Forecasting Sovereign Credit Spreads: *A Cointegration Model*

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Despite the rapid expansion of sovereign and corporate bond markets, there are few quantitative models for forecasting either credit spreads or the returns of high-yield bonds. My objective is to provide a forecast framework that works well with conventional credit market research.

No model would encompass all the market factors and fundamentals that professional investors usually take into consideration. My focus is rather on delivering one single piece of crucial information: *Is the credit spread of a sovereign bond wider or tighter than warranted by current global market conditions and fundamentals?* By fundamentals I mean the credit rating of the sovereign and a set of widely available relevant data that change more quickly than the standard ratings.

I will show that a forecasting model, in conjunction with very basic information provided by standard economic research, can generate considerable excess returns in an emerging market sovereign credit portfolio. This is a cointegration model that relates relative spreads of individual creditors to relative fundamentals. The ultimate objective is to support the efficient allocation of a portfolio across the available range of sovereign emerging market creditors.

The model contributes to this objective as follows:

1. In-sample estimates allow characterization of the relations between spreads and fundamentals in the past. Only if the relations are in line with theory and plausibility is it justified to assume that model parameters are stable and useful for forecasting.
2. At the end of a given sample, the model allows estimation of the deviation between the latest market spread ratio and its equilibrium (spread ratio error) to indicate whether a credit is cheap or dear relative to the market. Out-of-sample forecasts and model portfolio performance evaluation help to gauge the usefulness of model-based investment rules.

The approach is meant to complement fundamental balance sheet and economic analysis, not to substitute for it. Indeed, the model identifies spread errors relative to narrowly defined fundamentals, particularly the country rating. Either spreads or fundamentals might change to bring the system back into equilibrium. The role of fundamental economic research is to judge which adjustment is more likely, but comparatively little fundamental know-how is required to apply the model profitably.

I. LITERATURE

Sovereign credit spreads have been a rather exotic subject in the academic literature, partly because high-yield bond markets have gained importance only recently. Yet some theoretical considerations or empirical analyses provide a useful backdrop. On the theoretical side, research has focused on two groups of models:

- Structural models based on the seminal work of Black and Scholes [1973] and Merton [1974].
- Reduced-form models that describe a default event in terms of Poisson jumps that occur unexpectedly. This work includes Jarrow and Turnbull [1995], Duffie and Singleton [1997, 1999], Lando [1998], Chen and Poor [2003], and Jankowitsch and Pichler [2004].

The structural approach of Merton [1974], based on corporate zero-coupon bonds, uses the idea that the owners of corporate equity effectively have an option to default if their firm's assets become worth less than its liabilities. As a result, a corporate bond investor is effectively writing a European put option to the equity owner, where the firm's assets represent the underlying and the debt level represents the strike price.

Merton derives a closed-form solution for a corporate bond spread over the risk-free yield. The solution illustrates that the same factors that determine the value of a put option also determine a risky bond's yield spread. These include duration of outstanding debt (determining the time value of the option), firm leverage (which determines how much the put option is out of the money), and asset value volatility (which determines the volatility of the option's underlying).

Subsequent work has sought to ease some of the restrictions of the Merton model. Thus, Black and Cox [1976] propose a model that allows for bankruptcy before the maturity of the debt. Geske [1977] derives a closed-form solution for the spread of a coupon bond. Cox, Ingersoll, and Ross [1980] apply the Merton model to risky bonds with variable interest rates. Adding an important aspect, Turnbull [1979] incorporates corporate taxes and bankruptcy costs.

Structural spread models are not very tractable, limiting empirical evaluation to individual aspects of the model. Delianides and Geske [2001], for example, estimate how different factors contribute to corporate credit spreads in the U.S. market. They use the options theory-based Merton model to estimate the importance of a default spread, and find that default risk explains only a small part of the credit spread. Liquidity and market factors seem more important. They also suggest that the consideration of jumps for the stochastic diffusion process could contribute to the explanation of credit spreads.

Chan-Lau and Kim [2004] investigate the relation between equity and sovereign bond and credit default swap (CDS) spreads both theoretically and empirically. They use the Merton model to establish the relationship between equity and corporate bond prices.

As a loss in the firm's value reduces the expected payout from both equity and bonds, both assets should be positively correlated but non-linearly as equity value and credit quality increase. A highly leveraged firm is much more sensitive to negative shocks than a low-leverage firm. This supports the argument that credit spreads increase more than proportionately as credit risk increases.

Chan-Lau and Kim [2004] argue that the Merton model can be applied analogously to sovereign creditors, provided three plausible conditions are met. First, a country's asset value must equal its equity and debt. Second, a country's equity value suffers in the case of default. And third, a country would never default when it has assets well in excess of debt. Chan-Lau and Kim find empirical evidence that in many cases equity and bond and CDS spreads are related by a cointegrating relation.

Empirical researchers usually specify econometric models ad hoc with little reference to theoretical considerations. Thus, in a panel regression analysis for 17 emerging market countries for 1994-2001, Sy [2001] confirms the obvious: There is a positive relation between risk (as indicated by rating) and spreads. He also shows that spreads widen independently of ratings in times of crises, underscoring individual countries' dependence on the overall market. Finally, he finds that wide spreads (relative to rating) often are not followed by downgrades, but rather "auto-correct" downward. Narrow spreads, on the other hand, tend to herald upgrades.

