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What a Coincidence?

One Reason Why CDOs and ABS Backed by Aircraft, Franchise Loans, and 12b-1 Fees Performed Poorly in 2002

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Executive Summary

Investors should more strongly favor deals where credit risk is analyzed by actuarial methods.[1] Such deals include not only those backed by the mainstream ABS/MBS asset classes – mortgage loans, credit cards, auto loans, and student loans – but also certain deals backed by off-the-run assets. Such deals will generally benefit from having less model risk than deals where credit risk is analyzed by Monte Carlo simulations[2] or similar techniques that rely on many assumptions.

Model risk partly explains the poor credit performance of certain sectors of the structured finance markets in 2001 and 2002: (*i*) CDOs, (*ii*) aircraft ABS, (*iii*) franchise loan ABS, and (*iv*) mutual fund 12b-1 fee ABS. Credit risks in those types of deals are analyzed with Monte Carlo simulations or other non-actuarial methods. Those analytic tools have inadequately addressed *correlations* of risk among assets within a pool. Those tools also fall short in addressing the more subtle effects of "time-varying correlations" – correlations that change with the passage of time.

Investors reasonably can demand to be compensated for model risk. It is entirely real but hard to measure. Accordingly, the mainstream asset class may become increasingly appealing to investors. Also, off-the-run asset classes that readily lend themselves to analysis by the actuarial approach should tend to grow in appeal.

We expect spreads on securities from the troubled sectors to remain wide. Arguably they should be even wider than they are. We also expect that rating agencies will experience pressure to raise credit enhancement levels in order to avoid a repeat of last year's experience.

It may be possible to correct or improve the analytic methods used in the troubled sectors listed above. Recent academic literature hints at techniques that may show promise. However, implementing such techniques will pose challenges and may not provide complete solutions.

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

[2] A Monte Carlo simulation is a technique for solving a problem by generating random numbers as the inputs to a modeled process and then observing 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. (Weisstein, 1999).

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I. Introduction

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. However, some risks lend themselves to analysis more readily than others. One that continually presents formidable challenges is model risk, the risk that a model does not sufficiently describe reality to produce reliable results.

Over the past two years, certain areas of the securitization market have suffered disappointing levels of defaults and credit deterioration. In particular, the CDO, aircraft ABS, franchise loan ABS, and 12b-1 fee ABS sectors have been hammered by unprecedented volumes of downgrades.

A common theme running through those 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. Economic 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 such linkage can change with the passage of time. However, Monte Carlo simulations and other analytic techniques used for analyzing the credit risks of CDOs, aircraft ABS, franchise loan ABS, and 12b-1 fee ABS sometimes do not address linkages in a rigorous manner and generally do not reflect changing degrees of linkage at all. This shortcoming may have caused those techniques to under-predict the level of losses under recent stressful conditions – model risk coming home to roost.

CDOs: In the CDO sector, both S&P and Moody's took record numbers of downgrade actions in 2002 (Elengical et al., 2003; Tung, 2003; Fu and Harris, 2003; Nazarian et al., 2003). Moody's took downgrade actions on CDOs 747 times during the year. Moody's rating actions hit 471 of the 4921 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. However, neither probes more deeply and addresses the question of why defaults and downgrades in the corporate bond market reached their 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 9/11/01. Air travel has declined. As a result, lease rates on aircraft have declined and many aircraft have been retired from service before the end of their engineered lifespans. However, the underlying causes are older, namely geopolitical conflict and terrorism. Naturally, those causes can produce strong correlation effects through 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 that occurred 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 from 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:[3] 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 intra-day high of 11,909 on 14 January 2000; the S&P 500 reached an intra-day high of 1,553 on 24 March 2000; the NASDAQ reached an intra-day high of 5,133 on 10 March 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, thirty years ago, the S&P 500 lost roughly half its value, falling from an intra-day high of 121.74 on 11 January 1973 to an intra-day low of 60.96 on 4 October 1974. That decline had a fundamental cause, namely 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 intra-day high of 38,957 on 29 December 1989. The Nikkei has been falling ever since, and it recently reached an intra-day low of 7,661 on 25 April 2003. Many finance professionals now characterize the late 1980s run-up in the Nikkei as a "bubble." Regardless of whether bursting bubbles or fundamental stresses cause a market decline, either can effect *many* stocks simultaneously and, therefore, generate notable positive correlations in bear markets.

Model risk has proven itself a significant issue for structured finance. As structured finance professionals increasingly realize the effects of model risk, deals backed by assets for which credit risk can be analyzed with relatively simple actuarial methods will be more strongly favored. Such deals included 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 for analyzing 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 within 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, professionals 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.

The remainder of this paper is organized as follows: Part II describes some of the most common approaches used in for analyzing the credit risk in CDOs, aircraft ABS, franchise loan ABS, and 12b-1 fee ABS. Part III recaps some of the practical implications and proposes possible solutions. Part IV concludes. The appendix provides a background discussion on correlation in theory and in practice.

[3] 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)

II. Treatment of Correlations in Structured Finance

Correlation was not explicitly an issue in the early years of the ABS markets. The impact of credit risk correlations among pooled consumer assets was directly visible in the performance variability of the pools.[4] Structured finance professionals 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.

