Global Integration of Developed Credit Markets

Correlations with portfolio implications.

Ludovic Breger and Darren Stovel

Credit investors have historically been focused primarily on the U.S. market. And while the U.S. remains the dominant credit market, in recent years growth in the issuance of corporate bonds in other markets and currencies—particularly euro-denominated corporates—has made international issues more important. Multinational corporations now have access to a number of liquid credit markets, allowing for issuance in a variety of currencies. Investors may be able to choose from several similar bond issues from a single issuer but denominated in different currencies. Investors must thus often take a global perspective on credit analysis.

This raises several challenges for portfolio managers. One fundamental problem is determining how to assess portfolio exposure to spread changes. How highly correlated are issuers in different sectors but with the same credit rating? Are spreads on all bonds from the same issuer driven by the same factors, regardless of currency of denomination? And will these spreads react *at the same time* to these factors?

With spreads at historically low levels, portfolio managers are often investing in riskier instruments in search of higher yields, and controlling credit risk has become an increasingly critical aspect of portfolio management. Implementing sound risk management requires understanding not only the risk of individual assets but also how these risks and assets interact. It is particularly important to understand how much a portfolio is diversified across issuers, sectors, and markets. If markets are quite decoupled, we can obtain some diversification by

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investing in the same sectors in different markets. If they are not, then sector diversification will be more effective.

Kercheval, Goldberg, and Breger [2003] recently showed that the typical monthly spread returns of bonds issued within the same sector and rating category are weakly correlated and subject to volatilities that could vary by a factor of two to three. Desclee and Rosten [2003] indicate somewhat higher levels of intercurrency correlation, particularly among issuers with higher spreads.

We revisit the currency dependence of returns in portfolios that include U.S. dollar and euro-denominated bonds. Our findings have implications in terms of portfolio management and risk modeling.

DATA

The spreads to Treasury of U.S. dollar and euro-denominated bonds over March 31, 1999–June 30, 2003, form the core of our dataset and serve as a basis for issuer spreads. Issuer spread is defined as the equal-weighted average of all option-adjusted spreads of bonds issued by the same organization in a given market. Issuer-level credit spreads are then used to compute spread returns. We prefer issuer returns over bond returns because they are less sensitive to noise in reported prices. Sector-by-rating returns are obtained by averaging the returns of issuers with the same industry sector and rating.[1]

Our universe of U.S. dollar-denominated bonds is a combination of the Merrill Lynch U.S. Domestic Master and the U.S. Domestic High-Yield indexes ("Merrill Lynch Global Bond Indices" [2000]). Euro-denominated instruments are from the Merrill Lynch Broad Market and Euro High-Yield indexes and the Salomon Smith Barney Euro-Big index ("Performance Indexes" [1999]). Bond terms and conditions and sector classification and prices come from Reuters/EJV, IDC, Merrill Lynch, and Salomon Smith Barney. Standard & Poor's and Moody's reported bond ratings are combined into an average issuer agency rating (see Appendix A). Our bond universe represents 2,400 issuers, about 330 of which were active in more than one market.

The quality of price data is a prime consideration in study of bond spread data. Because many bonds are infrequently traded, prices reported by vendors are often fitted matrix prices rather than traded prices. For many bonds, we also have the choice between two or more price vendors. In an attempt to estimate the effect of these two sources of noise on our results, we separately analyze: issuers with more than \$500M and €500M nominal outstanding, issuers with three or more outstanding bonds, issuers with fewer than three bonds outstanding, and issuers with less than \$500M and €500M nominal outstanding. While the details of the results change, the conclusions are stable.

Another possible source of uncertainty in our results is that we make no adjustment for the term of the instrument, the seniority, or the collateral when we compute issuer spreads. Such adjustments are desirable but hard to implement in practice because of data limitations. For instance, some issuers may have only short debt or long debt, making it hard to come up with, say, a five-year constant-maturity spread. Seniority or collateral information is also often not available. We are virtually certain that these corrections would affect spread levels much more than spread returns and are ultimately a second-order effect for our purposes.

We allow the return horizon to vary for several reasons. First, it helps in testing the robustness of our results. Unless they are spurious, correlations should vary smoothly when the horizon changes.

Second, shorter horizons yield more observations and a higher statistical significance for the observed correlations (*see Appendix B*). We restrict the analysis to return series that overlap by at least two years to avoid drawing conclusions on results that are not statistically robust.

Finally, it is important to estimate the influence of the return horizon on correlations. Annualized risk is often derived from the volatilities of monthly, weekly, or even daily returns. If returns are much less correlated over shorter horizons than longer horizons, this approach may overpredict currency diversification and underforecast risk.