Kamin and Kleist [1999] calculate a broad measure for sovereign credit spreads in order to analyze their development during the 1990s. They seek to measure the impact of credit ratings, maturity, currency denomination, and G-3 interest rates, and find large regional differences between spreads that are not accounted for by maturity and risk. Kamin and Kleist suggest that high-grade credit spreads exhibit a pattern that is very different from low-grade country spreads. They do not find much of an impact for G-3 interest rates.

A considerable literature investigates the relation between spreads or ratings and macroeconomic indicators. A pioneering example is Cantor and Packer [1996], who use pooled ordinary least squares regression of credit ratings on macroeconomic factors for 35 sovereign credits. Beyond identifying the most significant macroeconomic factors, Cantor and Packer find that ratings explain a greater portion of spread variation than economic variables. More recent studies are Alfonso [2002] and Rowland [2004].

Rowland and Torres [2004] provide an extensive overview of this literature. Its salient feature is a lack of theoretical underpinning for the analytical form of the estimated models (mostly cross-country regressions) and thus no strong claim to structural stability.

Combining theory and a tractable analytical framework remains a challenge for the future. My work goes a short distance along that path, using a specification that builds on theoretical and empirical findings so far.

II. SIMPLE MODEL OF CREDIT RISK, RATING, AND SPREADS

Following standard convention in bond pricing theory, the long-term equilibrium price of a risky bond of issuer i is assumed to be equal to its discounted risk-adjusted payout. The long-term equilibrium price of a unit discount bond ($\tilde{P}_{i,t}$) can thus be represented as a simple exponential function:

$$\tilde{P}_{i,t} = Exp\left[-r_{T_{i,t},t} \cdot T_{i,t} - rp_{i,t}\right] \tag{1}$$

where $r_{T_{i,t},t}$ is the risk-free rate for the bond term, $T_{i,t}$ the term of the risky bond, and $rp_{i,t}$ the risk premium charged by the market.

This representation implies that the equilibrium spread over the risk-free yield exactly reflects the risk premium divided by the bond's (Macaulay) duration:

$$\tilde{S}_{i,t} \equiv -\tfrac{1}{T_{i,t}} \cdot Log\left[P_{i,t}\right] - r_{T_{i,t},t} = \tfrac{1}{T_{i,t}} \cdot rp_{i,t} \tag{2}$$

The credit risk premium alone should depend on the default risk of the issuer as reflected in its credit rating $(cr_{i,t})$ and the bond's duration. As a plausible general form of how these factors interact, we suggest the Cobb-Douglas function, which captures the notion that the risk premiums on maturity and default are probably non-linear and compound each other. It allows including a country-specific risk coefficient that represents differences in spread even for identical default risk and duration. This often reflects the different legal status of bonds or the influence of a local investor base.

The risk premium model:

$$rp_{i,t} = \beta_i \cdot cr_{i,t}^{\gamma} \cdot T_{i,t}^{\lambda} \tag{3}$$

represents the ratio of two country spreads as a ratio of durations, default risk, and other country-specific risk factors. In logarithmic form, the equilibrium spread ratio equals a linear combination of factors:

$$Log\left[\frac{\tilde{S}_{i,t}}{\tilde{S}_{j,t}}\right] = Log\left[\frac{\beta_i}{\beta_j}\right] + \gamma \cdot Log\left[\frac{cr_{i,t}}{cr_{j,t}}\right] + (\lambda - 1) \cdot Log\left[\frac{T_i}{T_j}\right] \tag{4}$$

We must take into account some important limitations of the market. First, there is no simple measure of sovereign credit risk. Second, procurement and analysis of information leading to sovereign risk assessment is costly and time-consuming.

I suggest taking the composite sovereign credit ratings (using the average of Standard & Poor's and Moody's) as a first proxy of credit risk. Because rating agencies change their assessment of risk rather infrequently, while markets alter their judgment more quickly and respond more flexibly to news, I introduce *fast fundamentals*. These could be market and economic data. Such data offer a significant advantage over ratings because they are more timely.

In consideration of information costs, a model should allow risky bond prices and spreads as indicated by market makers to diverge temporarily from their equilibrium trajectories. Grossman and Stiglitz [1980] suggest that 1) prices convey less information, the fewer people informed, and 2) the lower the cost of procuring pertinent information, the more people are informed. According to this rationale, there should be less information in emerging market bonds than in developed market segments.

First, emerging markets are a niche market as compared to major bond, foreign exchange, and stock markets, and have attracted considerably less research coverage and investor interest. Second, information is expensive and of lower quality, and data are scarcer. Many countries lack transparent reporting of government balance sheets. And economic indicators often require considerable interpretation and adjustment.

We want to capture the idea that there can be durable divergences of credit spreads from fair values that correct only gradually and in accordance with the size of the divergence (which determines the pricing value of information).