However, 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." Structured finance professionals had to develop new techniques for estimating the credit risk of such deals. In certain cases, they turned to mathematical models and Monte Carlo simulations. Unfortunately for some investors, those 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. However, among all the types, rating agencies often set the tone and define the frameworks that others use. Therefore, we will next consider analytic methods used by the rating agencies in the four sectors identified above: (*i*) CDOs, (*ii*) aircraft ABS, (*iii*) franchise loan ABS, and (*iv*) ABS backed by 12b-1 mutual fund fees. As detailed below, none of the rating agencies has yet to include the notion that correlations of credit risk can increase in crisis periods.

A. CDOs

In its early CDO rating methodologies, S&P did not explicitly focus on correlation. Instead, the rating agency considered the closely-related concepts of diversification and risk concentrations (Global CBO/CLO Criteria, 1998, pp. 35-36). For example, the early criteria establish 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 for dealing with correlated risks among pools of corporate bonds traces its roots back to the early 1990s (Lucas et al., 1991). Then, as now, Moody's methodology assigns a "diversity score" to the pool of bonds backing a CDO. The diversity scoring approach implicitly

[4] If the credit performance on individual assets had been independent and identically distributed (i.i.d.), 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. For example, 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: $s = \$1{,}000 \times \sqrt{100{,}000 \times 5\% \times 95\%}$. 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 larger, clearly implying that individual receivables are correlated with each other.

assumes no correlation of credit risk among companies in different industries. For companies in the same industry, the degree of correlation varies based 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 et al., 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 inter-industry correlations (Hrvatin and Peng, 2003). Fitch estimates default correlations by 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 as a tool for estimating a distribution of future credit losses.

The weaknesses of existing analytic methodologies have been identified for some time. In 1998, Skora (1998) noted that correlations and time-varying correlations threatened the sector by causing models to under-predict 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 when they were published.

B. 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. (Aircraft Securitization Criteria, 1999, p.24).

S&P models the cash flows from aircraft securitization transactions. The cash flow model assumes that two depressions occur during the life of a transaction. S&P imposes increasingly harsh 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 depression and on 88%-93% of the leases during the second depression. However, S&P's cash flow model also assumes that aircraft can be re-leased (at somewhat lower lease rates) within a year of default.

The 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, in the listing of the "key simulation variables," correlation does not appear. (Tuminello and Chen, 1999, pp.23-24). However, responding to recent events, Moody's has toughened some of the assumptions that it uses in its simulations for 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. However, correlations are not incorporated rigorously in the methodology (Labbadia, 2001).

C. Franchise Loan ABS

S&P does not use a simulation approach to rating franchise loan ABS. Instead, the rating agency 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; Welsher, 1998).

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 of capturing those correlation effects is not technically rigorous.

Moody's uses a loan-by-loan Monte Carlo simulation methodology for rating 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. For purposes of the time-varying mechanism, 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 arguably is 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 for analyzing 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 the 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, Fitch varies the assumed number of defaulting exposures based 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 depending on overall pool quality.

The tough experience of the franchise loan sector had driven evolution of Fitch's analytic process. In the 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).

D. Mutual Fund 12b-1 Fee ABS

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

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, 2000a).

Moody's does not explicitly address correlations in its 12b-1 fee Monte Carlo approach. Moody's initially illustrates the application of its simulation methodology using the 1929 and 1987 crashes (Dill, 1998, p.8, n.24). 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, p10).

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. In contrast to 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.

E. Summary of Existing Correlation Treatments

The following two tables summarize the rating agencies' treatment of correlation issues in their analyses of CDOs, aircraft ABS, franchise loan ABS, and 12b-1 fee ABS. As shown in the tables, Monte Carlo simulation has become a prominent tool for analysis in those areas, but the issue of time-varying correlations has not received any significant attention:

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				

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

III. Practical Implications and Possible Solutions

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

Second, 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. Thus, 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.

