 (46%)	-	-	-				
	50%	-	-	-	-	-				
Senior Unsecured (39%)	5%	-	-	-	-	-	-	-	-	-
	10%	-	-	-	-	-	-	-	-	-
	15%	-	-	-	-	-	-	-	-	
	20%	-	-	-	-	-	-	1 (39%)	-	
	25%	-	-	-	-	-	-	-		
	30%	-	1 (38%)	1 (38%)	1 (38%)	-	1 (38%)	-		
	35%	1 (37%)	1 (37%)	1 (37%)	-	1 (37%)	1 (37%)			
	40%	1 (36%)	1 (36%)	2 (36%)	2 (36%)	2 (36%)	2 (36%)			
	45%	3 (35%)	3 (35%)	2 (35%)	2 (35%)	2 (35%)				
	50%	3 (34%)	2 (34%)	2 (34%)	2 (34%)	1 (34%)				
Senior Subordinated (29%)	5%	-	-	-	-	-	-	-	-	-
	10%	-	-	-	-	-	-	-	-	-
	15%	-	-	-	-	-	-	-	-	
	20%	-	-	-	-	-	-	-	-	
	25%	-	-	-	-	-	-	1 (29%)		
	30%	-	-	-	-	-	-	-		
	35%	-	-	-	-	-	1 (29%)			
	40%	-	1 (28%)	-	1 (28%)	-	1 (28%)			
	45%	1 (28%)	1 (28%)	1 (28%)	2 (28%)	2 (28%)				
	50%	2 (27%)	2 (27%)	2 (27%)	1 (27%)	2 (27%)				
Subordinated (34%)	5%	-	-	-	-	-	-	-	-	-
	10%	-	-	-	-	-	-	-	-	-
	15%	-	-	-	-	-	-	-	-	
	20%	-	-	-	1 (35%)	-	-	-	-	
	25%	-	-	-	-	-	-	1 (34%)		
	30%	-	-	1 (34%)	-	-	-	-		
	35%	-	1 (34%)	-	-	-	-			
	40%	1 (33%)	1 (33%)	1 (33%)	-	1 (33%)	2 (33%)			
	45%	1 (32%)	2 (32%)	2 (32%)	2 (32%)	1 (32%)				
	50%	3 (32%)	2 (31%)	2 (31%)	2 (31%)	1 (31%)				

ENDNOTE

*Since BET depends on the probability of the default rather than maturity or rating separately, the impact of the probability of the default can be captured through the rating.

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