The pricing hypothesis is expressed in two tiers. The first describes a long-term equilibrium relationship between two countries' spreads:

$$\frac{S_{i,t}}{S_{j,t}} = e^{\beta_i/\beta_j} \cdot \left(\frac{RI_{i,t}}{RI_{j,t}}\right)^{\gamma} \cdot \left(\frac{T_{j,t}}{T_{i,t}}\right)^{1-\lambda} \cdot e^{u_{i,j,t}} \qquad (5)$$

where $S_{i,t}$ is the yield spread of creditor i at time t; $RI_{i,t}$ is a rating index that is higher, the greater the credit risk; and $u_{i,j,t}$ is a disturbance with unconditional zero mean but potential serial correlation.

The second tier describes the short-term dynamics of spreads as a process that depends on equilibrium deviations, exogenous variables, and a random news flow:

$$\Delta \mathbf{y}_{i,j,t} = \mathbf{c}_{i,j} + \sum_{s=1}^{l} \mathbf{Z}_{i,j,s} \cdot \Delta \mathbf{y}_{i,j,t-s} + \mathbf{b}_{i,j} \cdot u_{i,j,t} + \mathbf{D}_{i,j} \cdot \mathbf{x}_t + \varepsilon_{i,t} \qquad (6)$$

for

$$\mathbf{y}'_{i,j,t} \equiv \left\{ Log\left[\frac{S_{i,t}}{S_{j,t}}\right], Log\left[\frac{RI_{i,t}}{RI_{j,t}}\right], Log\left[\frac{T_{i,t}}{T_{j,t}}\right] \right\}$$

and

$$\mathbf{x}'_t \equiv \{FF_{1,t}, ..., FF_{n,t}\}$$

where $\mathbf{c}_{i,j}$ and $\mathbf{b}_{i,j}$ are 3×1 vectors; $\mathbf{Z}_{i,j,1}, \ldots, \mathbf{Z}_{i,j,l}$ are 3×3 matrices; $\mathbf{D}_{i,j}$ is a $3 \times n$ matrix; and $FF_{1,t}, \ldots, FF_{n,t}$ denote fast fundamentals, i.e., parameters that are available to the market at large and whose levels help to predict future changes in the credit rating.

The second tier of the model stipulates that changes in the log spread and rating ratios are affected by the error in the long-term relation, exogenous shocks, and fast fundamentals. The fast fundamentals could reflect, for example, a high oil price, which would improve an oil exporting country's rating outlook and reduce its spread, before rating agencies adjust their official stance.

We estimate this model for two reasons. First, I want to gauge whether the behavior of emerging market spreads, ratings, and durations is consistent with the common conceptions built into the model. Second, I want to use the framework for forecasting. If the model indicates a positive spread error, i.e., a spread ratio that is too wide in light of the current rating ratio between two bonds and the relative duration, one of two things should happen: The spread ratio should decline, or the rating ratio should increase.

III. EMPIRICAL ANALYSIS

An empirical evaluation of the model requires dealing with numerous data limitations. The most important is that we have much shorter time series for emerging market bonds and ratings than for the G-7 countries. Liquid markets for sovereign emerging market debt have developed only during the 1990s. Moreover, many countries that were considered emerging markets in the second half of the 1990s have since then either been elevated to high-grade status (e.g., Poland or Greece) or have dropped out of the investor universe by means of default (e.g., Argentina). While I have used one of the broadest and most consistent sets of data available, there are still uncomfortably few observations. The low power of estimates can be mitigated only by strict parsimony of specification.

I use U.S. dollar-based Merrill Lynch Emerging Market Sovereign Bond indexes for the ten largest emerging sovereign issuers and for the overall market on a weekly frequency for the sample period 1999-2004. The focus on USD-based bonds reflects a lack of alternatives. Euro-denominated emerging market debt has become gradually more important since 2000, but does not provide enough data history for most countries. Bond indexes are preferable to individual bond series, as they allow construction of longer time series and are a little less prone to price distortions that can result from individual trades or market distortions. It also seems preferable to base analysis on Merrill Lynch's IGOV rather than the more conventional EMBI of J.P. Morgan, as data and descriptions for the former are more easily accessible for academic research.[1]

I choose the ten largest emerging market countries on the basis of market capitalization of their outstanding USD debt in 2004. This group includes Brazil, Bulgaria, Colombia, Mexico, Peru, The Philippines, Russia, South Africa, Turkey, and Venezuela. All these countries provide consistent index data (spreads, returns, and duration) and continuous credit ratings since 1999. The overall market is approximated by the Merrill Lynch aggregate IGOV index, a broad dollar-based bond index for issues of sovereign creditors rated at BBB or lower. Bonds that are in default are excluded. For details, see Appendix A and "Bond Index Rules and Definitions" [2000].

Data analysis uses weekly rather than daily frequency in order to avoid any information overlap problem. While bonds are traded globally, liquid market making is often limited to the market opening hours in the time zone of the particular issuer. This means in practice that index spreads and returns for, say, Russia reflect the closing price in London in the London afternoon, while the same data for Mexico are based on New York afternoon prices. The two obviously describe different information sets, and relative excess return could all too often reflect the timing of the closing price. Weekly frequency makes 90% of the effective trading time overlaps and the impact of the few additional trading hours of the American market on Friday afternoon count for comparatively little.