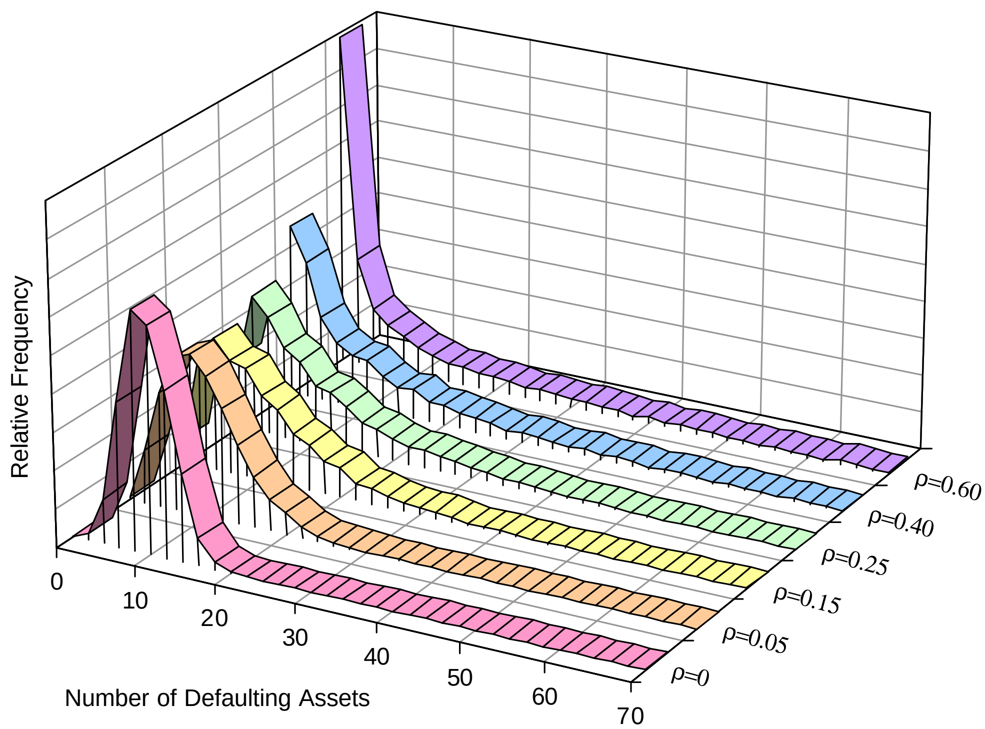
We can quantify the impact of underestimating correlation effects by using simulations. Suppose a pool consists of 100 assets: x_1, x_2, x_3… x_{100}. Suppose further that each asset has a 90% chance of paying \$1 and a 10% chance of paying \$0. For differing degrees of correlation among the assets, we can simulate the performance of the pool and then examine the results.[5] The chart below shows the results of such an exercise. Each series in the chart 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 front-most series shows the distribution of outcome where there was no correlation among the assets (r=0). That peak of the distribution is at 10 (*i.e.*, 10 assets in the pool default) and there were no cases where more than 20 assets defaulted. The second series shows the distribution of outcomes with a correlation of 0.05 between each pair of assets. The second series shows that increasing the correlation to 0.05 caused 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 occurrences of large numbers of defaults.

Notice how the "mode" (most frequent number) in the rear-most series (r=0.60) is at 0. This means that when correlation was highest, the most frequent outcome was that none of the assets defaulted. However, the tail of the distribution is the thickest. Close examination of the tails of the respective series shows that they consistently get thicker as correlation increases.

[5] We ran the simulations using @Risk software from Palisade Corporation. Our simulations consisted of 5,000 iterations each. We ran a separate simulation for each value of r.

Simulation Results: Distribution of Portfolio Losses at Different Correlation Levels
(100 Assets, 10% Default Rate)



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. The following table shows the results:

Distribution of Portfolio Losses at Different Correlation Levels
(100 Assets, **10%** Probability of Default; Simulation Results-Descriptive Statistics)

simulation correlation coefficient	r **= 0**	r **= 0.05**	r **= 0.15**	r **= 0.25**	r **= 0.40**	r **= 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
90th percentile	14	17	20	24	27	32
95th percentile	15	19	26	31	39	49
99th percentile	17	24	36	46	64	80
99.5th percentile	18	27	41	51	72	89
99.9th percentile	19	31	51	65	86	97

Note: The variances calculated from the simulation runs are smaller than they "should be" based on the discussion in the appendix. For any value of the correlation coefficient (r), the variance of the number of defaulting assets should be $[p(1\text{-}p)]\times[n+n(n\text{-}1)r]$. The sample variances of the simulation runs imply ***lower*** theoretical correlations than indicated by the coefficients listed in the top row. For example, the variance of 24.88 in the column labeled r=0.05 implies a theoretical correlation coefficient of 0.018. The corresponding values for the other columns are as follows: 0.061 for r=0.15, 0.106 for r=0.25, 0.199 for r=0.40, and 0.321 for r=0.60. This effect is by-product of the simulation process. Thus, the distributions shown in the chart and the percentiles reported in the table reflect smaller numbers of defaults than would produced by an "ideal" process. The difference produces an *optimistic* bias in the reported simulation results. This seems to be yet another example of model risk.

The last four lines of the table reveal that extreme outcomes become possible (and even frequent) 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. However, for a correlation of 0.25, 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 following results:

Distribution of Portfolio Losses at Different Correlation Levels (100 Assets, **3%** Probability of Default; Simulation Results-Descriptive Statistics)						
simulation correlation coefficient	***r* = 0**	***r* = 0.05**	***r* = 0.15**	***r* = 0.25**	***r* = 0.40**	***r* = 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
90th percentile	5	6	7	8	9	8
95th percentile	6	8	10	12	14	18
99th percentile	7	10	16	23	31	48
99.5th percentile	8	11	18	29	37	58
99.9th percentile	9	15	25	39	50	76
99.9th percentile ÷ mean	3.00	5.00	8.33	13.00	16.67	25.33

Suppose that the simulated assets back a CDO. Suppose further that the triple-A tranche is supposed 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. However, if the real correlation is higher, say 0.25 or 0.40, the necessary level of credit enhancement would rise to 39% or 50% – thirteen times and seventeen times expected losses, respectively.