CROSS-CURRENCY CORRELATIONS

Exhibit 1 compares the weekly and monthly spread returns of DaimlerBenz in the euro and U.S. dollar markets and shows correlations for different horizons. Five bonds contributed to the issuer returns in each market. The correlations of weekly and monthly returns are both relatively high and consistent with what we would expect from covered interest arbitrage. The correlation also increases with the return horizon to reach a maximum of about 0.6 at around 20 days.[2]

The cross-market coupling is significant for two- or even one-day returns, which is quite surprising, given that corporate debt is relatively illiquid compared to stocks. In an attempt to uncover the origin of this coupling, we plot in Exhibit 2 the contribution of each period to the total correlation as well as the total cumulative correlation for weekly returns.[3]

EXHIBIT 1
DaimlerBenz Spread Returns and Cross-Currency Correlations

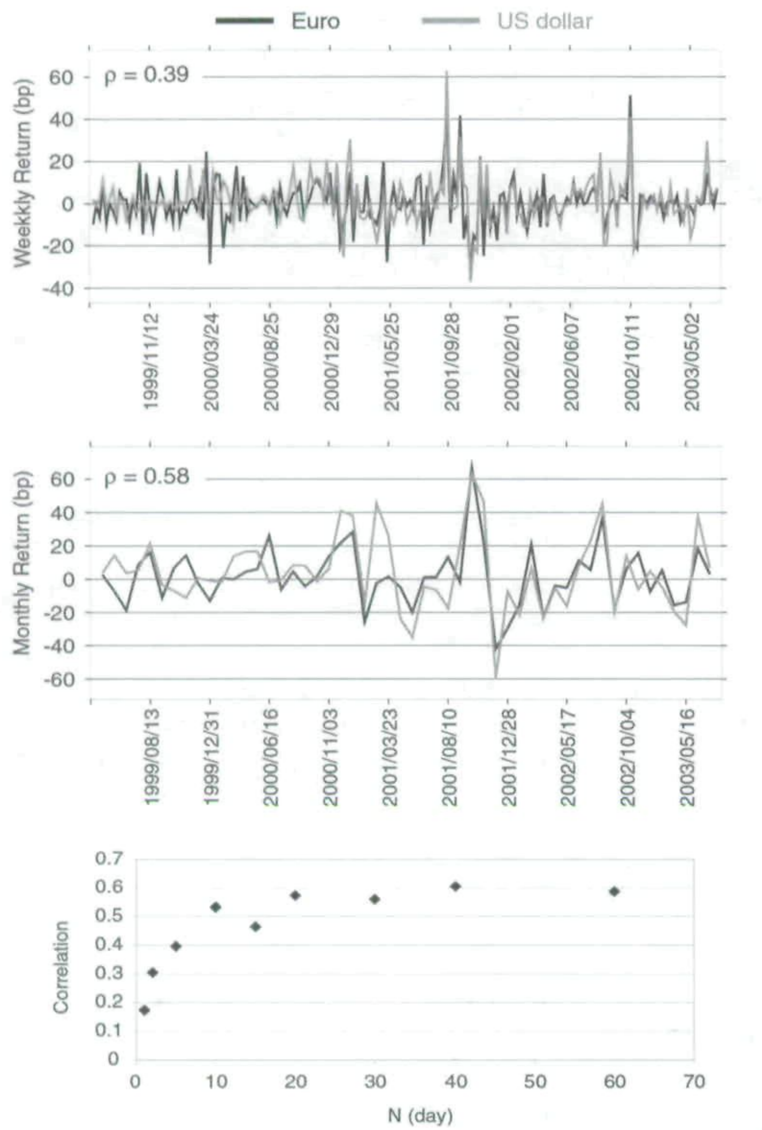
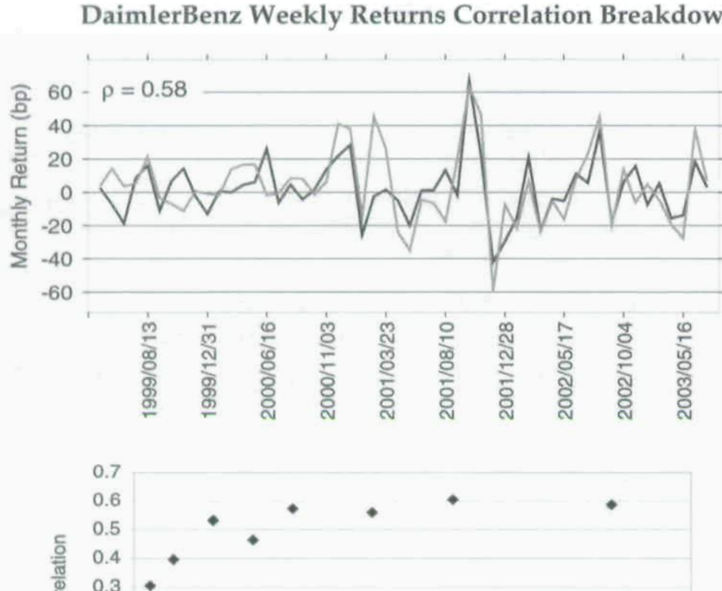


EXHIBIT 2
DaimlerBenz Weekly Returns Correlation Breakdown



This simple analysis shows very clearly that a few particularly large events are responsible for abrupt increases in the cumulative correlation and in the end most of the final observed correlation. Interestingly, though, all but one of these events can be associated with a rating downgrade or a global crisis such as the September 11, 2001, terrorist attack or the prelude to the war on Iraq. Returns for different horizons not shown here tell a similar story.