Weekly frequency is also preferred over monthly, because it allows obtaining a larger sample. Note that even with weekly samples there are just a total of 300 observations per series to estimate between 21 and 37 parameters.

Merrill Lynch also computes rating indexes for individual countries and the IGOV. They are a metric for the risk of the sovereign foreign currency debt, based on the sovereign foreign currency debt rating ceilings of Standard & Poor's and Moody's. For details of the index calculation, see Appendix B.

Finally, there are many candidates for the selection of fast fundamentals. Specification of optimal forecast models for individual countries would dwell extensively on that choice. I simplify the process by requiring the same fast fundamentals for each country and by concentrating on data that are available in real time.

There can be little doubt that forecasts could be improved by providing each country with a tailor-made set of exogenous variables, but I do not seek to optimize the forecast for each country; rather I want to support the credibility of the basic technology as a forecasting tool. Choices are limited to key global market indicators that are of plausible importance for the development of credit quality.

The reasons for the three indicators are:

- The oil price (measured as the USD price of West Texas Intermediate per barrel) has an obvious bearing on the creditworthiness of oil exporting countries versus oil importing countries.
- The USD 10-year Treasury yield is related to the funding costs of sovereigns with external borrowing requirements and should have a particularly strong impact on highly indebted governments.
- The euro-dollar exchange rate often affects the ratio of exports to external service. For example, a strong euro should benefit countries that export mainly to the euro area but owe most of their external debt in U.S. dollars, such as Bulgaria and Turkey.

Note that since the model is evaluating spread ratios rather than individual spreads, the factors may be relevant even for countries whose relationship to the financial indicators is rather tenuous. For example, in the case of spread ratios of individual countries relative to the market, a non-oil exporting country's spread suffers as long as there are enough oil exporters in the index.

Unit Root and Cointegration Tests

A useful way to capture the development of creditworthiness of countries is in a random process allowing domestic and global economic and political shocks to take the role of disturbances. Experience has proven that countries can move into high-grade market segments or descend into full-fledged default, and shocks to creditworthiness can have permanent components. I suspect that spreads and rating indexes, as well as their log ratios, are random processes with unit roots. In principle, there is no reason why duration should accordingly not also feature unit root behavior for very long periods.

Countries may seek to extend the duration of their bonds, although for our short sample the longer-term drift might have to compete with a trivial short-run mean-reverting mechanism; countries' index duration (Macaulay type) declines gradually and mechanically over time in the absence of bond issuance. With new issuance or when short-duration bonds drop out of the index, index duration usually moves up again in a discrete step.

Exhibit 1 shows the results of standard unit root tests, which broadly support the proposition regarding log spread and rating ratios. The augmented Dickey-Fuller and Phillips-Perron tests reject the null hypothesis in only two and three of ten countries (respectively). And neither of the two tests is able to reject the unit root for any of the log rating ratios. The picture is much less clear for the log duration ratios. Indeed, in the majority of tests, the unit root hypothesis for this indicator can be rejected.

Next I test the hypothesis that log spread, rating, and duration ratios are cointegrated using Equation (5), the linchpin of the model. A natural first check is to see whether spread, rating, and duration ratios are linked by a single cointegrating relation. In accordance with the theoretical considerations above, I allow for a trend in the endogenous variables as well as an intercept in the cointegrating relation.[2]

Exhibit 2 shows the results of two tests. First, the

Exhibit 1

Standard Unit Root Tests

	Log spread ratio to IGOV[a]				Log rating ratio to IGOV[b]				Log duration ratio to IGOV[c]			
	ADF test [d]		PP test[e]		ADF test[d]		PP test		ADF test[d]		PP test	
	ADF t-stat.[f]		Adj. t-stat.[f]		ADF t-stat.[f]		Adj. t-stat.[f]		ADF t-stat.[f]		Adj. t-stat.[f]	
Brazil	-1.520	-	-1.468	-	-1.468	-	-1.419	-	-2.532	-	-4.961	***
Bulgaria	-0.898	-	-0.773	-	-0.514	-	-0.322	-	-1.392	-	-4.111	***
Colombia	-2.389	-	-2.355	-	-2.009	-	-2.036	-	-2.853	*	-2.914	**
Mexico	-3.388	**	-3.923	***	-2.429	-	-2.420	-	-2.255	-	-2.418	-
Peru	-2.839	*	-2.754	*	-1.502	-	-1.482	-	-2.393	-	-2.537	-
Philippines	-0.628	-	-0.701	-	-0.020	-	0.184	-	-3.003	**	-3.048	**
Russia	-1.947	-	-2.018	-	-0.112	-	-0.109	-	-1.125	-	-1.146	-
South Africa	-2.544	-	-2.907	**	-2.015	-	-2.015	-	-5.622	***	-5.795	***
Turkey	-2.044	-	-1.989	-	-1.315	-	-1.213	-	-2.696	*	-2.696	*
Venezuela	-2.158	-	-2.208	-	-1.204	-	-1.184	-	-2.071	-	-3.251	**

