# Credit Risk of an International Bond Portfolio: A Case Study

Nisso Bucay and Dan Rosen

We apply the CreditMetrics methodology to estimate the credit risk of a portfolio of long-dated corporate and sovereign bonds issued in emerging markets. Credit risk is decomposed into default and downgrade risk. We assess the sensitivity of the loss distribution to various parameters. Asset correlations and transition probabilities have the highest impact on portfolio credit losses. As expected, estimates based on transition matrices published by rating agencies are similar, but differ from those using a transition matrix from KMV Corporation. Changes in the risk-free rate result in small changes to the mark-to-market value of the test portfolio, and thus to the losses.

Portfolio credit risk management is a key strategic activity of financial institutions. The efficient management of credit risk can save economic capital and protect an institution from unexpected levels of risk. In addition, it is used to measure performance by line of business and to determine a competitive and profitable pricing structure for products and services. For banks, portfolio credit risk is a key input used to estimate the regulatory credit risk capital for the banking book and specific risk for bond portfolios.

The new regulatory guidelines from the Bank for International Settlements (BIS) (1997) permit the use of internal models for specific risk. According to this framework, the models must adequately capture concentration risk, spread risk, downgrade risk and default risk (Verma et al. 1998 and Crouhy and Mark 1998). However, the current requirements are subject to some interpretation. The guidelines have been widely criticized, mainly because market risk, credit risk and specific risk are not dealt with in an integrated framework.

On the other hand, regulation for credit risk in the banking book is based on the BIS Capital Accord (1988) which does not currently permit the use of internal models. In recent years, regulators and market participants have sought to reform the regulatory framework to align regulatory capital with economic capital (the International Swap and Derivatives Association (ISDA) 1998, the Institute of International Finance (IIF) 1998 and the Federal Reserve System Task Force 1998). Some of the criticisms of the Accord as it pertains to credit risk include that it

- disregards asset quality to distinguish credit risk
- uses an accrual-based measure of capital that inadequately reflects solvency
- does not recognize the term structure of credit risk
- does not account for portfolio diversification

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- generates regulatory arbitrage.

One major driver for amending the Accord is the introduction of several methodologies for measuring portfolio credit risk. These models attempt to address the criticisms of the current regulation and to provide a base for effective credit management in financial institutions. They include CreditMetrics from JP Morgan (1997), CreditRisk$^+$ from Credit Suisse Financial Products (CSFP) (1997), Credit Portfolio View from McKinsey & Co. (Wilson 1997a and 1997b) and Portfolio Manager from KMV (Kealhofer 1996).

Credit risk poses modelling challenges beyond those posed by market risk modelling. For example, the loss distribution is far from normal (skewed and with fat tails) and measuring portfolio effects due to diversification is much more complex. Furthermore, the quality and availability of data is more problematic.

Basically, each of these models requires as input exposures, probabilities of credit events (i.e., default and migration), recovery rates and correlations. However, they differ in their distributional assumptions, restrictions, calibration and solution. Recent theoretical work has shown the mathematical equivalence of these models (Gordy 1998 and Koyluoglu and Hickman 1998) and recent empirical work compares the practical differences among the models (Crouhy and Mark 1998). In general, these studies show that all models yield similar results if the input data is consistent.

While each model has its particular advantages and disadvantages, they share several limitations. In particular, they all assume that during the period of analysis, the market risk factors, such as interest rates, are deterministic. Hence, they do not properly handle stochastic exposures. While this may be less relevant for portfolios of loans or floating rate instruments, it is clearly unacceptable for derivatives such as swaps and options. Ultimately, a comprehensive framework will require the full integration of market and credit risk.

In this study, we employ a CreditMetrics methodology to estimate the credit risk of a portfolio of long-dated corporate and sovereign bonds issued in emerging markets. We begin with a brief overview of the methodology, followed by a description of the test portfolio and market and credit data. The quality and availability of credit data is generally problematic; we discuss the steps taken to complete the dataset. We perform a thorough analysis of the credit risk in the portfolio and analyze the sensitivity of the risk to changes in the parameters of the analysis. Finally, we conclude with remarks on our findings and observations on the challenges of credit risk analysis.

## Overview of CreditMetrics

CreditMetrics calculates portfolio losses due exclusively to credit events, within a fixed time horizon, usually one year. Credit events include both default and migration. CreditMetrics is a particularly suitable methodology for bond portfolios because it presents a mark-to-market framework to measure losses due to both default and migration, accounting for portfolio effects. In addition, it uses generally available data such as credit spreads and transition matrices. Interested readers can refer to the CreditMetrics Technical Document (JP Morgan 1997).

In this section we provide a short summary of the main components of CreditMetrics. The computation of portfolio losses requires three steps.

### Determination of individual obligor exposure distributions

Exposures are the forward mark-to-market values for each obligor under each possible credit state, at the horizon. For example, consider a portfolio of bonds and suppose the rating system has seven rating classes (plus default). The value of the portfolio at the end of the horizon is calculated using the forward rates implied by today's term structures in each of the seven non-default ratings. In the default state, the value is based on the recovery rate for the appropriate seniority class. The probabilities of changing credit rating are summarized in the row corresponding to the rating of the obligor in a credit transition matrix, such as those provided by Standard & Poor's

(S&P 1998). The exposure distributions are summarized in obligor exposure tables.

### Monte Carlo simulation of joint obligor credit states

A Monte Carlo simulation samples a large number of scenarios on the joint credit states of each obligor at the horizon. The simulation is based on the one-period Merton framework (Merton 1974) in which joint default and migration correlations are driven by the correlations of the asset values of the obligors. Since asset values are not observable, the equity correlations of publicly traded firms are commonly used as a proxy for the asset correlations.

More specifically, CreditMetrics presents a multifactor model and provides correlation data between countries, regions and sector indices. Each obligor is mapped to the country, region and sector indices that most likely affect its financial performance, and to a specific risk component that captures the firm-specific volatility. Weights associated with the mappings should reflect which factors have the greatest impact.

### Distribution of portfolio loss

In each scenario on joint credit states, a portfolio mark-to-market is obtained by summing the exposure corresponding to the scenario credit state of each obligor, previously stored in the obligor exposure tables. The portfolio loss distribution is obtained by subtracting the portfolio mark-to-market in each credit state from the forward value of the portfolio had no credit event occurred. From this distribution one obtains all pertinent statistics including the mean, standard deviation, percentile losses and expected shortfall.

The market data inputs required by the model are risk-free zero curves for each currency and spread curves for each rating class in each currency. The probability of migration or default is described in a transition matrix, and a correlation matrix for country, region and sector indices is used to obtain the correlation of the asset values between obligors. Associated with each obligor is a mapping to these indices and a credit-rating classification.

## Case study description

We begin by describing the portfolio as well as the market and credit data, followed by a presentation of the details of the analysis and its outcomes. The time horizon for the estimation of credit risk is one year. The date of the analysis is October 13, 1998. All cases were analyzed using Algorithmics Inc. software.