So the cross-currency correlation of DaimlerBenz returns is the result of a few events large enough to move more than one market that have taken place since the end of 2000. What about other companies?

Issuer Correlations

First we compute the cross-market return correlation for all issuers active in both the euro and U.S. dollar credit markets, allowing again for different return horizons. The top panels of Exhibit 3 show *weekly* spread returns plotted as a function of the average issuer spread (left) and spread return volatility (right). The bottom panels show *monthly* spread returns plotted as a function of the average issuer spread (left) and spread return volatility (right).[4]

We see in all plots a large amount of scatter. Issuers with comparable spreads can behave very differently. Yet correlations on average seem to increase with the spread or volatility.

In Exhibit 4 we separately regress correlations on spreads and volatilities, and find statistically significant results in all cases, as indicated by the high t-statistics and F-values. Comparison of the left-hand and right-hand graphs in Exhibit 3 shows that spread and volatility appear to be inter-

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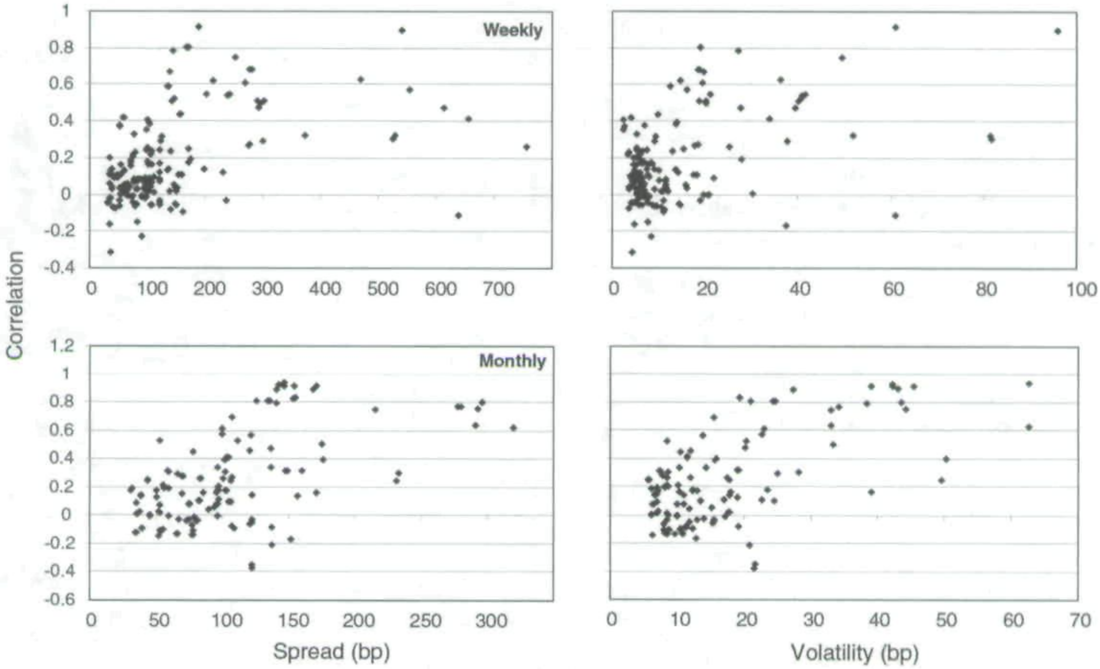
EXHIBIT 3

Issuer Correlations



of a few exceptional returns. This is precisely what we observed for Daimler-Benz.

Exhibit 5 shows the average contribution of each period to issuer correlations for both weekly and monthly returns. Most of the exceptional returns followed the September 11, 2001, terrorist attack and the collapse of Enron, and were positive spread returns. In a number of cases, the exceptional returns were recorded at different times in the two markets, yielding low or sometime even negative correlations.

We attribute the increase in average spread correlations to two effects. First, issuer returns that are associated with exceptional events such as global crisis or rating downgrades are lower for higher-grade issuers (AAA, AA, and A) than for lower-grade issuers, and therefore more sensitive to noise. Returns that are high relative to the background noise and that occur in both markets at the same time are more likely for low-grade issuers. In other words, the flight to quality tends to occur across markets for low-grade organizations.

Second, we know that the link between the value of a bond and the equity price of its issuer becomes stronger as credit quality declines. The returns of high-yield bonds issued in different currencies but linked to the same equity should naturally be more correlated than the returns of high-grade bonds.