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 in the preceding table as follows:

Distribution of Portfolio Losses at Different Correlation Levels (100 Assets, **3%** Probability of Default; Variable Loss Severity)						
simulation correlation coefficient	***r* = 0**	***r* = 0.05**	***r* = 0.15**	***r* = 0.25**	***r* = 0.40**	***r* = 0.60**
mean (35% severity)	1.35	1.35	1.35	1.35	1.35	1.35
99.9th percentile (70% severity)	6.60	10.50	17.50	27.30	35.00	53.20
99.9th percentile ÷ mean	4.67	7.78	12.96	20.22	25.93	39.41

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.

The magnitude of the correlation effects shown above suggests that flawed assumptions about correlation can cause structured finance professionals to greatly underestimate the risk of pooled assets. As discussed in part II, the prevailing methods of credit analysis for CDOs, aircraft ABS, franchise loan ABS, and 12b-1 fee ABS place only modest emphasis on correlations. In particular, certain techniques for analyzing CDOs have relied on the assumption that there is no inter-industry 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.*, *r*=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.

Based on the strong influence of correlation on the number defaulting assets in the simulation pools, we believe that the credit quality of many CDO senior tranches is 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 arguably is fair to conclude that the magnitude of such effects is sufficient to push true credit quality of CDO senior tranches into the double-A or single-A risk levels. We do not expect that many 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, structured finance professionals will have a variety of alternatives for addressing the weaknesses of existing 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. However, doing so may be impractical because of data limitations. Directly measuring credit risk correlations is a difficult exercise. 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 combining the methods described by Longin (2000) with those described by Kim and Finger (2000).[6] 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, in the context of deals backed by mutual find 12b-1 fees, crisis times might include all the significant stock market declines on record.[7] For aircraft deals, crisis times could include periods in which aircraft prices were depressed. In addition, because the air travel industry has experienced only a limited number of stressful episodes, it arguably would be appropriate also to use data about crisis periods in the shipping and railroad industries. Using the estimated distribution of outcomes in future crises, structured finance professionals might be able to price credit risk more accurately and to set credit enhancement levels more reliably. However, the danger with 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 estimated distributions to be too thin.[8] In essence, this approach is similar to ordinary stress testing with the added feature of a rigorous basis for defining stress cases.

Simply using tougher loss assumptions or simply higher assumed correlations[9] might offer a third alternative. However, it is not exactly clear how much higher losses or assumed correlations would need to be to counterbalance the weaknesses of the existing approaches. Overly conservative assumptions would make structures uneconomical.

[6] See the appendix for a further discussion of the referenced papers.

[7] 1903 (Rich Man's Panic), 1907 (Panic of 1907), 1917, 1929-32, 1937, 1962, 1966, 1973-74, 1987, 2001-2002.

[8] Remarks of Prof. Stephen Ross of the Massachusetts Institute of Technology, keynote address at a conference titled Risk Management: The State of the Art (13 Jan 2000, at New York University Leonard Stern School of Business). Ross contends that model builders need to look at more scenarios – especially negative ones – than they have been. In addition, in designing 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.

[9] *E.g.*, lower diversity scores in the case of Moody's CDO methodology or positive inter-industry correlations in S&P's CDO Evaluator.

IV. Conclusion

As a general matter, structured finance professionals should remain ever vigilant of over-reliance on models. Some of the problems that they face 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 hypothosis 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.297-98).

Finance professionals can take comfort in knowing that professionals in other techinical disciplines face similar challenges – sometimes for even higher stakes. For example, regarding the proposed nuclear waste repository at Yucca Mountain, Nevada, a recent article 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, Ewing notes.
>
> The mathematical approach, in his opinion, 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 conditions – 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," Ewing states. "Uncertainties throughout the model are rolled together, which makes it hard to tell whether any of the barriers are effective." (Nadis, 2003)

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 can expect smoother sailing in the future. If not, the shortcommings of "concentration limit" rules and of existing 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 from those sectors will remain under a cloud. Investors reasonably will demand wider spreads for deals from those sectors. Investors will favor deals where the credit risk of underlying assets can be fairly assessed with an actuarial analysis.

Appendix: Correlation in Theory and in Practice

Experience shows us that events in the everyday world are linked. Statisticians measure and describe the degree of interdependence between events by means of a statistic called the *correlation coefficient*, which is customarily represented with the Greek letter Rho (r). More formally, the correlation coefficient measures how closely two random variables co-vary. A correlation coefficient can have a value from -1 to 1. A correlation coefficient of -1 means that two variables move in opposite directions. A correlation coefficient of 1 means that the two variables always move together. A correlation coefficient of 0 means that the two variables are uncorrelated.[10]

When events display strong correlation, there may be a causal relationship between them. For example, at baseball games, hotdog sales and mustard consumption show a strong correlation. On the other hand, sometimes the presence of strong correlation between two events is merely coincidental or reflects a linkage to a third event which may be hidden. For example, there is a strong positive correlation between the size of a person's foot and the size of his vocabulary.[11]

A correlation coefficient describes only the *overall* degree of linkage between two events. The calculation of a correlation coefficient, in effect, describes the *average* degree of linkage between