[a] *Dependent variable is natural log of ratio of country index spread and IGOV (market) index spread.*
[b] *Dependent variable is natural log of ratio of country rating index and IGOV (market) weighted rating index.*
[c] *Dependent variable is natural log of ratio of country index duration and IGOV (market) index duration.*
[d] *Augmented Dickey-Fuller test level, test equation with intercept, maximum lag determined by Schwarz information criterion.*
[e] *Phillips-Perron test, test equation with intercept, maximum lag determined by Schwarz information criterion.*
[f] *Unit root is rejected at 1%, 5%, and 10%, indicated by ***, **, * using McKinnon p-values.*

unrestricted rank cointegration (trace) test is used to check whether (based on the estimated likelihood loss) the hypothesis of one cointegrating relation can be rejected against the alternative hypothesis of more than one cointegrating relation. Second, the maximum eigenvalue test statistic is used to try to reject the null hypothesis of one cointegrating relation and the alternative hypothesis of two cointegrating relations. The null hypothesis of no cointegration is also compared to the alternative hypothesis of one cointegrating relation.

Exhibit 2 shows that none of the trace and maximum eigenvalue test statistics indicates rejection of the null hypothesis of a single cointegrating relation. The empirical evidence thus seems evidence against multiple cointegrating relations or variable stationarity.

At the same time, it is also difficult to reject the even more restrictive hypothesis of no cointegration and invalidate the assertion that the residuals in spread, ratings, and duration might be non-stationary. We dismiss this hypothesis on theoretical grounds, however, and tend to suspect that the low power of the test is a consequence of the small sample.

In-Sample Evaluation: Statistical Inference

We draw in-sample inference for two reasons. First, it helps to choose among three basic model versions, given the plausibility of the signs of key coefficients. Second, we want to extract some basic characterization of the behavior of emerging market dynamics.

In principle, model specification should be governed by theory. Yet, in this context the limited available data require us to weigh the potential of exhaustive structure against the benefit of parsimony. That is, there are two principal choices. Should the model include the proposed set of fast fundamentals, or are ratings good enough and flexible enough? And second, should one include duration as an endogenous variable, or is the technical short-run mean reversion of that variable too significant a distortion?

Exhibit 3 provides some perspective by offering a glance at cointegrating coefficient estimates for three distinct model versions. The *basic model* features only the three endogenous variables, log spread, rating, and duration ratios. The *large model* includes the three endogenous variables and all three proposed fast fundamentals. Finally, the *best model* includes only two endogenous variables, eliminating duration, plus the fast fundamentals.

According to our initial simple model the cointegrating relation between spreads and the rating index (indicating risk) should be positive; that is, higher rating indexes should be associated with higher spreads. This requires that the coefficient of the log rating ratio in Exhibit 3 be negative. At the same time, the relation between spreads and duration should be positive, requiring the related coefficient to be negative as well.

Neither the basic nor the large model performs well under this criterion. In the basic model, six of ten countries post the expected significant negative coefficient. Three countries, Bulgaria, Mexico, and South Africa, post a significant positive coefficient. Interestingly, these

EXHIBIT 2

Cointegration Tests [a]

Test:	Trace test		Max. Eig. Test		Max. Eig. Test	
Null hypothesis:	One cointegrating relation		One cointegrating relation		No cointegrating relation	
Alt. hypothesis:	More than one coint. relation		Two cointegrating relations		One cointegrating relation	
Statistic:	Trace Stat.	b	ME Statistic	b	ME Statistic	b
Brazil	28.80	-	11.31	-	13.52	-
Bulgaria	6.28	-	5.75	-	34.13	***
Colombia	29.68	-	7.52	-	11.90	-
Mexico	10.60	-	7.46	-	29.75	***
Peru	10.93	-	9.00	-	12.74	-
Philippines	10.47	-	14.07	-	20.97	-
Russia	10.77	-	8.92	-	13.73	-
South Africa	12.41	-	10.19	-	26.84	***
Turkey	9.97	-	7.62	-	17.68	-
Venezuela	10.92	-	9.25	-	15.08	-

[a] *Based on cointegration with three series: log spread ratios, log rating ratios, and log duration ratios.*
[b] *Unit root is rejected at 1%, denoted.* ***

EXHIBIT 3

Cointegration Relations—Coefficient Estimates [a]

Coefficient of Log Spread Ratio Normed to Unity, Sample 1999-2004

	Log rating ratio [b]						Log duration ratio [c]			
	Basic model		Large model		Best model		Basic model		Large model	
	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.
Brazil	-4.23	1.48	-3.56	0.76	-4.10	0.89	-0.88	0.37	0.86	0.19
Bulgaria	2.98	1.07	0.76	1.87	-2.37	1.92	0.98	0.14	1.50	0.26
Colombia	-1.28	0.84	7.76	9.76	-2.73	1.36	-1.27	0.59	-18.65	4.50
Mexico	0.24	0.20	0.58	0.38	0.48	0.48	0.75	0.11	0.58	0.14
Peru	-1.64	0.78	-0.30	0.97	-0.48	1.13	0.04	0.26	0.50	0.25
Philippines	-2.57	1.51	0.75	4.35	-3.58	2.41	1.03	0.67	-4.09	1.43
Russia	0.07	0.35	-3.21	0.76	-2.17	0.68	5.17	0.75	2.07	1.11
South Africa	6.62	1.95	8.32	1.96	5.40	1.33	-2.08	0.50	-1.87	0.56
Turkey	-3.50	0.79	-2.61	1.05	-2.01	1.12	-0.42	0.28	0.59	0.33
Venezuela	-3.85	0.70	18.81	11.73	-2.34	1.00	0.66	0.23	-19.87	4.16

