CDO and ABS Underperformance: A Correlation Story

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Thank goodness for risk. Investors get paid to take risk, and analysts get paid to write about it. Curve risk, spread risk, liquidity risk, credit risk, prepayment risk, structural risk, and other risks are on professionals' radar screens all the time. Measuring and pricing risk correctly are central functions for many, if not most, finance professionals.

Yet some risks lend themselves to analysis more readily than others. One that presents formidable challenges all the time is model risk, the risk that a model does not describe reality well enough to produce reliable results.

In the past two years, certain areas of the securitization market have suffered disappointing levels of defaults and credit deterioration. The collateralized debt obligation, aircraft asset-backed securities, franchise loan ABS, and 12b-1 fee ABS sectors have been hammered by unprecedented volumes of downgrades.

A common theme in these sectors—and a probable explanation for the disappointing performance—is model risk. The most popular models and analytic techniques for measuring credit risk in the assets backing such deals seemingly failed to capture linkages and the changing degrees of linkage among the credit risks of the securitized assets. The economics literature addresses such linkages and changing linkages under the rubrics of *correlation* and *time-varying correlation*.

Most securitization professionals agree that the credit risks on separate assets can be linked. Most would readily acknowledge the possibility that the degree of a linkage can change with the passage of time. Monte Carlo simulations and other analytic techniques used to analyze the credit risks of CDOs, aircraft ABS, franchise loan ABS, and 12b-1 fee ABS sometimes do not address linkages in a rigorous manner, however, and generally do not reflect changing degrees of linkage at all. This shortcoming may have caused these techniques to underpredict the level of losses under recent stressful conditions—model risk coming home to roost.[1]

CDOs: In the CDO sector, both S&P and Moody's took record numbers of downgrade actions in 2002 (Elengical et al. [2003]; Fu and Harris [2003]; Nazarian et al. [2003]; and Tung [2003]). Moody's took downgrade actions on CDOs 747 times during the year. Moody's rating actions hit 471 of the 4,921 outstanding CDO tranches. S&P took 306 downgrade actions.

Both rating agencies identify the poor performance of the high-yield corporate bond market as a major cause of the troubles that afflicted CDOs. Neither has probed more deeply to address the question of why defaults and downgrades in the corporate bond market reached these recent highs. With the benefit of hindsight, it seems reasonable to ascribe at least some portion of the blame to loose accounting and auditing practices, a breakdown of corporate ethics, and irrational exuberance in the equity markets (particularly the tech sector). Such factors have the potential to affect numerous businesses at once, and can be *exogenous forces* that drive credit risk correlations to increase during periods of stress.

Aircraft ABS: Fitch notes that over 80% of the aircraft-related transactions that it had rated were downgraded in 2002 (Mrazek and Duignan [2003, p. 16]). The proximate cause of the troubles in the aircraft ABS sector is the events of September 11, 2001. Air travel has declined. As a result, lease rates on aircraft have fallen, and many aircraft have been retired from service before the end of their engineered lifespans.

The underlying causes in fact are older, namely, geopolitical conflict and terrorism. Naturally, those causes can produce strong correlation effects throughout the entire aviation industry.

Franchise Loan ABS: The franchise loan ABS sector took an even worse beating in 2002 than it had in 2001. According to S&P, 22 franchise loan ABS defaults occurred in 2002, adding to the nine in the prior year. During 2002, S&P took 54 downgrade actions on franchise loan ABS from nine separate deals (Erturk et al. [2003, p. 6]). Moody's took 109 downgrade actions on franchise loan ABS in 2002; 70 of those actions were in the second half of the year (Tung [2003, p. 3]). Fitch took 54 separate rating actions on securities in 29 deals (Mrazek and Duignan [2003, p. 17]).

Even before 2002, Fitch had identified some sources of trouble for the franchise loan ABS sector, including heightened competition among lenders, aggressive underwriting, and unreliable valuations (Wells et al. [2001]). Like CDOs and aircraft ABS, the franchise loan ABS sector seems also to have been a victim of exogenous forces driving high correlations.

Mutual Fund 12b-1 Fee ABS:[2] Although it is only a small piece of the structured finance landscape, the 12b-1 fee ABS sector experienced more than its share of pain in 2002. S&P took 41 downgrades on ABS backed by mutual fund fees during the year (Erturk et al. [2003, p. 6]). Moody's took 19 downgrade actions in 2002, adding to the 20 that it had taken in 2001 (Tung [2003, p. 4]).