[10] In practice, one calculates a correlation coefficient from a series of observations of two events. For example, the two series could be the daily price movements of two stocks. If the price movements of the first stock are represented by x_1, x_2, …, x_n, and the price movements of the second are represented by y_1, y_2, …, y_n, then the correlation coefficient describing the relationship between the price movements of the two stocks is calculated as follows:

$$r_{xy} = \frac{\mathrm{Cov}(x,y)}{s_x s_y} = \frac{n\sum_{i=1}^{n}(x_i - m_x)(y_i - m_y)}{\sqrt{n\sum_{i=1}^{n}x_i^2 - \left(\sum_{i=1}^{n}x_i\right)^2} \times \sqrt{n\sum_{i=1}^{n}y_i^2 - \left(\sum_{i=1}^{n}y_i\right)^2}}$$

where:

$r_{x,y}$	=	the coefficient of correlation between x and y
Cov(x,y)	=	the covariance between x and y
s_x	=	the standard deviation of x
s_y	=	the standard deviation of y
m_x	=	the mean of x
m_y	=	the mean of y
n	=	the number of observations in each series

The calculation captures the overall extent to which the prices of the two stocks have tended to move together. A similar calculation can be done to determine the correlation coefficient between any two events that produce a series of observations.

[11] The hidden variable is age. Swanson (2003) gives the following additional examples of spurious correlations:

- the higher the public rate of ice cream consumption, the higher the rate of violent crime (summer heat)
- more fire trucks that arrive at a fire, the more the damage that is caused by the fire (intensity of fire)
- high mineral content in groundwater and high levels of heart disease (stressful, labor-intense industry located in area)
- regions of higher income have more homelessness (high housing costs)
- geographic correlation between number of churches and rate of violent crime is actually about .85 (urban v. small towns)
- watching sports on television correlates with facial hair (male gender)
- rainfall and agricultural yield are negatively correlated (Colder temperatures cause both rain and lower yield)
- the more doctors in a region, the higher the death rate (more doctors are needed where people are sicker)
- the number of ducks in an area and the amount of clothing people wear (both fluctuate with the seasons)
- the higher the average winter temperature, the larger the percent of the public that is Baptist (Southern U.S. region)

events. It does not reveal whether the degree of linkage remains relatively stable or varies. Most importantly, it does not reveal whether linkages change under extreme or unusual conditions.

A. Illustration of Correlation Effects

Let's start by considering an example that shows how correlations can increase the variability of losses on a pool of assets. Readers who prefer to avoid math can skip past the shaded material.

Consider a pool of n assets, $x_1 \ldots x_n$. Each asset has a principal amount of \$1 and a probability of default p. If an asset does not default, it pays \$1. If it defaults, it pays \$0. The expected loss on each asset is $\$1 \times p$. For example, if p=10%, the expected loss on each asset would be 10¢. The variance of loss on a single asset (s^2) would be $p \times (1-p)$. The standard deviation of loss on a single asset (s) would be $\$1 \times \sqrt{p \times (1-p)}$. Thus, if p=10%, the standard deviation of losses on a single asset would be 30¢.

The expected loss on the whole pool of assets would be $\$1 \times n \times p$. If the risk of default on each asset is independent of the risk of default on each other asset, the variance of loss on the whole pool (s^2_{Pool}) would be $n \times p \times (1-p)$. If we had a pool of 100 assets and if p=10%, the variance of losses on the whole pool would be 9 and the standard deviation of losses would be \$3, or 3% of the principal balance of the pool. If the pool had only 20 assets, the variance would be \$1.8. In that case, the standard deviation would be \$1.34, or 6.7% of the principal balance of the pool.

Now suppose that there is uniform correlation among the risk of loss on all the assets in the pool. That is, for all pairs of assets x_i and x_j, the correlation coefficient (r) is the same. In this case, we can figure out the variance and standard deviation of losses on the whole pool by adding up all the elements of the "covariance matrix" for the pool. The covariance matrix contains the covariances for each pair of assets in the pool. The diagonal of the matrix contains each asset's variance. Here is what the covariance matrix would look like:

$$\begin{matrix} Var(x_1) & Cov(x_1,x_2) & \cdots & Cov(x_1,x_{n-1}) & Cov(x_1,x_n) \\ Cov(x_2,x_1) & Var(x_2) & & & \vdots \\ \vdots & & \ddots & & \vdots \\ Cov(x_{n-1},x_1) & & & \ddots & Cov(x_{n-1},x_n) \\ Cov(x_n,x_1) & \cdots & \cdots & Cov(x_n,x_{n-1}) & Var(x_n) \end{matrix}$$

We know that the variances of all the assets are the same because all the assets are identical. We also know that the covariances are the same because we have assumed uniform correlation between each pair of assets. The covariance between any pair of assets equals the product of their standard deviations times their correlation coefficient ($s_I \times s_j \times r_{ij}$). Because the standard deviations of all assets are identical and the correlations are uniform, we can denote the covariance between each pair of assets as $s^2 r$ or $p(1-p)r$. Thus, the covariance matrix becomes simply the following:

$$\begin{matrix} p(1-p) & p(1-p)r & \cdots & p(1-p)r & p(1-p)r \\ p(1-p)r & p(1-p) & & & p(1-p)r \\ \vdots & & \ddots & & \vdots \\ p(1-p)r & & & p(1-p) & p(1-p)r \\ p(1-p)r & p(1-p)r & \cdots & p(1-p)r & p(1-p) \end{matrix}$$