### Portfolio data

The test portfolio of emerging market bonds has been compiled by a group of financial institutions participating in an initiative to assess the state of the art of portfolio credit risk models. The portfolio consists of 197 traded bonds issued in 29 countries by 86 obligors. The mark-to-market

| Instrument Type | Issuer Type (percent) | | | | | | Mark-to-Market Value (millions of USD) |
|---|---|---|---|---|---|---|---|
| | Sovereign | Municipal | Public Corporations | Private Corporations | Financial Institutions | Total | |
| Brady Bonds | 26.4 | 0.0 | 1.0 | 0.0 | 0.0 | 27.4 | 3,581 |
| Fixed Rate Bonds | 36.5 | 2.0 | 3.0 | 18.9 | 10.7 | 71.1 | 5,178 |
| Floating Rate Notes | 0.0 | 0.0 | 0.0 | 0.5 | 1.0 | 1.03 | 30 |
| TOTAL | 62.9 | 2.0 | 4.0 | 19.4 | 11.7 | 100.0 | 8,789 |

**Table 1:** Percent of instrument type by issuer type

value of the portfolio is 8.8 billion USD. The composition of the portfolio in terms of the type of bonds and issuers is presented in Table 1. Most instruments are denominated in US dollars. However, 11 fixed rate bonds, accounting for 11% of the mark-to-market value, are denominated in seven other currencies (DEM(4), GBP(1), ITL(1), JPY(1), TRL(1), and XEU (2)and ZAR(1)). For a definition of these currencies, see the Appendix.

Bond maturities range from a few months to 98 years; the portfolio duration is approximately five years. Table 2 presents the breakdown of the portfolio by bond maturity.

| Maturity (years) | Instrument Type | | | Total |
|---|---|---|---|---|
| | Fixed Rate Bonds | Brady Bonds | Floating Rate Notes | |
| | 140 | 54 | 3 | 197 |
| 0 – 1 | 2 | | | 2 |
| 1 – 2 | 14 | | 2 | 16 |
| 2 – 3 | 14 | | | 14 |
| 3 – 4 | 13 | 1 | 1 | 15 |
| 4 – 5 | 18 | | | 18 |
| 5 – 7 | 32 | 3 | | 35 |
| 7 – 10 | 28 | 12 | | 40 |
| 10 – 15 | 7 | 10 | | 17 |
| 15 – 20 | 3 | 8 | | 11 |
| 20 – 30 | 7 | 18 | | 25 |
| > 30 | 2 | 2 | | 4 |

**Table 2:** Maturity of positions by instrument type

Two of the obligors issue bonds with different ratings. These modelling issues are discussed in the Appendix.

### Market and credit data

The market data includes risk-free zero curves and spreads by rating class for each currency. In several instances where the data is incomplete, assumptions are made to extend the risk-free curves and to create consistent spreads for all asset classes and currencies. The assumptions made are summarized in the Appendix.

We analyze the portfolio using transition matrices from Standard & Poor's, Moody's and KMV Corporation. The rating system for each is based on seven rating classes (plus default). Tables A1 to A3 in the Appendix present these matrices.

We assume recovery rates are constant and equal to 30% of the risk-free value for all but two obligors. This is consistent with various studies on recovery rates for all types of corporate bonds (Izvorski 1997) though it may be conservative for some sovereign bonds. For Peru and Vietnam, a recovery rate of 30% results in higher losses from migrating to a CCC rating than to the default state. Peru and Vietnam are assigned recovery rates of 20% and 10%, respectively. These rates are more consistent with their credit spreads.

### Joint credit migration model

Each issuer is mapped to a country/sector/specific volatility combination. The mappings are presented in Table A4 in the Appendix. In practice, it is desirable to estimate these mappings directly from historical data, when available. We make the following general assumptions to arrive at these mappings.

Sovereign issuers are linked to either a country index, if it is available, or to a set of regional indices based on their weight, if any. Generally, at least 50% of the credit migration of sovereign issuers is explained by the country and region indices. This assumption guarantees reasonable correlations among sovereign obligors. In cases for which information is not readily available, such as Kazakhstan, the issuer is linked to regional indices that have a large proportion of countries in emerging markets. This yields reasonable correlations of these obligors to the portfolio.

Non-sovereign issuers are mapped to indices according to their country of residence and primary business. We assume that at least 50% of their credit migration is explained by the indices if their business is tradeable in nature and the domestic market is open to foreign trade (an exception would be some telecommunication services). The bulk of the returns of corporations producing non-traded goods or services, such as construction or electricity, is attributed to firm-specific volatility. Most corporations have the same percentage of return explained by market indices as does their sovereign issuer. For corporations that belong to an industry that is global in nature (e.g., autos or oil) or for corporations with a global market presence (e.g., Cementos Mexicanos), the percentage may be higher.

## Analysis

First, we present a credit risk analysis of the losses of the test portfolio from the perspective of a risk manager. The distribution of portfolio losses is calculated according to the standard CreditMetrics approach as described above. We characterize the loss distribution based on the mean and several useful measures of the dispersion of the distribution, discuss the results and explain their implications on capital and reserves. The risk contribution of individual obligors is explored as well as their marginal risk. Finally, we analyze sampling errors from the Monte Carlo simulation to measure the robustness of the results. As a second step, we examine the sensitivity of the portfolio credit risk to changes in the market and credit data and to various parameters of the analysis.

### Base case

The benchmark analysis is based on the portfolio, market and credit data described above. The Standard & Poor's matrix defines the transition probabilities. The portfolio loss distribution is calculated using 20,000 Monte Carlo scenarios on joint credit migration.

The portfolio loss distribution (Figure 1) shows the losses due to both credit downgrades and default. As expected, due to the nature of credit risk, the loss distribution is skewed and has a long fat tail.

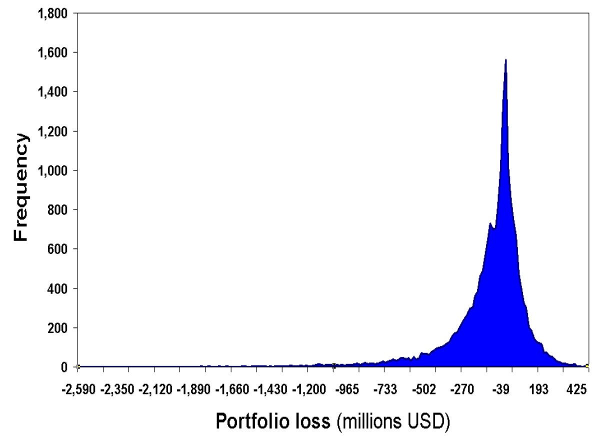


**Figure 1:** One-year credit loss distribution

We consider several statistics of the distribution. The mean of the loss distribution defines the **expected losses**. The standard deviation measures the symmetrical dispersion around the mean. The **maximum losses** are the maximum loss that is expected to occur at a given confidence level. For example, the probability that the actual losses exceed the Maximum losses (99%) is 1%. The **unexpected losses**, or **CreditVaR**, are equal to the maximum percentile losses less the expected losses. **Expected shortfall** is the expectation of losses beyond a given threshold, say 99%. A bank sets aside reserves (generated through the income statement) to cover expected losses and capital (balance-sheet item) to cover unexpected losses.

Table 3 presents the relevant statistics derived from the credit loss distribution illustrated in Figure 1. In addition to the expected losses and standard deviation, we also report maximum percentile losses, Credit VaR and expected shortfall, at the 99% and 99.9% percentiles.