The troubles in the 12b-1 fee ABS sector trace back to the stock market declines that started after the early 2000 peaks (the DJIA reached an intraday high of 11,909 on January 14, 2000; the S&P 500 reached an intraday high of 1,553 on March 24, 2000; the Nasdaq reached an intraday high of 5,133 on March 10, 2000). From a long-term perspective, the stock market declines of the past two years should not be seen as shocking. Stock market declines or corrections are hardly unprecedented or unknown.

For example, 30 years ago, the S&P 500 lost roughly half its value, falling from an intraday high of 121.74 on January 11, 1973, to an intraday low of 60.96 on October 4, 1974. That decline had a fundamental cause, the recession triggered by the OPEC oil embargo following the October 1973 Yom Kippur war.

Fifteen years later, the Nikkei 225 index hit its all-time intraday high of 38,957 on December 29, 1989. The Nikkei has been falling ever since, and it recently reached an intraday low of 7,661 on April 25, 2003. Many finance professionals now characterize the late 1980s run-up in the Nikkei as a bubble. Whether bursting bubbles or fundamental stresses cause a market decline, either can affect many stocks simultaneously and therefore generate notable positive correlations in bear markets.

Model risk has proven a significant issue for structured finance. As structured finance professionals increasingly realize the effects of model risk, they will more strongly favor deals backed by assets whose credit risk can be analyzed with relatively simple actuarial methods.[3] Such deals include not only the traditional asset classes—mortgage loans, credit cards, auto loans, student loans, and home equity loans—but also certain types of off-the-run assets as well. The actuarial approach used to analyze such deals presents few, if any, model risk pitfalls.

The structured finance community may be able to protect itself from some future disappointments by embracing the concepts of correlation and time-varying correlation in the analytic framework for CDOs, aircraft ABS, franchise loan ABS, and 12b-1 fee ABS. More generally, whenever the credit analysis of securitized assets depends heavily on Monte Carlo simulation methods or probability-based models, we should consider the possible consequences of time-varying correlations, even if it is impractical to model such consequences explicitly. Major adjustments also may be appropriate for other analytic methods that rely on concentration limits without explicit treatment of correlations.

I. TREATMENT OF CORRELATIONS IN STRUCTURED FINANCE

Correlation was not explicitly an issue in the early years of the asset-backed securities markets. The impact of credit risk correlations among pooled consumer assets was directly visible in the performance variability of the pools. Practitioners analyzed consumer receivables on an actuarial basis and measured historical performance fluctuations at the pool level. Thus, credit risk correlation among individual assets was implicitly captured in such analyses. Estimates of expected losses and stress cases all devolved from pool-level measurements.[4]

The situation became tougher as structured finance expanded to include deals backed by small numbers of corporate or commercial credits. In such cases, it was impractical or impossible to use an actuarial approach based on the historical performance of similar pools. Analysts had to develop new techniques to estimate the credit risk of such deals. In certain cases, they turned to mathematical models and Monte Carlo simulations. Unfortunately for some investors, these techniques appear not to have fully captured important credit risk correlations. In addition, those techniques almost never addressed the issue of time-varying correlations.

Many types of market participants face the challenge of analyzing credit risk. The rating agencies, however, often set the tone and define the frameworks that others use. Our discussions of the analytic methods the rating agencies use in the four particular sectors indicate that none of the rating agencies has yet to recognize that correlations of credit risk can increase in crisis periods.

CDOs

In its early CDO rating methodologies, S&P did not explicitly focus on correlation. Instead, it considered the closely related concepts of diversification and risk concentrations ("Global CBO/CLO Criteria" [1998, pp. 35-36]). For example, the early criteria established a baseline industry concentration limit of 8%. If a deal permitted an industry concentration above that level, the rating approach would counterbalance the concentration of risk by assuming that the corresponding bonds carried ratings lower than their actual ratings. Depending on the degree of excess industry concentration, the assumed ratings could be one to three notches lower than the actual ratings.

Later, S&P changed its CDO rating methodology to include explicit treatment of correlations. The rating agency's CDO Evaluator product uses a Monte Carlo simulation approach. For CDO collateral consisting of corporate bonds, the approach assumes a constant correlation of 0.3 for companies within a given industry and no correlation among companies in different industries (Bergman [2001]).

Moody's approach to dealing with correlated risks among pools of corporate bonds traces its roots to the early 1990s (Douglas and Lucas [1989]; Lucas, Kirnon, and Moses [1991]). Then, as now, Moody's methodology assigns a *diversity score* to the pool of bonds backing a CDO. The diversity scoring approach implicitly assumes no correlation of credit risk among companies in different industries. For companies in the same industry, the degree of correlation varies depending on the number of companies and the proportion that each represents of the entire collateral pool.