The n diagonal elements of the matrix each are $p \times (1-p)$ and the $n \times (n-1)$ non-diagonal elements each are $p \times (1-p) \times r$. Thus, summing the whole matrix to get the variance of losses on the pool reduces to the following:

$$s^2_{Pool} \quad = \quad n\left[p(1-p)\right] \; + \; n(n-1)\left[p(1-p)r\right] \quad = \quad \left[p(1-p)\right] \times \left[n + n(n-1)r\right]$$

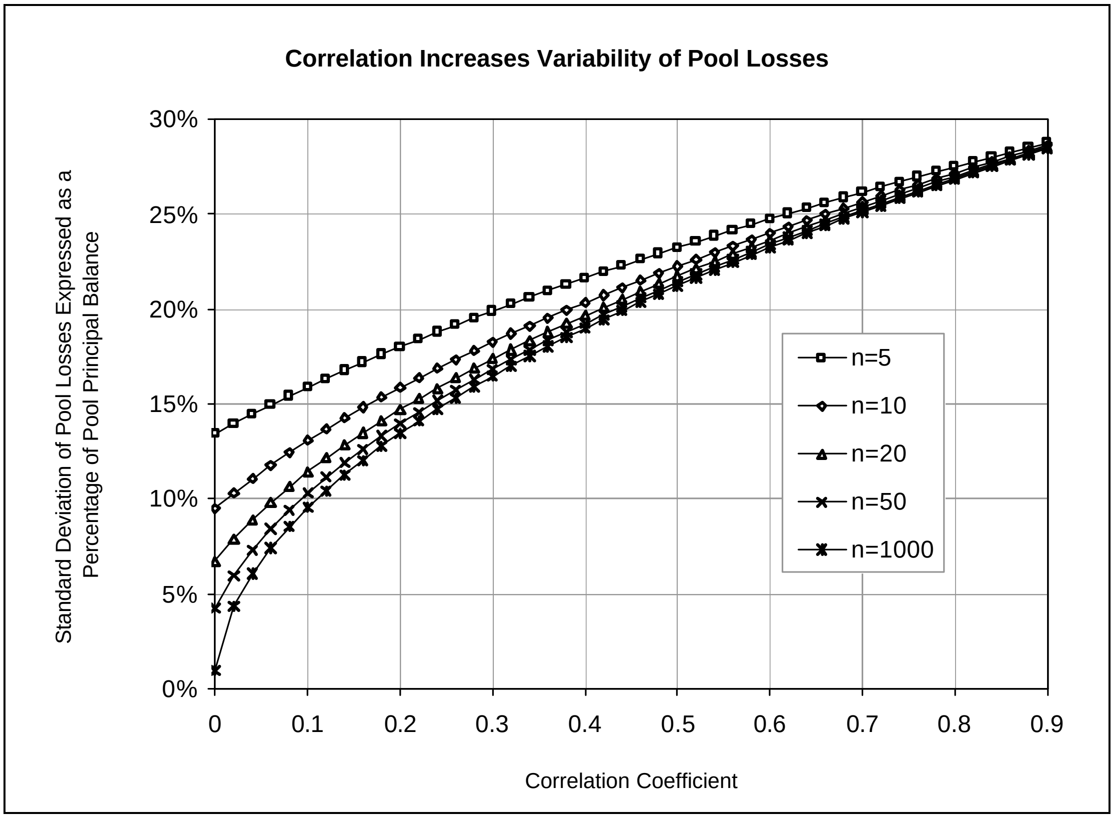
Naturally, the standard deviation of losses on the pool is simply the square root of the variance, so:

$$s_{Pool} \;=\; \sqrt{p(1-p)} \times \sqrt{n + n(n-1)r} \;=\; s \times \sqrt{n + n(n-1)r}$$

To express the standard deviation of losses on the pool as a percentage of the principal balance of the pool, we simply divide by n:

$$s_{Pool\%} = \frac{s_{Pool}}{n} = \frac{s \times \sqrt{n + n(n-1)r}}{n}$$

We can make a chart to examine how sensitive the variability of pool losses would be to changes in the degree of correlation among the assets. In the chart below, each line corresponds to a pool with a different number of assets (n). The x-axis is the correlation coefficient with respect to losses on the assets. The y-axis shows the standard deviation of pool losses expressed as a percentage of the pool principal balance ($s_{\text{Pool\%}}$).



So, correlation among the risk of default on the assets composing a securitized pool can significantly increase the variability of pool losses. In the case of pools backed by 20 or more assets, even a modest degree of correlation (*e.g.*, 0.2 or 0.3) can drastically increase the variability of losses on the whole pool compared to what they would be if there was no correlation. Thus, all else equal, a pool of assets is riskier – and should require more credit support – if there is correlation of credit risk among its constituent assets. In addition, correlation causes greater relative increases in risk for pools with larger numbers of assets.

B. Illustration of Time-Varying Correlations

We can explore the significance of time varying correlations with a simple numerical example. The example shows how a positive correlation of credit risk between two assets can produce higher losses on a portfolio comprised of the assets. In addition, the example shows how correlation between extreme outcomes can be very important but might not be revealed by the calculation of a correlation coefficient.