The portfolio requires 95 million USD (or about 1% of the mark-to-market value) in credit reserves to cover expected portfolio losses. The capital to cover unexpected losses is 10 to 18 times the reserves, or between 11% and 19% of the mark-to-market value, depending on the confidence level chosen. Note that CreditVaR (99%) is about four times the standard deviation. If the distribution were normal, it would be about twice the standard deviation.

| | Base Case |
|---|---|
| Expected losses | 95 |
| Standard deviation | 232 |
| Maximum losses (99%) | 1,026 |
| CreditVaR (99%) | 931 |
| Expected shortfall (99%) | 1,320 |
| Maximum losses (99.9%) | 1,782 |
| CreditVaR (99.9%) | 1,687 |
| Expected shortfall (99.9%) | 1,998 |

**Table 3:** Statistics for one year loss distribution (millions of USD)

Although fairly popular, maximum percentile losses (VaR and CreditVaR) are point estimates in the tail of the distribution and present undesirable properties for risk management purposes (Artzner et al. 1998). In particular, VaR is not always a sub-additive risk measure. This means that, under some circumstances, a given portfolio may have higher VaR than its parts and, hence, diversification would have an adverse effect (Embrechts et al. 1998). This is particularly accentuated for credit risk where the distribution is non-normal and has long tails. An alternative measure of extreme losses, with better properties, is given by expected shortfall. Expected shortfall gives an indication of extreme losses, should they occur. Although it has not become a standard in the financial industry, expected shortfall is likely to play a major role, as it currently does in the insurance industry (Embrechts et al. 1997).

From Table 3, we see that expected shortfall at the 99% level is 30% higher than the maximum losses; it is only about 12% higher than the Maximum losses (99.9%).

Table 4 ranks the 10 obligors that contribute the most to the standard deviation of the portfolio loss distribution. This report identifies those obligors with the largest individual contributions to portfolio credit risk, the so-called Hot Spots in the portfolio. Note that the order remains almost unchanged if the obligors are ranked by Maximum losses (99%).

Table 4 summarizes the contribution of the obligors to expected losses, standard deviation and Maximum losses (99%). In each case, the contribution is the percentage decrease in the corresponding statistic if the obligor is removed from the portfolio.

Note that the expected portfolio losses are the sum of the expected losses of every obligor. Since expected losses are unaffected by correlations, they cannot be reduced through diversification. However, correlations are important for unexpected losses, as given by the standard deviation or maximum percentile losses. While expected losses are additive, unexpected losses are not. Hence, the contribution to unexpected losses of an obligor is very different from its individual standard deviation or percentile loss. This is why diversification can be used to decrease unexpected losses.

From Table 4 it is apparent that risk is heavily concentrated in the first five obligors. While they account for only 33.5% of the mark-to-market value of the portfolio, they contribute to around 51% of expected losses, close to 62% of the standard deviation and about 66% of extreme losses.

Notice that some results seem counterintuitive. For example, the mark-to-market of the positions in Peru is 42% lower than that of the Mexican debt. Although both countries have the same rating, Peru's contribution to expected losses is 12% higher than that of Mexico. Furthermore, Peru's contribution to capital requirements is five times larger. The former is a consequence of the longer maturities of the Peruvian positions; the latter is mainly because the Peruvian positions have a higher positive correlation to the rest of the portfolio.

The risk contribution of an obligor (whether standard deviation or percentiles) is approximately the product of the size of the position and the marginal risk of increasing the position by one unit. It is useful to understand whether the higher risk contribution of an obligor arises because of a very large position, a high marginal risk, or both. Figure 2 plots the marginal risk of every obligor (marginal standard deviation as a percent of mean exposure) against the mean exposure. A similar plot can be created for marginal CreditVaR or expected shortfall.

| Obligor | Rating | Mark-to-Market (millions of USD) | Risk Contribution to Portfolio (%) | | |
|---|---|---|---|---|---|
| | | | Expected losses | Standard deviation | Maximum losses (99%) |
| Brazil | BB | 880 | 14.55 | 17.10 | 20.27 |
| Venezuela | B | 398 | 6.16 | 14.10 | 12.25 |
| Russia | BB | 756 | 9.81 | 12.21 | 14.31 |
| Argentina | BB | 624 | 9.87 | 9.33 | 10.47 |
| Peru | BB | 283 | 10.33 | 9.00 | 8.30 |
| Colombia | BBB | 605 | 2.30 | 2.97 | 3.26 |
| Russia I | CCC | 48 | 1.29 | 2.51 | 1.80 |
| Mexico | BB | 488 | 9.20 | 1.96 | 1.69 |
| Morocco | BB | 124 | 1.58 | 1.36 | 0.82 |
| Philippines | BB | 448 | 6.67 | 1.22 | 0.26 |

**Table 4:** Hot Spots report

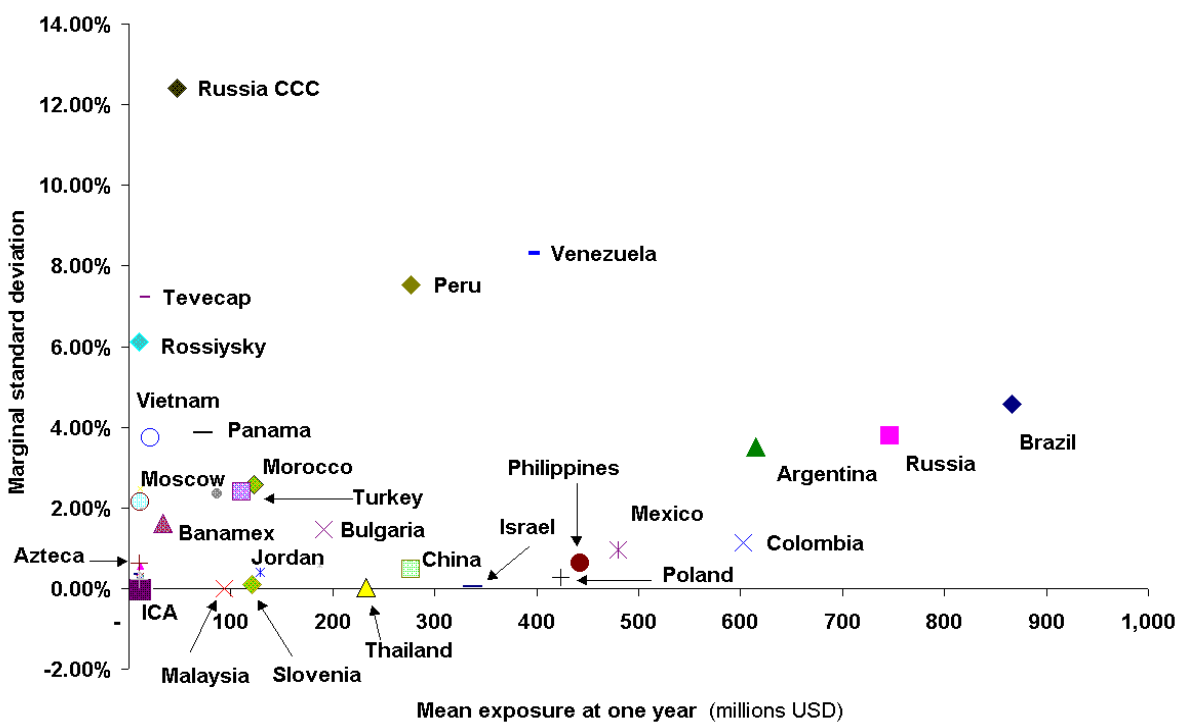


**Figure 2:** Marginal risk (standard deviation) vs. mean exposure

| | Base case (20,000 scenarios) | | | Estimate with 40,000 scenarios |
|---|---|---|---|---|
| | Lower bound | Estimate | Upper bound | |
| Expected losses | 91 (3%) | 95 | 99 (5%) | 94 |
| Standard deviation | 220 (5%) | 232 | 244 (5%) | 231 |
| Maximum losses (99%) | 963 (6%) | 1,026 | 1,086 (6%) | 1,014 |
| Maximum losses (99.9%) | 1,586 (11%) | 1,782 | 1,973 (11%) | 1,730 |

**Table 5:** 95% confidence bounds for the estimates

For example, Venezuela, the second most important contributor to portfolio risk, has a large marginal standard deviation, 8.3%. This means that for every increase of 100 USD in the exposure to Venezuela, the risk of the portfolio increases by over 8 USD. Russia I (CCC) has the largest marginal risk (12.4%) but its exposure ranks seventh (48 million USD).