Beyond the device of diversity scoring, Moody's addresses the issue of correlation caused by the general economy by stressing assumed default rates above historical rates (Lucas, Kirnon, and Moses [1991, p. 9]; Backman and O'Connor [1995, p. 11]; Gluck and Remeza [2000, p. 3]).

Fitch recently revised its CDO rating methodology to explicitly reflect interindustry correlations (Hrvatin and Peng [2003]). Fitch estimates default correlations using equity price correlations as a proxy. The development sample for Fitch's empirical correlations consists of monthly returns from October 1995 through October 2002. Correlations between industry pairs range from –0.13 to 0.93. The average correlation between industry pairs is 0.40. Although some details remain vague, Fitch's new approach seems to use Monte Carlo simulations to estimate a distribution of future credit losses.

The weaknesses of the common analytic methodologies have been identified for some time. In 1998, Skora noted that correlations and time-varying correlations threatened the sector by causing models to underpredict losses. Skora also noted that outliers and extreme events were the most important inputs for the calculation of probability distributions. Many market participants would have been better off had they been swayed by Skora's views at that time.

Aircraft ABS

S&P's aircraft ABS rating methodology considers diversification within a pool of securitized aircraft. S&P focuses particularly on the diversification of a deal's exposures among airlines (i.e., the lessees of the aircraft). S&P considers concentration limits relating to individual airlines, to groups of airlines in each rating category, and to airlines based in different countries and regions (see "Aircraft Securitization Criteria" [1999, p. 24]).

S&P models the cash flows from aircraft securitization transactions. The cash flow model assumes that two recessions occur during the life of a transaction. S&P imposes increasingly rigorous stress assumptions for securities with progressively higher ratings. Thus, for securities to attain a rating of AA, they must withstand defaults on 75%-88% of the underlying leases during the first recession and on 88%-93% of the leases during the second recession. S&P's cash flow model also assumes that aircraft can be re-leased (at somewhat lower lease rates) within a year of default.

This approach addresses correlations only indirectly.

Ultimately, it seems not to have applied enough stress to handle the impact of recent events. S&P recently stated:

> Aircraft securitizations have been under tremendous stress over the past 18 months as air traffic volume has declined significantly. The consequent negative impact on aircraft values and lease rates has caused a dramatic reduction in lease cash flows for all rated aircraft securitizations. Standard & Poor's has taken several rating actions to reflect the ability of each transaction to meet its obligations to pay note interest and principal on a timely basis. However, Standard & Poor's expects that the commencement of war in Iraq, continued risk of terrorism, and the rationalization of large airline fleets will have a further impact on asset quality and performance of these transactions (Burbage et al. [2003]).

Moody's approach to rating aircraft ABS explicitly uses Monte Carlo simulations (Tuminello and Chen [1999, p. 14]). Although Moody's describes diversification as an important factor in its aircraft ABS rating process, it does not detail how it captures diversification in the simulation process. In fact, correlation does not appear in the listing of the key simulation variables (Tuminello and Chen [1999, pp. 23-24]). Responding to recent events, Moody's has toughened some of the assumptions in its simulations of new deals (Ekmekji et al. [2003, p. 7]).

Fitch follows an approach similar to S&P's. Like S&P, Fitch uses cash flow stress scenarios (Fitch's stresses appear slightly milder than S&P's). Fitch notes that concentrations by aircraft type, country, region, and date of lease expiration will influence its cash flow stress assumptions, but it does not incorporate correlations rigorously in the methodology (Labbadia and Powell [2001]).

Franchise Loan ABS

S&P does not use a simulation approach to rate franchise loan ABS. Instead, it analyzes the fundamentals of loan pools destined for securitization. In fact, S&P notes that the analytic process may include participation by the agency's corporate ratings group ("New Assets" [1998]; Welsher [1998]). More specifically, S&P describes its methodology as follows:

> Standard & Poor's uses a three-part cash flow approach to assess the creditworthiness of a particular pool. First, Standard & Poor's analyzes obligor concentrations, then viable brands are distinguished from nonviable brands, and finally, the remainder of the pool is assessed ("New Assets" [1998], p. 76).

Although S&P's stated approach highlights the importance of obligor concentrations, it captures risk correlations through rough rules of thumb. For example:

> The cash flow stress scenario will require the largest obligor in a pool to be defaulted at the end of year one for an investment-grade rating and may require additional obligors to be defaulted over time for higher rating categories as well ("New Assets" [1998, p. 76]).

S&P also considers brand concentrations (i.e., correlation of risk among stores operating under the same franchise label) and brand viability, but the method used to capture those correlation effects is not technically rigorous.