EXHIBIT 4

Regression of Correlations on Spreads and Volatilities

Weekly returns

Regressor	Coefficient	R^2	t-value	F-value
spread	0.0009	0.24	7.5	56
volatility	0.0080	0.23	7.5	56
spread	0.0005		3.5	
and volatility	0.0050	0.28	3.5	36

Monthly returns

Regressor	Coefficient	R^2	t-value	F-value
spread	0.0030	0.32	8.1	90
volatility	0.0170	0.40	9.5	49
spread	0.0010		3.5	
and volatility	0.01	0.42	3.5	36

To further illustrate this point, we show in Exhibit 6 the coefficient β_{EQ} from Cheyette and Tomaich [2003] for the euro and U.S. dollar markets. This coefficient measures the dependence of bond returns on equity returns as a function of spread. The exhibit shows coefficients derived from U.S. dollar data, euro data, and a combination of U.S. dollar and euro. Clearly, β_{EQ} increases with declining credit quality. In other words, bond returns become increasingly linked to the equity returns of issuers with poorer credit ratings.

Liquidity is another obvious factor that could affect cross-market correlations. Issuers with large and liquid debt should have spreads that promptly adjust to extreme events, regardless of the market. There are at present not enough data to verify whether this intuition is statistically founded, but we note that a few of the highest correlations observed are for very liquid issuers. DaimlerBenz ($\rho_{20\ days} = 0.58$), Ford Motor Credit Company ($\rho_{20\ days} = 0.88$), and General Motors Acceptance Company ($\rho_{20\ days} = 0.68$) all have higher-than-average cross-market correlations and are some of the most actively traded bonds.

Common Factor Correlations

Studies of market factor returns have shown mixed results. Kercheval, Goldberg, and Breger [2003] argue for a weak cross-market correlation. Desclee and Rosten [2003] find a stronger cross-currency coupling that increases with declining credit quality.

Sector-by-rating cross-market correlations are shown in Exhibit 7. Again, high factor correlations were for the most part the result of a few large global events such as September 11 or the sudden spread increase of July 2002. For monthly returns, correlations are higher and increase with spread and volatility.[6] For weekly returns, correlations are low and show no obvious dependence on spread or volatility. Issuer and factor correlations are comparable on average for monthly returns but not for weekly returns.

The absence of pronounced correlations for weekly returns can again be interpreted in terms of liquidity and exceptional returns. It takes longer to move the large number of bonds that together determine the average sector-by-rating spread, some of them perhaps illiquid, than to move the handful of bonds that determine the spread of an issuer.

Exhibit 1 shows that the DaimlerBenz spread changes induced by the September 11 attacks occurred over less than a week—the corresponding weekly and monthly returns are quite similar. For a large sectorwide spread change to happen, a number of issuer spread changes need to develop over the same period. This is less likely to occur for short time horizons.

As an illustration, Exhibit 8 plots the industrial BBB returns. The weekly returns that followed September 11, 2001, are only about half of the corresponding monthly returns. Weekly and monthly Daimler returns in Exhibit 1 have (on the contrary) comparable magnitudes.

Kercheval, Goldberg, and Breger [2003] find somewhat lower correlations between the euro and U.S. dollar markets, but their data are for May 31, 1999, through May 31, 2001. This result is consistent with our findings, because this period was relatively quiet compared to the period that immediately followed.