[a] *Positive coefficient means negative relation between log spread ratio and log rating ratio (or log duration ratio).*
[b] *Log rating ratio is log of ratio of country rating indexes (higher ratio = higher relative riskiness).*
[c] *Log duration ratio is log of ratio of country and duration indexes (higher ratio = higher relative duration).*

are the three countries with the lowest average spread and the best credit ratings over the sample period. This feeds the suspicion that for higher-grade sovereigns the role of actual creditworthiness may be less important than the role of other market factors.[3] There is also no clear pattern in the signs of the log duration coefficient.

In the large model, the coefficients look even less plausible, showing disturbingly large negative relations (positive coefficients) between spreads and credit quality in Colombia, South Africa, and Venezuela. Importantly, these are coupled with a huge sensitivity of the spread to changes in duration. A possible cause could be that the impact of several large new issuances of bonds dominates the dynamics of spreads over the sample.

The model properties improve considerably in the best model, if duration is excluded from the cointegrating relation. In this case, eight of ten countries post the correct sign for the relation between log spread and log rating ratios. Only one country, South Africa, has a significant positive coefficient.

EXHIBIT 4
Error Correction Coefficients

	Impact on change in spread						Impact on change in rating*					
	Basic model		Large model		Best model		Basic model		Large model		Best model	
	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.
Brazil	0.000	0.010	0.010	0.023	-0.015	0.023	0.005	0.002	0.010	0.003	0.012	0.004
Bulgaria	-0.013	0.010	-0.005	0.008	-0.012	0.007	-0.004	0.002	-0.001	0.001	-0.004	0.001
Colombia	-0.041	0.015	-0.005	0.002	-0.055	0.019	0.003	0.002	0.001	0.000	0.002	0.003
Mexico	-0.180	0.039	-0.224	0.042	-0.190	0.040	-0.013	0.007	-0.018	0.008	-0.014	0.007
Peru	-0.080	0.024	-0.104	0.030	-0.103	0.027	0.000	0.003	-0.004	0.004	-0.003	0.004
Philippines	0.003	0.008	-0.017	0.006	-0.016	0.014	0.002	0.001	0.001	0.001	0.004	0.002
Russia	-0.024	0.021	-0.038	0.016	-0.054	0.017	0.000	0.007	0.016	0.005	0.005	0.004
South Africa	-0.041	0.009	-0.059	0.011	-0.090	0.017	0.001	0.001	0.000	0.001	-0.002	0.002
Turkey	-0.049	0.019	-0.071	0.022	-0.077	0.023	0.006	0.002	0.005	0.003	0.005	0.003
Venezuela	-0.044	0.024	-0.003	0.002	-0.080	0.025	0.007	0.003	0.000	0.000	0.004	0.003

**Positive error means that spread is wide relative to equilibrium.*

Exhibit 4 reports results of a second plausibility check, looking at the error correction coefficients, i.e., the response of future spread and rating changes to current errors in the cointegrating relation. The response of the log spread ratio to a positive cointegration error (a log spread ratio that is "too wide") should be subsequent narrowing. This means the coefficient should be negative.

The empirical evidence confirms this for eight out of ten countries in the basic model (all significant), nine of ten countries in the large model (eight significant), and all ten countries in the best model (nine significant).

By the same token, we would expect a high log spread ratio to herald rising log rating ratios, as on many occasions the market may respond more quickly than rating agencies to changes in creditworthiness. Error correction coefficients should be positive. This holds true for only six of ten countries in the best model (five coefficients are significant coefficient). Again, in the higher-grade countries, Bulgaria, Mexico, and South Africa, spreads seem to be affected by non-rating factors.

Finally, we investigate the impact of the fast fundamentals on upcoming changes in log spread ratios (Exhibit 5). The fundamentals are the natural logarithms of the U.S. dollar price of oil, the euro-dollar exchange rate, and the ten-year U.S. Treasury yield.

Not surprisingly, the impact of a specific fundamental on the log spread ratio depends on the country. A high oil price, for example, entails spread declines in the major oil exporting countries of the sample, Mexico, Russia, and Venezuela. It also has a strong negative impact on South Africa's spread ratio, although this could reflect the positive correlation between oil prices and the prices of other raw material prices that count among South Africa's key export items.

The impact of other financial variables is subject to more interpretation (and speculation). According to the best model, a strong euro (or weak U.S. dollar) tends to reduce the log spread ratio of countries with high USD-denominated debt stock relative to gross domestic product, such as Brazil, Bulgaria, and Turkey. Yet it doesn't apply to others of that category, such as Colombia, Russia, and Venezuela, possibly because a weak USD hurts these countries' terms of trade, which depend considerably on USD-denominated oil and natural resource exports. The impact of long-term U.S. yields is even more convoluted and would require careful interpretation for each country.