Moody's uses a loan-by-loan Monte Carlo simulation methodology to rate franchise loan ABS. The methodology generally assumes 100% correlation of risk among properties operated by a single obligor. The approach partially captures the effect of other correlations by using time-varying default probabilities for each obligor; the default probability for each obligor doubles during periods of recession. The model assumes that recessions last for one year and occur (on average) once every five years (Chisholm and O'Connor [2000]). This approach is arguably the closest that any of the rating agencies has come to explicitly using a time-varying correlation mechanism in its analysis.

Fitch uses a two-part model to analyze the credit risk of franchise loan ABS. One of the two parts is the Fitch Concentration Model, which "measures borrower concentration risks and provides detailed analysis of the quality of the collateral as the main drivers for losses within a given pool" (Wells et al. [2001, p. 3]). The other part of the model is a loan default and recovery model, which seems not to address correlation issues. Fitch argues that:

> The synergies provided by the two-step process allow for a more comprehensive analysis, as a borrower default approach with varying recovery rates applied does not give effect to poorly underwritten loans. Similarly, a purely statistical analysis applied on an individual loan-level does not give effect to borrower concentration risks within a given pool (Wells et al. [2001, pp. 3-4]).

Fitch's correlation model works by analyzing the impact of multiple borrower defaults on a transaction. Fitch ranks borrower exposures by the order of the projected net losses that would result from each borrower's default. Then, depending on the target rating level for the related securities, Fitch stresses the transaction cash flows by assuming that the borrowers at the top of the ranking all default.

Fitch does not use a constant number of top exposures that it assumes will default under the stress scenarios associated with different rating levels. Rather, it varies the assumed number of defaulting exposures depending on the overall quality of the underlying pool (presumably more exposures are assumed to default in weaker pools). Thus, Fitch's approach seems to be based on concentration limits that are allowed to vary by overall pool quality.

The tough experience of the franchise loan sector has driven the evolution of Fitch's analytic process. In a spirit of caution, Fitch:

> views the use of analytical modeling in developing ratings for franchise transactions as an ongoing evolutionary process and continues to evaluate the need for refinements based on changing market demands (Wells et al. [2001, p. 5]).

Mutual Fund 12b-1 Fee ABS

All three of the U.S. rating agencies use a Monte Carlo simulation approach to analyze ABS backed by mutual fund 12b-1 fees (Erturk [2000a]; Dill [1998, p. 8]; Sharifi-Mehr et al. [1999, p. 5]). In describing its rating approach to 12b-1 fee ABS, S&P specifically notes correlation issues several times. It stops short of addressing correlation as an issue that can drive the severity of a bear market.

In fact, S&P seems to hold a contrary view:

> Aside from the long bear market of the early 1970s, typically, the equity market and well-managed equity funds tend to generate positive expected returns in the long run. For example, the market crash of 1987 and the liquidity crunch observed during the fall of 1998 both provide evidence that the duration of market dislocations or corrections is limited, and both support the intuition that the market risk is minimized when the investment horizon is long enough (Erturk [2000a]).

Shortly after the U.S. equity markets started their decline, S&P published a short (but ill-timed) report asserting that securitizations of mutual fund 12b-1 fees do not display greater credit volatility than ABS backed by other asset classes (Erturk [2000b]).

Moody's does not explicitly address correlations in its 12b-1 fee Monte Carlo approach. It initially illustrates the application of its simulation methodology using the 1929 and 1987 crashes (Dill [1998, p. 8]). Then, in an apparent reversal, the rating agency seemingly rejects the implications of those events and instead simply uses a mutual fund's own historical returns as the main basis for simulating its future performance (Dill [1998, p. 10]).

Fitch's approach, like S&P's and Moody's, highlights Monte Carlo simulation as a preferred tool for assessing credit risk in securitizations of mutual fund 12b-1 fees. Unlike the other rating agencies, Fitch explicitly addresses the varying correlations among different sectors (Sharifi-Mehr et al. [1999, p. 5]). The methodology does not employ time-varying correlations.

Summary of Correlation Treatments

Exhibits 1 and 2 summarize the rating agencies' treatment of correlation issues in their analyses of CDOs, aircraft ABS, franchise loan ABS, and 12b-1 fee ABS. While Monte Carlo simulation has become a prime tool of analysis in these areas, the issue of time-varying correlations has not received any significant attention.

II. PRACTICAL IMPLICATIONS AND POSSIBLE SOLUTIONS

Investors should reasonably expect to be paid for model risk. All else equal, they should favor deals that are less subject to model risk. This suggests an advantage in favor of ABS backed by assets that can be analyzed actuarially.