To minimize risk and have a well-diversified portfolio, a risk manager would seek small exposures to obligors with high marginal risk and large exposures to obligors with low marginal risk. To reduce portfolio risk, the risk manager looks for outliers, that is, positions with high exposure and high marginal risk. Note that the five obligors that contribute the most to the risk according to Table 4 correspond to the outliers in Figure 2. Brazil, Argentina and Russia have lower marginal risk, but very large positions.

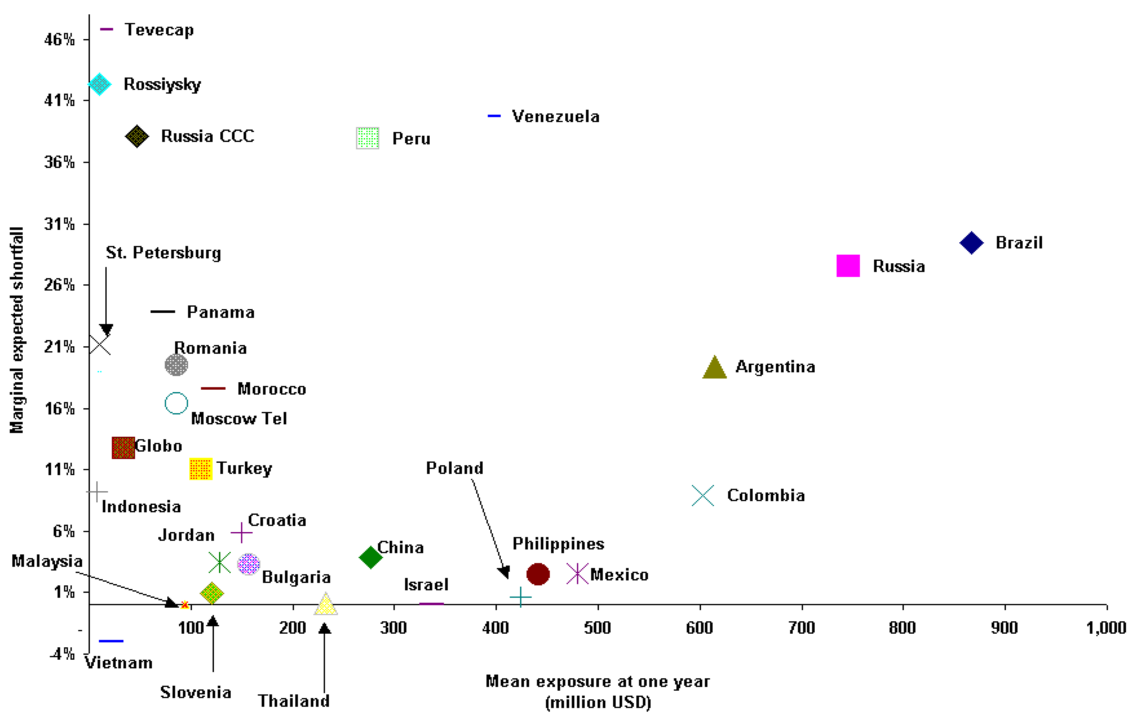


**Figure 3:** Marginal risk (expected shortfall) vs. mean exposure

In contrast, Venezuela and Peru have both a large marginal risk and a large exposure. Note that some obligors (e.g., Malaysia and ICA) act as hedges in the portfolio. Increasing their positions reduces portfolio risk since they have a negative correlation with the portfolio and, hence, their marginal risk is negative.

Similar to Figure 2, Figure 3 presents the marginal risk versus exposure plot, but using expected shortfall as a risk measure. In this case, the main outliers in Figure 2 stand out even more as outliers when we use an extreme loss measure. Note that the ranking of firms based on marginal shortfall or marginal standard deviation are different. For example, Tevecap has the highest marginal shortfall but has the fourth highest marginal standard deviation; similarly, Russia CCC has the highest marginal standard deviation but ranks fifth in terms of marginal shortfall.

### Sampling errors

The statistics presented in Table 3 are point estimates based on 20,000 Monte Carlo scenarios on joint credit events. More appropriately, we can characterize these estimates using confidence bounds. Confidence bounds on the mean and standard deviation are estimated using standard methods found in most statistics texts; the bounds on percentiles are estimated using rank statistics (Pritsker 1997).

Table 5 presents the 95% confidence bounds for the mean, standard deviation and maximum losses at the 99% and 99.9% percentiles. For example, while the point estimate of the Maximum losses (99%) is 1.03 billion USD, with 95% confidence the true losses are within 12% of this value (963 million USD, 1,086 million USD). At higher percentiles, the confidence bounds widen. Hence, the certainty of the results diminishes. Numbers in parenthesis indicate the percentage deviation from the estimate.

Table 5 also summarizes the results of a simulation with 40,000 scenarios. Notice that the difference between estimates of the two simulations is much smaller than the bounds with 20,000 scenarios. For example, while the bounds for the Maximum losses (99.9%) are about 11% of the estimate, the difference between the two simulations is a mere 1%. This suggests that the results from the base case are reliable and that increasing the number of scenarios results in unnecessary additional computation. Note that, in general, the non-parametric bounds on maximum losses are fairly conservative. Also, the accuracy of the MC simulation is roughly a function of the square of the number of scenarios. Hence, for example, doing four times as many scenarios reduces the uncertainty in the results by about half.

## Effect of credit parameters on portfolio losses

In this section, we assess the impact of various modelling assumptions on credit losses. In each case we present the expected losses, standard deviation, maximum percentile losses and CreditVaR at the 99% and 99.9% levels. For CreditVaR the number in parenthesis states the number of standard deviations from the mean, which is an indication of the non-normality of the loss distribution.

### Independent credit migration

In the base case, credit migration correlations are driven by a multifactor model based on the mappings presented in Table A4 in the Appendix. In this test, we estimate the loss distribution assuming that the obligors' default or migration are uncorrelated. This is modelled by setting the specific volatility component to 100% for each obligor in Table A4 in the Appendix.

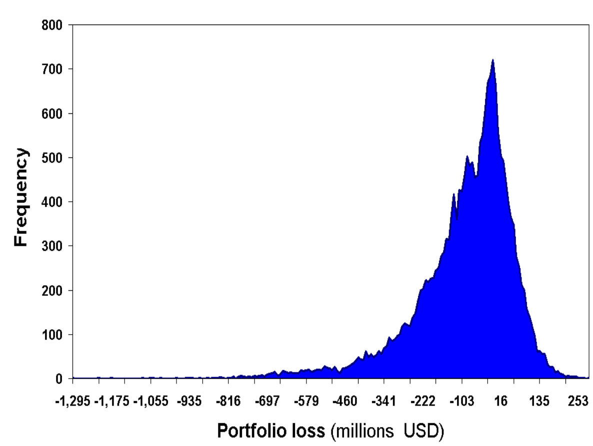


**Figure 4:** Credit loss distribution independent migrations

Figure 4 illustrates the loss distribution assuming that obligors' default/migration are independent. The loss distribution in this case has a higher mass towards the mean of the distribution and a tail that is not as fat as that of the base case. This can also be concluded by noting that the extreme losses are "closer" to the mean (3.6 and 5.1 compared to 4.0 and 7.3 standard deviations).