Note that a negative coefficient in Exhibit 5 means that a country's spread *relative* to the market would shrink if the log Treasury yield rises; it does not mean that the absolute spread narrows. Thus the signs of the coefficients should indicate which country is more and which less sensitive to U.S. yields. Without detailed analysis, it is not easy to rationalize, though, why, say, Russia suffers more from rate yield increases than Turkey.

What do we learn from the inferences of the best model for the behavior of spread ratios? Three findings are worth pointing out:

- First, spread errors can be persistent.
- Second, in the best model, the evidence is stronger for spread error corrections by markets than by rating agencies. This suggests that spread deviations due to sluggish price adjustments are a more regular

occurrence than spread errors in anticipation of rating changes.

- Third, estimated spread errors appear to have a significant impact on future spread dynamics. Their detection may thus be useful for forecasting.

Out-of-Sample Properties: Can We Make Money?

The ultimate test of the usefulness of our framework is its ability to support an investment strategy. Many emerging market investment funds manage their portfolios against the benchmark of a broad emerging markets index. One key element of portfolio decisions is the weighting of individual sovereign creditors relative to their share in the benchmark index. The IGOV is one such benchmark.

We investigate the usefulness of the spread error correction model for the forecast of spread changes in two steps.

- For a first rough check, we compute standard measures of forecast accuracy and association, including hit rates.
- Second and more important, we compute the excess returns of a portfolio that systematically underweights (overweights) the sovereigns for which our model estimates a negative (positive) spread error.

Exhibit 6 characterizes the variable to be forecast, i.e., the change in the log spread ratio. Most important, the statistics carry all hallmarks of a zero-mean white noise. T-statistics fail to reject the null hypothesis of a zero mean for all countries; nine of ten are nowhere close to a significant error probability. Furthermore, Ljung-Box Q statistics fail to reject the null hypothesis of no autocorrelation in the series (at a minimum 10% level) for all countries except Mexico and South Africa. The white noise property of the series supports the view that short-term changes in spreads are dominated by random shocks and very hard to predict.

For a basic forecast evaluation, I reestimate model coefficients throughout the sample every week, using only data available before the forecast week. Since one needs a reasonable minimum history before the first forecast, I start with projections from January 1, 2002, based on samples going back to the beginning of 1999. Thus, for the first prediction in the forecast sample there are three years of data for estimating all model data. The underlying sample for the estimates then doubles to almost six years toward the end of the time series, presumably making coefficient estimates for later observations in the sample more accurate.

Exhibit 7 provides some basic forecast evaluation. It suggests first of all that compared to a trivial forecast model (that predicts future weekly spread changes as zero at all time) the model adds no value. Indeed, the spread error correction model does not enhance accuracy, nor do its forecasts exhibit any association with actual spread changes. The mean absolute errors are on average slightly higher than simple standard deviations of the log spread changes, and the average correlation coefficient is virtually zero.

Our lack of success here may largely reflect the very short estimation samples, particularly for the models that predict the first two years of the sample. Indeed, it would not be unreasonable to expect forecast models based on just three years to produce worse forecasts than the the-

EXHIBIT 5

Estimated Spread Impact of Global Financial Variables

	Large model						Best model					
	Oil price		EUR-USD		10y USD yield		Oil price		EUR-USD		10y USD yield	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Brazil	-0.01	0.01	-0.02	0.04	0.01	0.03	-0.01	0.01	-0.05	0.04	-0.02	0.03
Bulgaria	0.00	0.01	0.03	0.03	0.00	0.02	-0.03	0.02	-0.03	0.04	0.03	0.03
Colombia	-0.02	0.01	0.05	0.03	0.01	0.02	-0.01	0.01	0.04	0.03	0.05	0.02
Mexico	-0.01	0.01	0.07	0.03	0.02	0.02	-0.02	0.01	0.11	0.03	-0.01	0.02
Peru	0.03	0.01	0.00	0.03	0.01	0.02	0.02	0.01	-0.03	0.03	-0.02	0.02
Philippines	0.01	0.01	0.09	0.03	0.01	0.02	0.03	0.01	0.01	0.03	0.03	0.02
Russia	-0.03	0.02	0.22	0.07	0.08	0.03	-0.04	0.02	0.18	0.05	0.08	0.04
South Africa	-0.04	0.02	0.02	0.03	0.00	0.02	-0.04	0.01	0.00	0.03	0.08	0.02
Turkey	0.05	0.02	-0.09	0.04	0.00	0.02	0.04	0.01	-0.10	0.04	-0.04	0.03
Venezuela	-0.03	0.02	-0.02	0.03	-0.01	0.02	-0.02	0.01	-0.03	0.03	-0.02	0.02

Positive coefficient denotes increase in log spread ratio. Countries represented by shaded variables are oil exporting countries.