Even if it is impractical to precisely quantify correlation-related model risks, it generally is possible to outline their boundaries. Diversification should always have a positive impact on the credit quality of pooled assets. Thus, the lower bound of credit quality for a pool ought to be the weighted-average credit quality of its constituent parts. The overall credit quality of a pool of triple-B-rated assets ought to be *at least* triple-B. Adding credit enhancement ought to boost the credit quality further. Difficulties arise only when we overestimate the combined beneficial effects of diversification and credit enhancement.

We can quantify the impact of underestimating correlation effects by using simulations. Suppose a pool consists of 100 assets: $x_1, x_2, x_3, \ldots, x_{100}$. Suppose further that

EXHIBIT 1

Use of Monte Carlo Simulations in Credit Analysis

Sector	CDOs	Aircraft ABS	Franchise Loan ABS	12b-1 Fee ABS
Standard & Poor's	✔	✗	✗	✔
Moody's	✗	✔	✔	✔
Fitch	✔	✗	✗	✔
✔ = used. ✗ = not used.				

EXHIBIT 2

Treatment of Credit Risk Correlation Issues

Sector	CDOs	Aircraft ABS	Franchise Loan ABS	12b-1 Fee ABS
Standard & Poor's	Static correlations in Monte Carlo simulation	Concentration limits	Analysis of obligor and brand concentrations	Unspecified treatment of correlation in Monte Carlo simulation
Moody's	Diversity scores	Unspecified treatment of correlation in Monte Carlo simulation	Unspecified treatment of correlation in Monte Carlo simulation	Unspecified treatment of correlation in Monte Carlo simulation
Fitch	Static correlations in Monte Carlo simulation	Concentration limits	Concentration limits	Static correlations in Monte Carlo simulation

each asset has a 90% chance of paying \$1 and a 10% chance of paying nothing. For differing degrees of correlation among the assets, we can simulate the performance of the pool and then examine the results.[5]

Exhibit 3 shows the results of such an exercise. Each series plotted in Exhibit 3 shows the distribution of simulation outcomes for a different correlation coefficient. Each distribution reflects the relative frequency with which different numbers of assets defaulted in the simulation.

For example, the first series in Exhibit 3 shows the distribution of outcomes when there is no correlation among the assets ($\rho = 0$). The peak of that distribution is at 10 (i.e., 10 assets in the pool default), and there are no cases when more than 20 assets default. The second series shows the distribution of outcomes with a correlation of 0.05 between each pair of assets. Increasing the correlation to 0.05 causes more than 20 assets to default in a number of cases. The other series in the chart show that higher correlations cause the tails of the distributions to thicken and create notably frequent large numbers of defaults.

Notice that the mode (most frequent number) in the last series ($\rho = 0.60$) is at 0. This means that when correlation is highest, the most frequent outcome is that none of the assets defaulted. The tail of the distribution, however, is the thickest. Close examination of the tails of the respective series shows that they consistently get thicker as correlation increases.

We can also consider the simulation results in terms of their extremes. We can examine how the 99th percentile (and other levels) shifts because of correlations. Exhibit 4 shows the results.

The last four lines of Exhibit 4 reveal that extreme outcomes become possible (and even common) when there is correlation of default risk among the assets in a pool. In the case of no correlation, the 99.9th percentile level is 19 defaults. For a correlation of 0.25, however, the 99.9th percentile has 65 defaults. The difference is quite important. If credit enhancement for a pool had been sized to cover the 99.9th percentile assuming no correlation, the enhancement would be insufficient more than 10% of the time if the real correlation were 0.25.

We can observe the correlation effects even more starkly when the probability of each asset defaulting is somewhat lower. Repeating the same simulation process, but assigning each asset a 3% probability of default, produces the results shown in Exhibit 5.

Suppose that the simulated assets of Exhibit 5 back a CDO. Suppose further that the triple-A tranche is sup-

EXHIBIT 3

Simulation Results—Distribution of Portfolio Losses at Different Correlation Levels
(100 assets, 10% default rate)