Table 6 presents the statistics of the distribution and compares them with those of the base case. Expected portfolio losses do not depend on correlations. Thus, the expected losses are not affected by the assumptions on correlations and credit reserves are not impacted. However, correlations do affect the measures of the dispersion of the distribution and, hence, the economic capital. Assuming independent migrations, CreditVaR is about 57% of credit capital in the base case. The order of magnitude of this difference remains when we use expected shortfall and not percentile.

| | Specific volatility | |
|---|---|---|
| | Base case | Specific volatility = 100% |
| Expected losses | 95 | 94 |
| Standard deviation | 232 | 150 |
| Maximum losses (99%) | 1,026 | 629 |
| CreditVaR (99%) | 931 (4.0) | 535 (3.6) |
| Maximum losses (99.9%) | 1,782 | 855 |
| CreditVaR (99.9%) | 1,687 (7.3) | 762 (5.1) |

**Table 6:** Statistics for a test of independent credit migration (millions of USD)

This experiment shows that the estimation of the joint correlation model, which captures concentration risk, has a substantial impact on credit capital. Yet, it is perhaps the most difficult part of the model to estimate, since this is generally not a directly observable process and a link must be inferred to some observable correlations (index or equity returns) via a constructive model. In the case of the multifactor model, the higher the weight on specific volatility, the stronger the portfolio diversification effect, and the smaller the concentration risk. If one wishes to have more conservative estimates, smaller specific volatility weights should be used (assuming that the index correlations are generally positive). The difference between correlated and uncorrelated losses is an indication of the contribution of the systemic component to concentration risk.

### Transition matrices

The results associated with the base case in Table 3 are the estimates of portfolio credit losses based on a transition matrix published by Standard & Poor's. Table 7 presents the results obtained using transition matrices published by Moody's and KMV. The transition matrices used and their sources are presented in the Appendix.

Results based on the Moody's transition matrix are very similar to those obtained in the base case. This similarity is expected since transition matrices published by rating agencies are historical estimates and the rating criteria are broadly comparable.

The results obtained using the KMV matrix are substantially different. In this case, expected losses are about 90% higher, the standard deviation is 45% higher and percentile losses are 17% and 2% higher at the 99% and 99.9% percentile, respectively. Figure 5 illustrates the portfolio loss distribution calculated using the KMV transition matrix. The distribution has a much higher mass around the mean and a shorter tail than the distribution illustrated in Figure 1. This is also reflected by the lower number of standard deviations from the mean of the extreme losses (3.0 and 4.9 standard deviations).

| | Migration and default transition matrix | | |
|---|---|---|---|
| | S&P | Moody's | KMV |
| Expected losses | 95 | 98 | 180 |
| Standard deviation | 232 | 227 | 336 |
| Maximum losses (99%) | 1,026 | 1,035 | 1,197 |
| CreditVaR (99%) | 931 (4.0) | 936 (4.1) | 1,017 (3.0) |
| Maximum losses (99.9%) | 1,782 | 1,753 | 1,819 |
| CreditVaR (99.9%) | 1,687 (7.3) | 1,655 (7.3) | 1,639 (4.9) |

**Table 7:** Statistics for a test on transition matrices (millions of USD)

The KMV transition matrix has a much higher probability of transition to neighboring credit states, and generally, lower default probabilities. This leads more often to smaller losses due to migration (since there is a higher probability of moving to a neighbouring credit state), and less often to large losses due to default. The KMV matrix is based on expected default frequencies (EDFs) generated by KMV Corporation for non-financial companies in the United States.

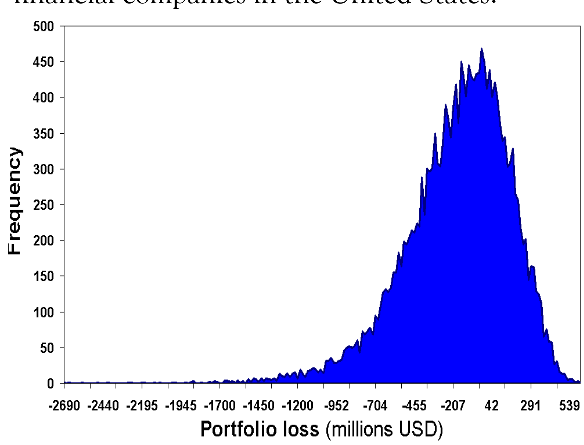


**Figure 5:** One year credit loss distribution with the KMV transition matrix

The EDFs derived by KMV are firm specific based on Merton's (1974) model. As such, probabilities of default are a function of the firm's capital structure, the volatility of asset returns and the current asset value. In this framework, default rates are continuous. KMV's methodology is best suited for publicly traded companies for which the value of equity is market determined.

### Default risk

Credit capital in the base case (Table 3) comprises both the losses due to obligor default and those due to downgrades to lower ratings, as both affect the mark-to-market of the bonds. We wish to understand what portion of these losses arise from default events only. Other portfolio models such as CreditRisk+ and KMV estimate losses due exclusively to default.

In the CreditMetrics framework, losses due to default can be isolated by modifying each row of the transition matrix. Shifting the probability mass of every credit migration, except for default, to the diagonal creates a transition matrix with only two possible future states—no change in credit state or default. A larger number of scenarios is necessary to calculate an accurate distribution, since the chances of a credit event are much lower (i.e., the probability of moving from any credit state, except CCC, is smaller). This test is based on 50,000 Monte Carlo scenarios.

Table 8 presents the relevant statistics for the loss distributions due exclusively to default using default probabilities from Standard and Poor's and from KMV. The results are compared with those from the loss distribution due to both migration and default. The results are fairly different for the two cases.

Using the KMV probabilities, expected losses due to default are four times lower than if both default and migration are allowed (i.e., they account for about 21% of the total expected losses). At a higher level of confidence, the losses due to default are a larger proportion of total losses, about 50% and 71% of the total losses for the 99% and 99.9% levels, respectively.

| | S&P | | KMV | |
|---|---|---|---|---|
| | Default and migration | Default only | Default and migration | Default only |
| Expected losses | 95 | 61 | 180 | 38 |
| Standard deviation | 232 | 147 | 336 | 121 |
| Maximum losses (99%) | 1,026 | 755 | 1,197 | 603 |
| CreditVaR (99%) | 931 (4.0) | 694 (4.7) | 1,017 (3.0) | 565 (4.7) |
| Maximum losses (99.9%) | 1,782 | 1,482 | 1,819 | 1,293 |
| CreditVaR (99.9%) | 1,687 (7.3) | 1,421 (9.7) | 1,639 (4.9) | 1,254 (10.4) |

**Table 8:** Default risk only (millions of USD)

In contrast, default losses account for a larger portion of the credit losses calculated using Standard & Poor's transition matrix: around 64% of expected losses, and 74% and 85% of maximum percentile losses (99% and 99.9%, respectively). These results are consistent with the fact that KMV's transition matrix gives larger probabilities to migrations, and lower probabilities to default, than that of Standard & Poor's.

Recovery rates have a linear effect on losses given default; any increase in recovery rates decreases default losses in the same proportion. For example, if recovery rates increase by 50%, the Maximum losses (99%) using the KMV default-only transition matrix are 474 million USD.