Consider two alternative cases. Each case involves two assets, *x* and *y*, which experience credit losses. Each year, the world experiences one of 25 equally likely states. The following table enumerates the amount of credit losses on each of *x* and *y* under each state for each case. The table also shows the combined level of credit losses on both assets under each state for each case:

Losses on Hypothetical Assets *x* and *y* in Twenty Five Alternative States under Each of Two Cases ($)

Case	State/ Asset	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	*m*	*s*	*r*
A	*x*	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	5.46	1.66	0.92	0.43
	y	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	5.46	1.66	0.92	
	x+y	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	10.9	3.32	1.55	
B	*x*	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	5.46	1.66	0.92	0.43
	y	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	5.46	2	1.66	0.92	
	x+y	2	2	2	2	2	2	2	2	2	2	2	2	4	4	4	4	4	4	4	4	4	4	4	7.46	7.46	3.32	1.55	

The key difference between the two cases is that the combined losses on *x* and *y* reach a more extreme level in case A ($10.9) than they do in case B ($7.46). This is because the worst losses on the two assets occur in the same state (#25) in case A, but in different states (#24 and #25) in case B.

Interestingly, the basic descriptive statistics used for describing the level and dispersion of possible outcomes for *x* and *y* are the same in both cases. The mean level of losses is $1.66 for each asset in both cases. Similarly, the standard deviation of losses is 92¢ for each asset in both cases. In fact, the correlation coefficient relating the levels of losses on the two assets is the same in both case A and case B (0.43). Thus, the basic descriptive statistics fail to capture the fact that *extreme* outcomes in case A are more highly correlated than in case B.

We can explore the linkage of extreme credit losses on *x* and *y* by looking at the possible outcomes in a different way. Call states #1 to #23 "regular conditions" and states #24 and #25 "crisis conditions." If we calculate the correlation between *x* and *y* separately under regular and crisis conditions we observe some interesting results. In case A, credit losses on *x* and *y* display perfect negative correlation (r = -1) during regular conditions, and perfect positive correlation (r = 1) during crisis conditions. Conversely, in case B the opposite relationships hold: credit losses on *x* and *y* display perfect positive correlation during regular conditions and perfect negative correlation in crisis conditions. Thus, comparing case A with case B, correlations of credit losses on assets *x* and *y* vary between states that occur at different times and, therefore, can be characterized as "time-varying."

Market participants can make better decisions if they look beyond basic descriptive statistics and consider the possibility of time-varying correlations. Suppose that a hypothetical securitization is backed by assets *x* and *y*. Depending on whether case A or case B applies, the pricing of the securities or the appropriate level of credit enhancement would be different. However, if market participants consider only basic descriptive statistics they will be unable to differentiate between case A and case B.

C. Correlations in Financial Literature

Correlation and time-varying correlation have attracted interest among academic researchers. Both have been extensively addressed in the context of the equity markets, but less so in the debt setting. A few examples from the equity side include the following:

- Erb et al. (1994) examined the correlation of equity index returns in the G-7 countries. They considered three-year and five-year return horizons from 1972 through 1993. They concluded that correlations are higher during recessions than during boom times.

- Longin and Solnik (1995) considered international equity correlations from 1960 to 1990. They found evidence that correlations vary over time and that correlations are stronger during times of high volatility of returns. Subsequently, they focused on the question of correlation among extreme returns (Longin and Solnik, 2001). That is, the degree to which returns in different national markets are correlated at their extremes. In their second paper, they rejected the linkage between correlation and volatility. Instead, they found that inter-market correlation increases in bear markets but not in bull markets.
- Goetzmann et al. (2001) examined correlations in international equity markets over the past century and a half. They concluded that the correlation of returns across markets has varied substantially over time.
- Jia and Adland (2002) examined returns in the shipping industry. They found that correlation among returns from owning different types of ships varied over time. They found that correlation was greatest during market downturns.

Fixed income markets have received less attention. Academics have focused a fair degree of study on credit risk correlations, but relatively little on the subject of time-varying correlations of credit risks.[12] A rare example is Annaert et al. (2002). They examined correlation among spread movements for bond indices comprised of cohorts of European bonds having different ratings and maturities. They concluded that correlations among credit spread movements for the various cohorts were not necessarily time-varying during the period from 1998 to 2000. However, they also reached the seemingly contradictory conclusion that the *covariances* among the spread movements were time-varying.

Outside of academic circles, several practitioners have produced important works on the subject of credit risk correlation. For example, Lucas et al. (1991) were among the first to confront the issue of default correlations in the context of rating CDOs. Later, Lucas (1995) followed-up with one of the seminal papers on the correlation of default risks.

Subsequently, Carty (1997) examined empirical one-year rating transition rates[13] for Baa-rated corporate bonds and compared them to an estimate of what the transition rates would have been if credit performance among the subject bonds was uncorrelated. He found *highly significant* evidence of correlation and concluded that the effects of correlation would be important for understanding the overall credit risk characteristics of bond portfolios.