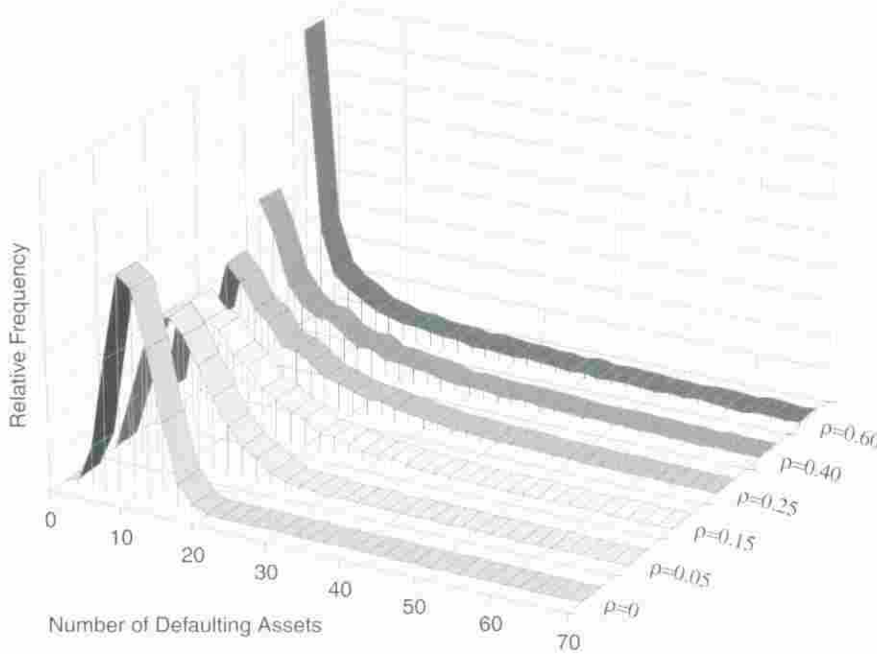

EXHIBIT 4

Distribution of Portfolio Losses at Different Correlation Levels
(100 assets, 10% probability of default)

Simulation Correlation Coefficient	$\rho = 0$	$\rho = 0.05$	$\rho = 0.15$	$\rho = 0.25$	$\rho = 0.40$	$\rho = 0.60$
Mean	10.00	10.00	10.00	10.00	10.00	10.00
Variance	8.76	24.88	63.21	103.79	185.90	295.14
Standard Dev.	2.96	4.99	7.95	10.19	13.63	17.18
90^{th} Percentile	14	17	20	24	27	32
95^{th} Percentile	15	19	26	31	39	49
99^{th} Percentile	17	24	36	46	64	80
99.5^{th} Percentile	18	27	41	51	72	89
99.9^{th} Percentile	19	31	51	65	86	97

posed to have sufficient credit enhancement to survive a 99.9th percentile stress. Assuming no correlation implies that 9% credit enhancement—three times the expected losses—would be sufficient to support the triple-A tranche. Assuming a slight correlation of 0.05 implies that the triple-A tranche would need 15% credit enhancement—five times expected losses. If the real correlation is higher, however, say, 0.25 or 0.40, the necessary level of credit enhancement would rise to 39% or 50%—13 times and 17 times expected losses.

To make the example more realistic, we can introduce the notion that the severity of loss following a default is less than 100%. For example, we can assume that the expected severity of loss is 35% and that the stressed severity for purposes of triple-A enhancement (99.9th percentile) is 70%. In that case, we would adjust the values from Exhibit 5 to produce Exhibit 6. Exhibit 6 shows that using higher assumed loss severities in the stressed case increases the implied multiple of expected losses that must be covered to support the triple-A tranche.

EXHIBIT 5

Distribution of Portfolio Losses at Different Correlation Levels
(100 assets, 3% probability of default)

Simulation Correlation Coefficient	$\rho = 0$	$\rho = 0.05$	$\rho = 0.15$	$\rho = 0.25$	$\rho = 0.40$	$\rho = 0.60$
Mean	3.00	3.00	3.00	3.00	3.00	3.00
Variance	2.83	5.50	11.89	21.67	36.88	73.64
Standard Dev.	1.68	2.34	3.45	4.66	6.07	8.58
90^{th} Percentile	5	6	7	8	9	8
95^{th} Percentile	6	8	10	12	14	18
99^{th} Percentile	7	10	16	23	31	48
99.5^{th} Percentile	8	11	18	29	37	58
99.9^{th} Percentile	9	15	25	39	50	76
99.9^{th} Percentile ÷ Mean	3.00	5.00	8.33	13.00	16.67	25.33

EXHIBIT 6

Distribution of Portfolio Losses at Different Correlation Levels—Variable Loss Severity
(100 assets, 3% probability of default)

Simulation Correlation Coefficient	$\rho = 0$	$\rho = 0.05$	$\rho = 0.15$	$\rho = 0.25$	$\rho = 0.40$	$\rho = 0.60$
Mean (35% severity)	1.05	1.05	1.05	1.05	1.05	1.05
99.9^{th} Percentile (70% severity)	6.30	10.50	17.50	27.30	35.00	53.20
99.9^{th} Percentile ÷ Mean	6.00	10.00	16.67	26.00	33.33	50.67

The extent of these correlation effects suggests that flawed assumptions about correlation can cause practitioners to greatly underestimate the risk of pooled assets. And, the prevailing methods of credit analysis for CDOs, aircraft ABS, franchise loan ABS, and 12b-1 fee ABS place only modest emphasis on correlations. The techniques for analyzing CDOs have relied particularly on the assumption that there is no interindustry correlation of credit risk. In light of actual experience, that assumption now seems unreasonable.