This can be calculated as follows. Losses due to default are given by a proportion of the risk-free value of the assets not recovered. This proportion, called the loss rate, is equal to one less the recovery rate. Thus, if the recovery rate increases by 50%, from 30% to 45%, the loss rate decreases from 70% to 55% and all the default results in Table 8 are reduced by the ratio of 55 to 70.

### Impact of interest rates

Interest rates, and in general market risk factors, affect credit risk in two ways. First, the changes in the mark-to-market value of the portfolio are directly affected by the market rates. This may not have a strong effect on portfolios of floating rate instruments or loans (generally these are not marked-to-market), it may have a moderate effect on bond portfolios and is of major importance for OTC derivatives such as swaps (Aziz and Charupat 1998). Second, changing market conditions affect credit parameters such as default probabilities, asset correlations and recovery rates. This impact affects all portfolios, but is difficult to measure.

In this test, we examine the impact of interest rates on the portfolio mark-to-market value and the impact of any change in value on the credit losses. To achieve this, the risk-free curves are shifted two (annual) standard deviations up and down. New discount curves for each credit rating are created by adding the rating spreads to each new risk-free curve. The obligors' exposures are calculated under each credit rating by discounting using the curves. The worst losses should occur when an obligor defaults or migrates and the level of interest rates is lower, since replacing the instrument is more costly.

Conversely, when interest rates go up, the replacement cost is lower.

| | Base Case | Stress scenarios – two standard deviation shifts | |
|---|---|---|---|
| | | Down | Up |
| Expected losses | 95 | 105 | 87 |
| Standard deviation | 232 | 250 | 216 |
| Maximum losses (99%) | 1,026 | 1,115 | 941 |
| CreditVaR (99%) | 931 (4.0) | 1,010 (4.0) | 854 (3.9) |
| Maximum losses (99.9%) | 1,782 | 1,934 | 1,608 |
| CreditVaR (99.9%) | 1,687 (7.3) | 1,829 (7.3) | 1,521 (7.0) |

**Table 9:** Impact of changes in interest rates (millions of USD)

Table 9 presents the statistics for the credit loss distributions for both cases. As expected, losses are higher (lower) when interest rates go down (up). Also as expected, for this bond portfolio interest rate changes have a moderate effect; credit losses do not change substantially with interest rate changes (around 10%). Clearly, the impact of other parameters such as transition matrices and obligor correlations are much greater and dominate the accuracy of the loss estimates.

### Diversification at a country level

Sovereign risk is a major determinant of credit risk in emerging markets. To assess the importance of reduced diversification within each country, every obligor is set to migrate jointly with its sovereign. The implicit assumption is that if a sovereign issuer defaults, all obligors in that country default as well. The rating of more creditworthy obligors is moved exclusively by the "health" of the country while lower-rated obligors may default though the sovereign does not.

The credit migrations between obligors within a country are set to be perfectly correlated. To achieve this

- the credit rating of each non-sovereign issuer is set to the minimum of the issuer's current credit rating and the credit rating of its sovereign
- all the obligors in a country are mapped to a single index; the weight associated with the specific volatility of each obligor is set to zero.

| | Base case | Tests on dependence | |
|---|---|---|---|
| | | Joint correlations = 0<br>Specific volatility = 100% | Sovereign joint correlation<br>Specific volatility = 0 |
| Expected losses | 95 | 95 | 95 |
| Standard deviation | 232 | 150 | 170 |
| Maximum losses (99%) | 1,026 | 629 | 723 |
| CreditVaR (99%) | 931 (4.0) | 535 (3.6) | 628 (3.7) |
| Maximum losses (99.9%) | 1,782 | 855 | 991 |
| CreditVaR (99.9%) | 1,687 (7.3) | 762 (5.1) | 896 (5.3) |

**Table 10:** Full vs. country diversification (millions of USD)

For simplicity, we assume that the credit processes of different countries are independent. To model independence, all the pairwise correlations among the indices (i.e., all off-diagonal entries in the covariance matrix) are set to zero.

The results are summarized in Table 10. To isolate the effect of diversification within each country, we compare the results to those of the test of independent credit migration (reproduced from Table 6). The difference between the two defines the maximum potential marginal reduction in losses that can be achieved by diversifying among obligors in each country. In this case, the maximum percentile losses (at the 99% and 99.9% level), assuming independence among all obligors, is 13% lower than assuming independence only among countries. This is expected since there are probably not enough bonds in the portfolio for diversification within country. In general, emerging markets' portfolios must seek diversification among sovereigns. Note that since this exercise modifies only migration correlations, the expected losses remain unchanged.

## Conclusions

In this case study we demonstrate the application of CreditMetrics to measure portfolio credit losses for a portfolio of bonds in emerging markets. We demonstrate the sensitivity of the loss distribution to various factors and find that

- the model used to estimate the migration correlation of counterparties has a large effect on portfolio losses
- concentration risk has a substantial contribution to portfolio credit risk
- the loss estimates obtained using historical transition matrices from different rating agencies are similar, whether we are investigating the possibility of migration or default or the possibility of default only
- the difference between estimates obtained using the rating agency matrices and the KMV matrix, particularly for estimating credit reserves, is substantial
- changes in the risk-free rate result in small changes to the mark-to-market value of this bond portfolio and thus to the losses
- risk reduction realized by diversification within countries is much smaller than risk diversification realized among sovereigns.

Analysis of credit losses for a bond portfolio requires a complete set of risk-free and spread curves for each rating class in all currencies, transition matrices, a reliable correlation model and consistent estimates of recovery rates. Gaps in the data are inevitable, particularly in emerging markets, but need not curtail credit risk management activities. Assumptions and estimates can be made to complete the dataset; these should be made explicit and the sensitivity of the results to the assumptions and estimates made should be tested. Better assessment of credit risk requires an improvement in the quality and availability of data in emerging markets. Further study on default, credit spreads and recovery rates for emerging markets debt stand out as productive areas of research. More work is also required to show the impact of interest rate scenarios when market and credit risk are correlated. Ultimately, a joint model of market and credit risk is required to get an accurate and complete picture of portfolio risk.

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## Appendix

In this appendix, we discuss the manipulations performed on the raw market and credit data that were necessary to derive a complete input dataset. We include the transition matrices that were used in the analyses and present the mappings of the obligors to the country/region/sector indices. The data inputs required by the model are listed below; those discussed or presented in this appendix are indicated by an asterisk.

The market data inputs required by the model are

- a term structure of interest rates for each currency.*

The credit data inputs required by the model are

- spread curves for each rating class in each currency*
- a credit rating classification for each obligor in the portfolio*
- transition matrices (migration and default probabilities)*
- a covariance matrix for the country, region and sector indices
- the mapping of each obligor to these indices.*

The portfolio data inputs required by the model are

- position data
- instrument data sufficient to value the positions in the portfolio.

### Multiple credit ratings

All instruments with the same rating that belong to the same issuer are aggregated under one obligor. However, in this dataset, two obligors (Thailand and Russia) issue bonds with two different ratings. In this instance, we consider each obligor to represent two different obligors with distinct ratings (Figure A1). Such situations arise, for example, when a given bond has a special guarantee that enhances its credit rating, so that an issuer can default on one bond but not on another.