Kim (2000) also found significant correlation among downgrades and defaults of speculative grade corporate bonds, measured annually. He found significant correlation of downgrades (but not defaults) measured semi-annually. Erturk (1999) reached the seemingly contradictory result that there is no default correlation among investment grade issuers of corporate bonds over short time periods. However, Nagpal and Bahar (2001) appear to resolve the apparent conflict by pointing out that (1) correlation increases over time for both speculative-grade and investment-grade bonds and

[12] For an extensive listing of papers on correlation of credit and default risk, see the listing maintained at DefaultRisk.com. http://www.defaultrisk.com/ps_correlations.htm.

[13] Rating transition rates describe the proportion of ratings at each rating level which remain the same or which change over a give time horizon. For example, Hamilton et al. (2002) show one-year rating transitions for Moody's-rated corporate bond issuers from 1985 to 2002 as follows:

Moody's One-Year Weighted-Average Rating Transition Rates for Corporate Bonds, 1985-2002

		Rating to:								
		Aaa	Aa	A	Baa	Ba	B	Caa-C	Default	WR
Rating from:	Aaa	87.80	7.90	0.30	0.00	0.00	0.00	0.00	0.00	4.10
	Aa	0.80	86.10	8.60	0.30	0.10	0.00	0.00	0.00	4.10
	A	0.00	2.30	87.00	5.60	0.70	0.20	0.00	0.00	4.30
	Baa	0.10	0.30	5.20	82.90	4.80	1.10	0.10	0.20	5.30
	Ba	0.00	0.00	0.50	5.10	75.10	8.30	0.60	1.40	8.80
	B	0.00	0.10	0.20	0.60	5.10	74.10	4.20	6.80	8.80
	Caa-C	0.00	0.00	0.00	1.00	1.60	6.00	59.70	21.50	10.20

The shaded boxes along the diagonal of the table show the proportion of ratings that remained stable over a one-year horizon.

(2) the correlation of default risks for investment grade bonds grows somewhat more slowly than for speculative grade bonds.

The relative paucity of empirical research on credit risk correlations may be attributable to the lack of readily available data on the pricing and credit performance of fixed income securities. Unlike the equity markets, most activity in the bond markets occurs "over the counter," outside the auspices of an organized exchange that tracks trades and disseminates prices. Researchers have no convenient access to daily or weekly prices on most corporate bonds or on structured finance instruments. In addition, defaults are (fortunately) so infrequent in most areas of the fixed income market that sample size problems are a vexing issue for statistical analyses.

D. Extreme Outcomes

As shown above, positive correlation of credit risks causes greater extremes in the performance of pooled credit risks. In a technical sense, positive credit risk correlation among individual assets thickens the tails of the distribution of credit losses on a whole pool. That is, the tails are thicker than they would be if the credit performance of the assets were uncorrelated. Statisticians refer to the tail-thickening effect as "kurtosis."

Recent research on distribution tails and on extreme outcomes suggests a possible way to analyze the effects of correlation even when correlations cannot be measured directly. For example, Longin (2000) proposes that risk managers should focus on extreme events in estimating a company's "VaR" or "value at risk." Longin proposes a modified VaR calculation based on an estimated distribution of extreme outcomes. His approach entails estimating the asymptotic distribution[14] of extreme outcomes by analyzing historical data. He argues that using an asymptotic distribution is desirable because it provides a rigorous framework that allows for future outcomes worse than any observed in the past (*i.e.*, out-of-sample results). Although Longin fashioned his approach in the context of "asset returns" and "VaR," the approach possibly could be adapted to handle pools of positively correlated credit risks. The key difference between Longin's approach and a traditional actuarial approach for analyzing a pool of securitized assets is that the actuarial approach considers all the historical performance, while Longin focuses exclusively on the extremes. Sometimes the narrower focus may be more appropriate, especially for evaluating credit risk for highly rated senior tranches.

Kim and Finger (2000) construct a framework for considering correlations during extreme conditions. They introduce a method for estimating correlation levels during periods of high volatility. They begin their paper by quoting Fed Chairman Greenspan as follows:

> Furthermore, joint distributions estimated over periods without panics will misestimate the degree of correlation between asset returns during panics. Under these circumstances, fear and disengagement by investors often result in simultaneous declines in the values of private obligations, as investors no longer realistically differentiate among degrees of risk and liquidity, and increases in the values of riskless government securities. Consequently, the benefits of portfolio diversification will tend to be overestimated when the rare panic periods are not taken into account. (Greenspan, 1999)

Kim and Finger define a two-state framework ("hectic times" and "quiet times"), in which the distribution of asset returns is different in each state. Asset returns have low volatility and low correlation during quiet days, while they have high volatility and high correlations during hectic days. Crousillat (2002) proposes a similar approach in the context of rating market value CDOs. He constructs a two-state framework with "high volatility" conditions and "low volatility" conditions. The high-volatility case generates greater stress in the rating analysis. These two papers are important because they explore the notions of time varying volatility (Crousillat, 2002) and correlation (Kim and Finger, 2000) in a hypothetical two-state context. They set the stage for applying such a two-state framework more broadly.

[14] With respect to a given phenomenon (*e.g.*, daily returns on a given stock), the term "asymptotic distribution" refers to the sampling distribution that would occur if the number of observations were infinite.

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