Moreover, even if the *average* degree of correlation among pooled assets is modest (e.g., $\rho = 0.15$), potentially higher correlations during periods of crisis can make bad situations worse. Recent experience with CDOs and the troubled ABS sectors clearly has shown that exogenous forces can temporarily increase correlations. Thus, even if one can successfully measure the overall correlation among pooled assets, a key piece of information may still be missing. The time-varying correlation effects can produce the same level of downside risk as the higher stable correlations.

Given the strong influence of correlation on the number of defaulting assets in the simulation pools, the true credit quality of many CDO senior tranches is arguably somewhat weaker than indicated by their triple-A ratings. Although it may be impractical to precisely peg the true degree of correlation (and time-varying correlation effects) in CDO collateral pools, it surely is fair to conclude that the extent of such effects is sufficient to push the true credit quality of CDO senior tranches into the double-A or single-A risk levels.

Few, if any, would have credit quality at lower levels, because the credit quality of a CDO senior tranche should always be *at least as strong as* the weighted-average credit quality of the underlying pool. From that starting point, diversification always has a positive influence.

Going forward, we should have a variety of alternatives to address the weaknesses of the typical analytic approaches. For methodologies that rely on Monte Carlo simulations, the cleanest solution would be to explicitly provide for correlations and for time-varying correlations among assets in securitized pools (although doing so may be impractical because of data limitations). Directly measuring credit risk correlations is difficult. Measuring the time-varying character of such correlations would be even more difficult. The reliability of such measurements might be questionable.

Another alternative could be to combine the methods described by Longin [2000] with those described by Kim and Finger [2000]. Such an approach would use a two-state model (i.e., regular conditions and crisis conditions), and draw on observations from past crisis times to estimate the distribution of outcomes in future crises. Past crisis times could be defined by strictly quantitative criteria, but a heuristic approach might be better.

For example, for deals backed by mutual fund 12b-1 fees, crisis times might include all the significant stock market declines on record.[6] For aircraft deals, crisis times could include times aircraft prices were depressed. In addition, because the air travel industry has experienced only a limited number of stressful episodes, it should be appropriate also to use data about crisis periods in the shipping and railroad industries.

Using the estimated distribution of outcomes in future crises, practitioners might be able to price credit risk more accurately and to set credit enhancement levels more reliably. The danger in such an approach is the temptation to use less than *all* available historical data. Using only a portion of available data might exclude extreme historical outcomes, causing the tails of the estimated distributions to be too thin. In essence, this approach is similar to ordinary stress-testing with the added feature of a rigorous basis for defining stress cases.[7]

Simply using tougher loss assumptions or higher assumed correlations might offer a third alternative, but it is not exactly clear how much higher losses or assumed correlations would need to be to counterbalance the weaknesses of the established approaches. Overly conservative assumptions would make structures uneconomical.

III. CONCLUSION

As a general matter, we should remain ever vigilant of overreliance on models. Some of the problems in evaluating asset performance risks will not readily lend themselves to quantitative models.

As Keynes observed in 1936:

> The object of our analysis is, not to provide a machine, or method of blind manipulation, which will furnish an infallible answer, but to provide ourselves with an organised and orderly method of thinking out particular problems; and, after we have reached a provisional conclusion by isolating the complicating factors one by one, we then have to go back on ourselves and allow, as far as we can, for the probable interactions amongst the factors themselves. This is the nature of economic thinking. Any other way of applying our formal principles of thought (without which, however, we shall be lost in the wood) will lead us into error. It is a great fault of symbolic pseudo-mathematical methods of formalising a system of economic analysis… that they expressly assume strict independence between factors involved and lose all their cogency and authority if this hypothesis is disallowed; whereas, in ordinary discourse, where we are not blindly manipulating but know all the time what we are doing and what the words mean, we can keep "at the back of our heads" the necessary reserves and qualifications and adjustments which we shall have to make later on, in a way in which we cannot keep complicated partial differentials "at the back" of several pages of algebra which assume that they all vanish. Too large a proportion of recent "mathematical" economics are mere concoctions, as imprecise as the initial assumptions they rest on, which allow the author to lose sight of the complexities and interdependencies of the real world in a maze of pretentious and unhelpful symbols (Keynes [1936, pp. 297-298]).