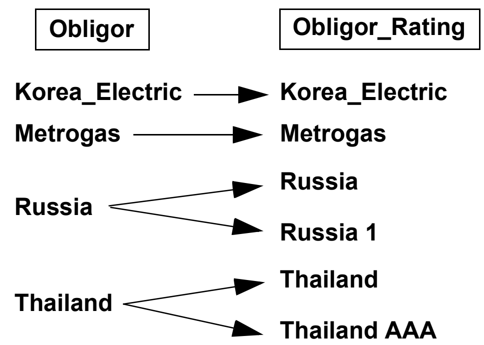


**Figure A1:** Mapping obligors to credit ratings

### Completing market and credit data

All but 11 fixed rate bonds are denominated in USD (DEM (4), GBP(1), ITL(1), JPY(1), TRL(1), XEU(2) and ZAR(1)). The market data required for a full credit risk analysis, given the composition of this portfolio, consists of eight risk-free curves (DEM, GBP, ITL, JPY, TRL, USD, XEU, ZAR) and spreads for seven credit states (AAA, AA, A, BBB, BB, B, CCC). The issues identified in this dataset pertain to both zero curves and spreads, particularly, though not exclusively, in emerging market countries. A problem that affects both emerging and industrialized countries is that some government curves cover only the short end of the term structure. Given that credit risk analyses are performed over a long-term horizon, extrapolation assumptions for the long end of the yield curve must be made.

### Risk-free zero curves

Two significant problems were encountered in building the required set of risk-free zero curves: the first was a lack of curves in three emerging market countries, the second a lack of data at the longer end of the term structure in the data of both emerging markets and industrialized countries.

We lack zero curves for XEU (European Currency Unit), TRL (Turkish Lira), and ZAR (South African Rand).

XEU

Using the DEM Government zero curve yields consistently negative spreads while the French

Franc Interbank rate curve yields small but positive spreads (except in the middle range of the term structure). The French Franc Interbank rate is used as the zero rate.

TRL

Although Turkey has strong economic links with Europe, its political and economic situation is distinct. Greece and Indonesia provide a basis for calculating TRL zero rates.

For rates up to one year, an "adjusted rate" for Greece is derived by adding the ratio of the Greek Interbank rate and the Turkish Government zero curve to the Greek Interbank rate. Likewise, an "adjusted rate" for Indonesia is derived by adding the ratio of the Indonesia Treasury rate and the Turkish Government zero curve to the Indonesia Treasury rate. The ratios are a crude adjustment for the difference in interest rate levels between Greece and Turkey and between Indonesia and Turkey. The zero rate for Turkish *lira* is determined as the average of the Greek and Indonesian adjusted rates.

Beyond 365 days, there is no TRL Government curve, but there are spread curves for AA and B instruments. Rates for terms longer than one year are implicitly estimated by subtracting a constant equal to the spread between AA and B instruments at 365 days to days, *d*, at higher terms $(d > 365)$.

$$TRL\_AA_d = TRL\_B\ spread_d - (TRL\_B\ spread_{365} - TRL\_AA_{365})$$

ZAR

Similarly, beyond three years, there is no ZAR Interbank curve, but there are spread curves for AA and BB instruments. Rates for terms longer than three years are implicitly estimated by subtracting a constant equal to the spread between AA and BB instruments at three years to terms of greater length.

**Credit spreads**

The dataset is missing credit risk spreads for AAA ratings in currencies other than the USD, specifically, the AAA spreads for DEM, GBP, ITL, JPY and XEU. The missing spreads are derived by multiplying each AA spread in the above mentioned currencies by the ratio of the USD_AAA spread and the US_AA spread. For example,

$$DEM\_AAA\ spread_d = DEM\_AA\ spread_d \times \frac{USD\_AAA\ spread_d}{USD\_AA\ spread_d} \tag{A1}$$

This assumption implies that the relationship between AAA and AA spreads is constant across currencies and equal in relative terms to the spread on the US Government curve. This is a neutral proposal which should not have a significant effect on high quality issues. Since corporate governance and bankruptcy proceedings in Europe and in Asia are very different from those in the United States, this may not be a neutral approach for lower quality ratings in countries like Japan, Germany and Italy.

XEU

The USD_ AA spread is used as a basis for estimating the XEU_ AA spread according to Equation A1. Since the low spread in the medium range of the term structure results in a very steep "V" graph, the rates between 153 and 1,096 days $(153 \le d \le 1096)$ are smoothed according to

$$XEU\_A_d = \frac{XEU\_A_{61}}{XEU\_AA_{61}} \times XEU\_AA_d$$

## Transition matrices

| | AAA | AA | A | BBB | BB | B | CCC | D |
|---|---|---|---|---|---|---|---|---|
| AAA | 90.8% | 8.3% | 0.7% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% |
| AA | 0.7% | 90.9% | 7.7% | 0.6% | 0.1% | 0.1% | 0.0% | 0.0% |
| A | 0.1% | 2.4% | 91.3% | 5.2% | 0.7% | 0.2% | 0.0% | 0.1% |
| BBB | 0.0% | 0.3% | 5.9% | 87.5% | 5.0% | 1.1% | 0.1% | 0.2% |
| BB | 0.0% | 0.1% | 0.6% | 7.7% | 81.2% | 8.4% | 1.0% | 1.0% |
| B | 0.0% | 0.1% | 0.2% | 0.5% | 6.9% | 83.5% | 3.9% | 4.9% |
| CCC | 0.2% | 0.0% | 0.4% | 1.2% | 2.7% | 11.7% | 64.5% | 19.3% |
| D | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% |
| Standard & Poor's (July 1998) | | | | | | | | |

**Table A1:** S&P's transition matrix

| | AAA | AA | A | BBB | BB | B | CCC | D |
|---|---|---|---|---|---|---|---|---|
| AAA | 93.4% | 5.9% | 0.6% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| AA | 1.6% | 90.6% | 7.5% | 0.3% | 0.1% | 0.0% | 0.0% | 0.0% |
| A | 0.1% | 2.3% | 92.4% | 4.6% | 0.5% | 0.1% | 0.0% | 0.0% |
| BBB | 0.1% | 0.3% | 5.5% | 88.5% | 4.8% | 0.7% | 0.1% | 0.2% |
| BB | 0.0% | 0.1% | 0.4% | 5.2% | 86.9% | 5.9% | 0.2% | 1.3% |
| B | 0.0% | 0.0% | 0.1% | 0.5% | 6.4% | 84.2% | 1.9% | 6.8% |
| CCC | 0.0% | 0.0% | 0.0% | 0.6% | 2.1% | 4.1% | 69.2% | 24.1% |
| D | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% |
| CreditMetrics Technical Document (JP Morgan 1997) | | | | | | | | |

**Table A2:** Moody's transition matrix

| | AAA | AA | A | BBB | BB | B | CCC | D |
|---|---|---|---|---|---|---|---|---|
| AAA | 66.3% | 22.2% | 7.4% | 2.5% | 0.9% | 0.7% | 0.1% | 0.0% |
| AA | 21.7% | 43.0% | 25.8% | 6.6% | 2.0% | 0.7% | 0.2% | 0.0% |
| A | 2.8% | 20.3% | 44.2% | 22.9% | 7.4% | 2.0% | 0.3% | 0.1% |
| BBB | 0.3% | 2.8% | 22.6% | 42.5% | 23.5% | 7.0% | 1.0% | 0.3% |
| BB | 0.1% | 0.2% | 3.7% | 22.9% | 44.4% | 24.5% | 3.4% | 0.7% |
| B | 0.0% | 0.1% | 0.4% | 3.5% | 20.5% | 53.0% | 20.6% | 2.0% |
| CCC | 0.0% | 0.0% | 0.1% | 0.3% | 1.8% | 17.8% | 69.9% | 10.1% |
| D | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% |
| CreditMetrics Technical Document (JP Morgan 1997) | | | | | | | | |