EXHIBIT 5

Contributions to Average Issuer Correlations

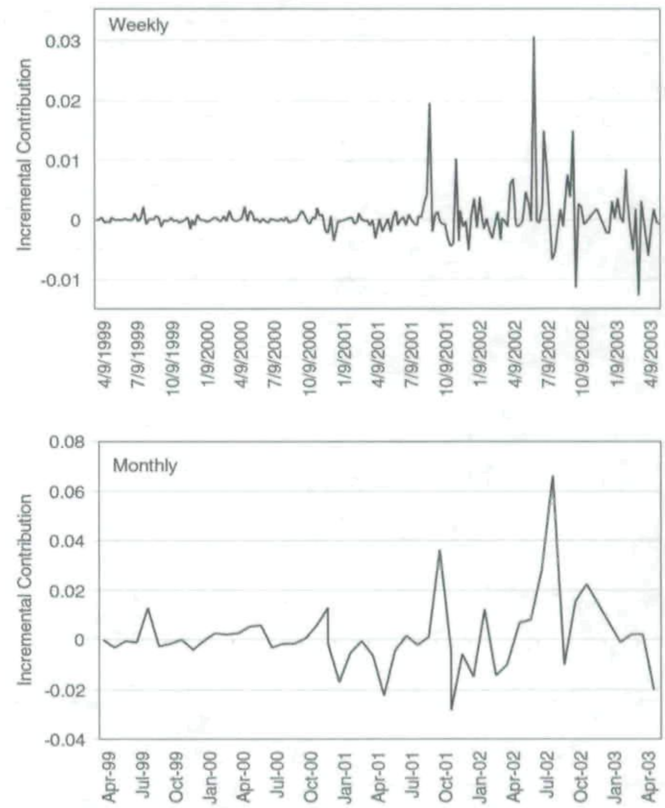


EXHIBIT 6

Link Between Bond and Equity Returns

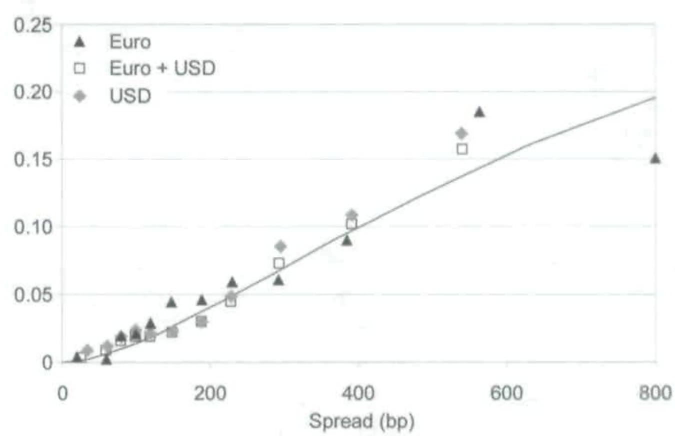


EXHIBIT 7
Sector-by-Rating Correlations

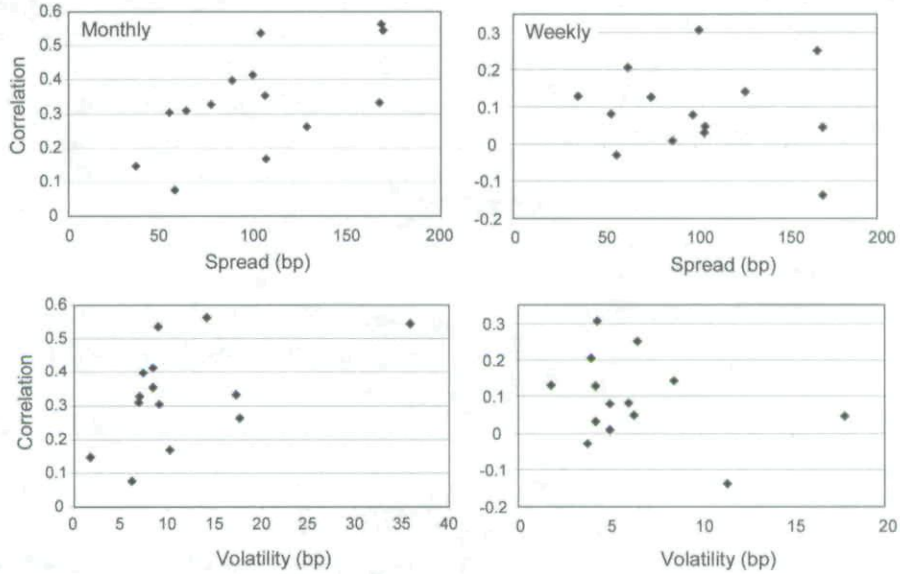
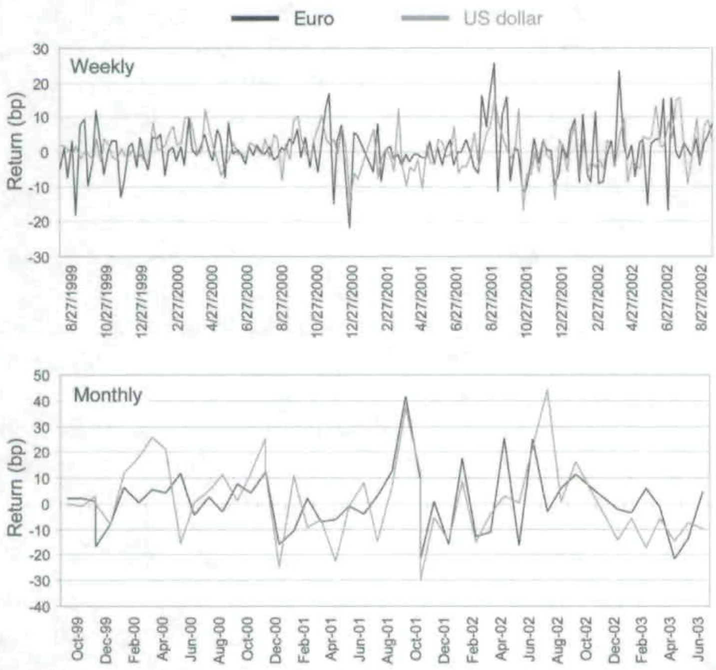


EXHIBIT 8
Industrial BBB Returns



IMPLICATIONS FOR PORTFOLIO MANAGEMENT

Within the same market, the spreads of higher-grade bonds (AAA, AA, and A) behave in a remarkably similar fashion with very high intermarket factor correlations. Cross-market correlations are on the contrary quite low. For such securities, currency diversification is clearly much more efficient than name diversification.