Finance professionals can take comfort in knowing that professionals in other technical disciplines face similar challenges—sometimes for even higher stakes. For example, regarding the proposed nuclear waste repository at Yucca Mountain, Nevada, Nadis reports the following:

> In this case, the Environmental Protection Agency has set the annual exposure limit of 15 millirems (about a third the strength of a medical x-ray) measured at 18 kilometers from the repository over 10,000 years. Satisfying this standard rests on a probabilistic assessment that incorporates thousands of assumptions—an approach never before applied to such a complex system. Some parameters (such as the density of water) are well known; others (such as the likelihood of volcanic activity) vary by a factor of 100,000. No one has figured out how to combine all these uncertainties ….
>
> The mathematical approach … keeps us from seeing how the individual components are working. For example, much stock is being placed in Alloy 22, a relatively untested metal that is supposed to confine wastes over the long haul. The corrosion rate for the alloy depends on geochemical condi-

tions—such as the pH and carbon dioxide content of the groundwater—that are inherently difficult to predict. "We're betting on a new material about which we know little, while making optimistic assumptions about its behavior under conditions we can only guess at," [a scientist] states. "Uncertainties throughout the model are rolled together, which makes it hard to tell whether any of the barriers are effective" (Nadis [2003, pp. 48-49]).

Identifying problems or weaknesses is the first step in correcting them. Correlations and time-varying correlations and related model risks offer a reasonable explanation for the recent poor credit performance of certain areas of the structured finance market. If the structured finance community confronts and achieves some measure of success in tackling the problems stemming from correlations and time-varying correlations, the market can reasonably expect smoother sailing in the future. If not, the shortcomings of concentration limit rules and of current Monte Carlo simulation techniques will keep a spotlight on the issue of model risk indefinitely.

Unless and until the the sell-side addresses the analytic weaknesses (model risk) associated with CDOs, aircraft ABS, franchise loan ABS, and 12b-1 fee ABS, deals in those sectors will remain under a cloud. Investors will reasonably demand wider spreads for deals from those sectors. Investors will favor deals enabling the assessment of the credit risk of underlying assets with an actuarial analysis.

ENDNOTES

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[1]Monte Carlo simulation generates random numbers as the inputs to a modeled process and then observes the distribution of results over many trials. The technique is most useful for obtaining numerical solutions to problems that are too complicated to solve analytically (see Weisstein [1999]).

[2]Some ABS are backed by the projected cash flows from the so-called 12b-1 fees that some mutual funds charge their investors (Dill [1998]).

[3]Actuarial methods of credit analysis use abundant historical data on the actual performance of assets over the long term. Ideally, the data span multiple business cycles and reveal how performance varies under a wide range of economic conditions and in response to unexpected shock events.

[4]If the credit performance on individual assets had been independent and identically distributed (iid), the pools would have displayed only infinitesimal credit performance volatility because of the large number of individual assets—thousands in the case of auto loan ABS and even more in the case of credit card ABS.

Consider a hypothetical $100 million pool of 100,000 credit card receivables. Each receivable is $1,000 and has a 95% probability of not defaulting. Each receivable has 5% probability of defaulting and of being charged off. The distribution of charge-offs on the whole pool is described by a binomial distribution. Clearly, the expected charge-off rate for the whole pool would be 5%, or $5 million. The standard deviation of the distribution would be $68,920, given by the formula:

$$\sigma = \sqrt{\$1{,}000 \times 100{,}000 \times 5\% \times 95\%}$$

That is, the standard deviation of losses would be roughly 0.0689% of the pool balance, and three standard deviations would be about 0.207%. Thus, the odds of charge-offs varying from 5% by more than 0.207% would be only around 1 in 100. The real-world fluctuations are substantially greater, clearly implying that individual receivables are correlated with one another.

[5]We use software from Palisade Corporation for the simulations. Each simulation consists of 5,000 iterations. Each value of ρ is addressed in a separate simulation.

[6]1903, 1907, 1917, 1929-1932, 1937, 1962, 1966, 1973-1974, 1987, and 2001-2002.

[7]Ross [2002] contends that model builders need to look at more scenarios—especially negative ones—than they have been. To design scenarios, model builders need to look beyond recent observations and statistics. Ross contends that model builders should consider all the bad things that have ever happened in all different countries over extended periods. In essence, he encourages looking beyond statistics to economic history.

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