**Table A3:** KMV's transition matrix

## Mapping obligors to indices

| Country | Obligor | Credit Rating | Specific Volatility (in percent) | Index 1 | Index 2 | Index 3 |
|---|---|---|---|---|---|---|
| Argentina | Argenfin | BB | 50 | Banking | EMF Latin America | |
| | Argentina | BB | 40 | EMF Latin America | | |
| | Arggas | BBB | 40 | EMF Latin America | Energy | Utilities |
| | Arggasnor | BBB | 50 | EMF Latin America | Energy | Utilities |
| | Argglobal | BB | 50 | EMF Latin America | | |
| | Buenos Aires | BB | 50 | EMF Latin America | | |
| | Galicia | BB | 30 | Banking | EMF Latin America | |
| | Hipotecario | BB | 40 | Banking | EMF Latin America | |
| | Mendoza | BB | 50 | EMF Latin America | | |
| | Metrogas | BBB | 60 | EMF Latin America | Energy | Utilities |
| | Multicanal | BB | 20 | EMF Latin America | Broadcasting and Media | |
| | RioPlata | BBB | 50 | Banking | EMF Latin America | |
| | Sideco | BB | 50 | EMF Latin America | Metals & Mining | |
| | Telecomarg | BBB | 50 | EMF Latin America | Telecommunications | |
| | Telefarg | BBB | 50 | EMF Latin America | Telecommunications | |
| Brazil | BNDES | BB | 50 | Banking | EMF Latin America | |
| | Brazil | BB | 30 | EMF Latin America | | |
| | Ceval | BB | 40 | EMF Latin America | Food | |
| | Eletrobras | BB | 90 | EMF Latin America | Energy | Utilities |
| | Espirito Santo | BB | 90 | EMF Latin America | | |
| | Globo | BB | 50 | EMF Latin America | Broadcasting and Media | |
| | Rio de Janeiro | BB | 20 | EMF Latin America | | |

**Table A4:** Mapping of obligors to market indices

| Country | Obligor | Credit Rating | Specific Volatility (in percent) | Index 1 | Index 2 | Index 3 |
|---|---|---|---|---|---|---|
| | Safra | BB | 10 | Banking | EMF Latin America | |
| | Saneamento | BB | 60 | EMF Latin America | | |
| | Simonsen | B | 50 | Banking | EMF Latin America | |
| | Tevecap | B | 10 | EMF Latin America | Broadcasting and Media | |
| | Unibanco | BB | 40 | Banking | EMF Latin America | |
| Bulgaria | Bulgaria | B | 90 | EMF Latin America | Pacific ex Japan | |
| Chile | ChileVapores | BBB | 40 | EMF Latin America | Transportation | |
| | TelChile | A | 50 | EMF Latin America | Telecommunications | |
| China | China | BBB | 40 | EMF Latin America | Pacific ex Japan | |
| | China State Bank | BBB | 20 | Pacific Ex Japan | | |
| Colombia | Colombia | BBB | 30 | EMF Latin America | | |
| | Ganadero | BBB | 40 | Banking | EMF Latin America | |
| Croatia | Croatia | BBB | 40 | EMF Latin America | Pacific ex Japan | |
| Indonesia | IndFinCorp | BBB | 50 | Banking | | |
| | Indonesia | CCC | 50 | Indonesia General | | |
| | IndonesiaInti | CCC | 50 | Indonesia General | | |
| Israel | Israel | A | 20 | Europe 14 | North America | |
| Jordan | Jordan | BB | 50 | Europe 14 | | |
| Kazakhstan | Kazakhstan | BB | 80 | EMF Latin America | Pacific ex Japan | |
| Korea | EximKorea | BB | 20 | Korea General | | |
| | HanaBank | B | 50 | Korea Banking | | |
| | Hyundai | BB | 20 | Korea General | | |
| | KDB | BB | 20 | Korea General | | |
| | Korea | BB | 20 | Korea General | | |
| | KoreaElectric | B | 40 | Korea General | | |
| Lithuania | Lithuania | BBB | 20 | EMF Latin America | Pacific ex Japan | |

**Table A4:** Mapping of obligors to market indices

| Country | Obligor | Credit Rating | Specific Volatility (in percent) | Index 1 | Index 2 | Index 3 |
|---|---|---|---|---|---|---|
| Malaysia | MalayanBanking | BBB | 20 | Malaysia Banking | | |
| | Malaysia | A | 20 | Malaysia General | | |
| | Malaysiapetrol | A | 50 | Malaysia General | | |
| | TelekomMalaysia | A | 60 | Malaysia General | | |
| | TenagaNasional | A | 10 | Malaysia General | | |
| Mexico | Ahmsa | BB | 30 | Mexico General | Metals Mining | |
| | Azteca | B | 50 | Mexico General | | |
| | Banamex | BB | 30 | Mexico General | | |
| | Bufete | BB | 80 | Mexico Construction & Building Mat | | |
| | Cemex | BB | 20 | Mexico Construction & Building Mat. | Construction | |
| | Durango | BB | 30 | Mexico Metals Mining | | |
| | Electra | B | 50 | Mexico General | | |
| | ICA | BB | 40 | Mexico Construction & Building Mat. | Construction | |
| | Mexico | BB | 20 | Mexico General | | |
| | Pemex | BB | 20 | Mexico General | Energy | |
| | Televisa | BB | 50 | Mexico General | Broadcasting and Media | |
| Morocco | Morocco | BB | 20 | EMF Latin America | Pacific ex Japan | |
| Panama | Panama | BB | 40 | EMF Latin America | | |
| Peru | Peru | BB | 40 | EMF Latin America | | |
| Philippines | Philippines | BB | 50 | Philippines General | | |
| Poland | Poland | BBB | 50 | Poland General | | |
| Romania | Romania | BB | 20 | EMF Latin America | Pacific ex Japan | |
| Russia | Moscow | BB | 20 | EMF Latin America | Pacific ex Japan | |

**Table A4:** Mapping of obligors to market indices

| Country | Obligor | Credit Rating | Specific Volatility (in percent) | Index 1 | Index 2 | Index 3 |
|---|---|---|---|---|---|---|
| | MoscowTel | BB | 20 | EMF Latin America | Pacific ex Japan | |
| | Mosenegro | BB | 20 | EMF Latin America | Pacific ex Japan | |
| | Petersburg | BB | 20 | EMF Latin America | Pacific ex Japan | |
| | Rossiysky | B | 20 | EMF Latin America | Pacific ex Japan | |
| | Russia | BB | 20 | EMF Latin America | Pacific ex Japan | |
| | Russia I | CCC | 20 | EMF Latin America | Pacific ex Japan | |
| Slovakia | Slovakia | BBB | 50 | EMF Latin America | Pacific ex Japan | |
| Slovenia | Slovenia | A | 50 | EMF Latin America | Pacific ex Japan | Italy General |
| South Africa | SouthAfrica | BB | 50 | South Africa General | | |
| Thailand | Bangkok | BB | 30 | Thailand Banking | | |
| | Thailand | BBB | 20 | Thailand General | | |
| | ThailandAAA | AAA | 20 | Thailand General | | |
| Turkey | Turkey | B | 60 | EMF Latin America | Pacific ex Japan | Europe 14 |
| Venezuela | Venezuela | B | 20 | EMF Latin America | | |
| Vietnam | Vietnam | CCC | 70 | Pacific Ex Japan | | |
| Regional indices (Morgan Stanley Capital International 1997) | | | | | | |

**Table A4:** Mapping of obligors to market indices