Intramarket correlations are significantly higher for lower-grade issuers. As a result, high-yield portfolios will benefit from name or even sector diversification more than they benefit from currency diversification.

Return Horizon

An important result of our analysis is that the global integration of credit markets depends on the return horizon. Interestingly enough, cross-market correlations observed using monthly returns are generally comparable to correlations observed for returns at any horizon longer than one week (see, for instance, Exhibit 1). This is not surprising, considering that most of the extreme spread changes that are responsible for these correlations are large market drops that develop over a week or less.

There are two immediate implications. First, for monthly returns, covariances and risk forecasts will scale relatively well with the return horizon. Second, correlations observed for monthly returns will also be robust in value at risk analysis, which focuses on extreme losses following large and often rapid positive spread returns.

Global versus Local Factors

For risk forecasting, the spread returns of bonds are often decomposed into a marketwide component and a bond-specific component, and the marketwide component is modeled using common factors that explain fluctuations in the average spread of bonds with the same rating and market sector.

For instance, the financial A common factor return in the U.S. would be the average spread return of bonds issued in U.S. dollars by U.S. BBB-rated utility companies. The vector of spread returns can then be expressed as:

$$r = Xf + r_{spec}$$

where

- X is the matrix of asset exposures;
- f is the vector of factor returns; and
- r_{spec} is the vector of asset residual returns not explained by factors, or specific returns idiosyncratic to individual assets.

If we assume that factor and specific returns are uncorrelated, we can write portfolio risk as:

$$\sigma^2 = {}^T h \Sigma h$$

with $\Sigma = {}^T X \cdot \Phi \cdot X + \Delta$

where

- h is the vector of portfolio holdings;
- Σ is the covariance matrix of asset returns;
- Φ is the covariance matrix of factor returns; and
- Δ is the matrix of specific variances.

Whether or not credit markets are globally integrated is a central question in building a global factor model. A model based on a set of global credit factors would be the natural choice if credit markets were well integrated. Because they can be constructed from a larger set of bonds, global factors have the advantage of less sensitivity to noise and greater granularity. They could also be used when there is too little corporate debt to support a set of sector-by-rating local factors. If, on the contrary, credit markets were decoupled, we would prefer a model based on currency-dependent credit factors.

Our analysis shows a relatively complex picture. The degree of integration depends on credit quality but also very much on the issuer itself. It changes with time, and is largely the result of a few extreme events. Global factors will yield accurate risk forecasts for highly diversified global portfolios but much less accurate forecasts for portfolios of, say, euro- or U.S.-dollar denominated bonds. In this case, modeling spread risk using local currency-dependent factors seems to be the appropriate approach.

There are other compelling reasons for using currency-dependent spread factors. Spread volatilities are currency-dependent (see Kercheval, Goldberg, and Breger [2003]). Market-specific instruments such as *Pfandbriefe* in the euro zone also require market-specific factors.[7]

Proxies

Even in the most developed markets, where there are usually enough bonds to construct granular factor returns, data considerations are crucial in building a credit model. Three types of issues are typically encountered.

First, there are sometimes limited historical data. For instance, prior to 1999, there was no euro market per se. In addition, there was relatively little outstanding debt outside the public sector, and virtually no high-yield market. This complicates the construction of the factor global covariance matrix because we have to accommodate return series with very different lengths. We generally have interest rate factor returns back to the early 1990s, while euro credit returns start only in 1999.

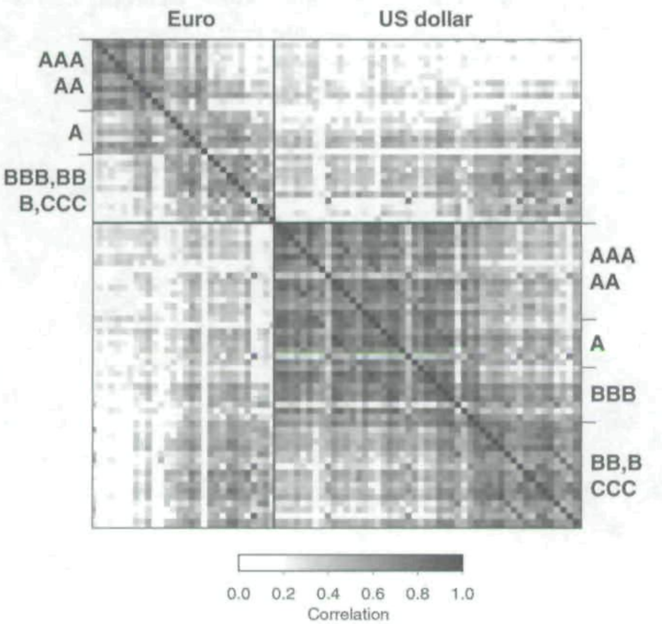
In theory, we could use a statistical method known as the EM algorithm to estimate missing returns using a maximum-likelihood estimator (see Dempster, Laird, and Rubin [1977]). In practice, this approach works only when there are few missing values relative to the number of observations. When there are too many missing values, such as in the euro market, EM solutions can be unstable, and a better approach is to find proxies for missing returns.

MSCI Barra euro, U.S. dollar, and sterling credit models are based on a set of sector-by-rating credit factors, where factor returns represent the average spread returns of similarly rated bonds issued in the same industrial sector. On any given date, there are never enough bond data to construct a complete set of returns. For instance, there are currently not enough data to construct a euro telecom A factor or a U.S. dollar telecom AA factor.

For return series that are for the most part complete, we can use the EM algorithm to fill in missing values. When there are either few returns or no returns at all, the only solution is to find priors.

EXHIBIT 9

Euro and U.S. Dollar Factor Return Correlations



There are many possible choices to proxy for a missing return. Examples are: 1) A rating-level return; that is, proxy the euro telecom A return by the average euro A return; 2) an external return; that is, proxy the euro telecom A return by its U.S. dollar counterpart; 3) a global proxy based on all available telecom A spread returns; or 4) a scaled return from the same market and sector but corresponding to a different rating.[8]

Our findings have far-reaching implications for the choice of proxies. Exhibit 9 shows the correlation matrix of U.S. dollar and euro credit factors computed using monthly returns between May 31, 1999, and August 31, 2003. Factors are ordered by market, rating, and sector from left to right and top to bottom. This graph clearly illustrates how cross-currency correlations become stronger with declining credit quality, not only for the same sector and rating but also within the same rating category. Another interesting feature is the high intermarket correlations for high-grade factors.

For high-grade assets, Desclee and Rosten [2003] and Kercheval, Goldberg, and Breger [2003] both observe higher spread risk in the U.S. dollar market than in the euro market. In Exhibit 10, we show examples of factor spreads and volatilities on July 31, 2003. Our results are consistent with those in other studies, but also show that the risk of high-yield bonds is in fact much less currency-dependent than the risk of investment-grade instruments.

EXHIBIT 10

Factor Spreads and Volatilities

	Factor	Spread to Treasury (bp)	Volatility (bp/yr)
Euro	Financial AAA	21	9
	Financial AA	34	9
	Financial A	51	15
	Financial BBB	92	52
	Industrial AAA	17	14
	Industrial AA	27	11
	Industrial A	43	23
	Industrial BBB	69	34
	BB	244	140
	B	523	356
	CCC	1125	495
U.S. dollar	Financial AAA	77	26
	Financial AA	50	34
	Financial A	73	33
	Financial BBB	122	42
	Financial BB	251	103
	Financial B	573	274
	Industrial AAA	39	30
	Industrial AA	46	27
	Industrial A	67	31
	Industrial BBB	115	41
	Industrial BB	243	113
	Industrial B	406	169
	CCC	880	324

Given the weak cross-market correlations and volatility differences for high-grade factors, approaches that involve proxying AAA to A returns with external or global proxies are clearly inappropriate. A much more desirable solution is to use a local rating proxy or even a local scaled proxy. External return and global spread return approaches are attractive only for lower-grade factors, given the higher cross-currency coupling and volatility similarities. High-grade returns are best proxied by local returns, while low-grade returns are best proxied by global returns.

This is good news for spread risk modeling. In all developed markets outside the U.S., there is relatively little high-yield debt. The euro high-yield market opened in 1997 but did not truly experience growth until 1999, when telecommunications companies started issuing debt. By the end of 2002, the Internet and technology bubble had brought this growth to a halt. Since then, only a few high-yield bonds have been issued in the euro zone, many of them by emerging market governments. In the sterling and Canadian dollar market, there is even less low-grade debt.

High-yield spread factors are nevertheless a critical component of any risk model because of the pronounced spread risk of junk bonds. Our findings suggest one can supplement local returns with external returns to construct a robust and detailed high-yield spread risk model.

SUMMARY AND CONCLUSIONS

Our findings highlight a number of considerations for managing credit portfolios. We have observed that investment-grade versus high-yield distinctions should be made in assessing correlations and credit risk diversification. As spreads on speculative instruments tend to be dominated by issuer-specific rather than market-specific factors, bonds from the same issuer in different markets tend to be highly correlated; bond correlations across markets for high-grade issuers tend to be less highly correlated. In general, the lower the credit quality, the higher the cross-currency linkage.

Another important distinction in considering spread change correlations is day-to-day versus extreme event correlations. A large part of the return correlation observed across the U.S. dollar and euro markets is driven by extreme global events such as the September 11, 2001, terrorist attacks or the 2002 credit crisis that followed the Enron debacle. Under more normal market conditions, the euro and the U.S. dollar credit markets are weakly linked, especially for highly rated debt.

Liquidity may also affect the timing of the observed spread changes in different markets. A lag in pricing makes measuring the true correlations challenging for shorter time periods, but in most cases periods longer than one week appear to give observed prices sufficient time to adjust across markets.

Accurate risk models need to include in one way or another currency-dependent factors, particularly for investment-grade instruments. For high-yield instruments, though, our results also provide some indication of how we might use global credit factors to estimate credit risk in markets with sparse corporate bond data.

In the coming years, a number of factors could further strengthen links between global credit markets. First, the development of electronic trading platforms should enhance the liquidity and the transparency of credit markets. The rapid development of derivative products such as credit default swaps will also help provide a common currency-independent reference and smooth out market idiosyncrasies. Finally, some market participants have started taking advantage of pricing discrepancies between the cash and derivatives markets. Such strategies will eventually contribute to aligning cash with credit derivative markets and cash markets with one another.

APPENDIX A

Averaging Agency Ratings

We combine bond ratings reported by Standard & Poor's and Moody's into an issuer rating as follows:

- Convert fine letter-based ratings (e.g., AAA, AA-, AA+) into equivalent integer ratings using equivalences.
- If there is more than one bond rating, take the (arithmetic) average of all S&P and Moody's equivalent integer ratings. If this average is not an integer, round up to the nearest integer. If only one rating is available, use that rating.
- Convert the result back into the coarse letter-based issuer average rating.

APPENDIX B

Significance Levels

We start with the hypotheses:

$$H_0: \rho = 0$$
$$H_1: \rho \neq 0$$

where ρ is the return series correlation coefficient.

The test statistic is given by:

$$t = r\sqrt{\frac{n-2}{1-r^2}}$$

where r is the sample correlation coefficient, and n is the number of returns. Under the null hypothesis, t follows a Student-t distribution with $n-2$ degrees of freedom. The null is rejected if

$$|t| > t_{n-2,1-\alpha/2}$$

where α is the significance level. As a result, for a given significance level and number of observations, only sample correlations that are higher than:

$$r_0 = \sqrt{\frac{t^2_{n-2,1-\alpha/2}}{n-2+t^2_{n-2,1-\alpha/2}}}$$

will be statistically significant.

APPENDIX EXHIBIT

Examples of Minimal Significant Correlations

	$\alpha = 0.20$	$\alpha = 0.10$
$n = 12$	0.4	0.5
$n = 24$	0.25	0.35
$n = 52$	0.2	0.25
$n = 104$	0.1	0.15

In the Appendix Exhibit, we provide the r_0 for a few typical values of n and α. Correlations based on one year of monthly returns are not statistically significant unless they exceed 0.4 to 0.5, which is generally not the case in this study. It takes at least 24 observations to separate correlations on the order of 0.3 from zero. Also note how weekly returns allow for a statistically robust measure of lower correlations.

ENDNOTES

[1]Our results are the same for spreads relative to swaps.

[2]See, for instance, Kercheval, Goldberg, and Breger [2003].

[3]For period i, the incremental correlation is

$$\Delta\rho_i = \frac{1}{N-1}\frac{(r_{1,i} - \bar{r}_1)(r_{2,i} - \bar{r}_2)}{\sigma_1\sigma_2}$$

The cumulative correlation is:

$$\rho_i = \frac{1}{N-1}\sum_{j=1}^{i}\frac{(r_{1,j} - \bar{r}_1)(r_{2,j} - \bar{r}_2)}{\sigma_1\sigma_2}$$

[4]The average spread is defined as the mean issuer spread observed in both markets over the analysis period. For return volatility, we compute the return standard deviations in each market and take the average.

[5]This can be seen by comparing the ratios of the coefficient obtained for the multiple regression to the coefficient obtained for the simple regression. For monthly returns, it is roughly 0.58 for volatility and 0.33 for spread. Also note that while the regression analysis confirms the dependence of correlations with spreads or volatilities, a non-linear model with a slope that declines with spreads would better fit our observations.

[6]As in the case of issuers, we verified that this dependence is statistically significant through regression analysis.

[7]Some more sophisticated models include both global and local factors and have the advantage of allowing alternative views. Note that global factors should pick up extreme returns, while local factors should pick up more typical returns.

[8]For instance, we could proxy the euro telecom A return r_{Tele-A} by

$$r_{Tele-BBB}\frac{s_{Tele-A}}{s_{Tele-BBB}}$$

where $r_{Tele-BBB}$, s_{Tele-A}, and $s_{Tele-BBB}$ are the euro telecom BBB spread return, the euro telecom A spread level, and the euro telecom BBB spread level.

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