EXHIBIT 6
Changes in Log Spread Ratio: Basic Descriptive Statistics

	Mean	Std.dev	t-stat for mean = 0	Error prob.	Ljung-Box Q-stat.*	Error prob.
Brazil	0.000	0.046	-0.056	0.955	15.61	0.210
Bulgaria	-0.002	0.050	-0.797	0.426	14.63	0.262
Colombia	0.001	0.054	0.451	0.652	17.61	0.128
Mexico	0.000	0.048	0.180	0.857	28.04	0.005
Peru	0.001	0.049	0.214	0.830	11.36	0.498
Philippines	0.004	0.045	1.488	0.138	14.30	0.282
Russia	-0.007	0.055	-2.107	0.036	9.42	0.667
South Africa	-0.002	0.056	-0.665	0.506	19.57	0.076
Turkey	0.000	0.059	0.025	0.980	16.00	0.191
Venezuela	0.000	0.052	-0.046	0.964	6.35	0.897
All	0.000	0.051	n.a	n.a.	n.a.	n.a

Testing the hypothesis of no autocorrelation for up to 12 weeks' lag.

EXHIBIT 7
Simple LSR (log spread ratio) Forecast Evaluation, Out of Sample*

	2002-04 Mean average error (MAE)	MAE/ stand. deviation	Correlation coefficient	2004 Mean average error (MAE)	MAE/ stand. deviation	Correlation coefficient
Brazil	0.036	1.074	-0.204	0.026	1.005	-0.019
Bulgaria	0.038	1.012	-0.045	0.040	0.969	0.125
Colombia	0.036	1.012	-0.169	0.026	0.966	0.196
Mexico	0.033	1.101	0.247	0.030	1.204	0.137
Peru	0.033	1.020	0.094	0.038	1.109	-0.021
Philippines	0.031	1.017	0.105	0.031	0.998	0.075
Russia	0.033	1.041	-0.018	0.033	1.038	0.221
South Africa	0.046	1.058	0.087	0.034	0.935	0.494
Turkey	0.039	1.034	-0.012	0.041	1.041	-0.011
Venezuela	0.039	1.058	-0.126	0.027	1.031	0.063
Average	0.036	1.043	-0.004	0.033	1.030	0.126

Based on best SECM model, out-of-sample 1-week ahead forecasts.

oretically reasonable prediction of an unchanged spread.

I check this suspicion by computing the same forecast statistics for only the last year of the sample (2004). Accuracy (measured as mean absolute error divided by standard deviation) improves in seven of ten countries but remains dismal. Yet correlation coefficients improved, with an average of 12.6%. Indeed, correlation coefficients are positive in seven of ten countries, and only marginally negative (between 1.1% and 2.1%) in the remaining three countries.

At first glance, hit rates paint only a modestly brighter picture and reveal a similar time pattern (*see Exhibit 8*). In this case, we define a hit rate as the ratio of correct predictions of the direction of spread changes to the total number of observations investigated. The average hit rate for all countries over three years is 51.4%. For 2002 and 2003, the hit rates are low, at 50.5% and 49.0%, respectively, while for 2004 the rate increases to 54.5%.

According to these statistics, the suggested crude SECM framework would not seem to be a convincing forecast tool or hold promise for the future, even as available time series grow longer. Note, however, that the standard forecast evaluation misses two important points:

- First, the essence of the model is that it identifies mispricing or *spread errors*. That means it should be particularly useful when prices are quite far from equilibrium. Conversely, the model understandably does poorly when spread errors are small. To put this differently, the SECM would ensure that whenever there is large mispricing investors do not miss the opportunity. Thus it is possible, if not plausible, that

EXHIBIT 8

Out-of-Sample Forecast Evaluation[a] (percent)

	Hit rates [b] based on SECM, forecasts applied unconditionally				High return hit rate [c] Top 20 absolute returns
	2002-2004	2002	2003	2004	2002-2004
Brazil	46.4	44.2	34.6	60.4	55.0
Bulgaria	49.9	43.1	51.9	54.7	45.0
Colombia	48.0	41.2	48.1	54.7	55.0
Mexico	55.2	52.9	63.5	49.1	50.0
Peru	53.9	56.9	55.8	49.1	75.0
Philippines	55.1	54.9	46.2	64.2	60.0
Russia	50.0	54.9	48.1	47.2	55.0
South Africa	57.5	49.0	51.9	71.7	80.0
Turkey	52.6	56.9	48.1	52.8	60.0
Venezuela	44.9	51.0	42.3	41.5	55.0
Average	51.4	50.5	49.0	54.5	59.0

[a] *Predicated on samples starting at the beginning of 1999 and running through the week prior to forecasted week.*
[b] *Ratio of weeks for which forecast indicates correct direction to total weeks forecasted.*
[c] *Ratio of top 20 returns correctly predicted by the spread error of the SECM.*

the model helps investors to outperform by being invested when the market makes big moves.

- Second, by construction the model is not meant to operate on autopilot. It identifies spread errors but also considers that they might be corrected by either spread movement or changes in credit ratings. Even a minimum of economic knowledge about a particular country, such as whether it is likely to be upgraded or downgraded, might greatly enhance the model's power. More generally, the model is designed to complement not substitute for fundamental analysis.

Encouragingly, both points are strongly supported by the empirical evidence. Consider first the last column in Exhibit 8, a high return hit rate. This represents only the highest 20 weekly returns for the whole sample period, and indicates for what percentage of these crucial weeks the spread error estimated by the SECM would have predicted the right direction of the spread dynamics.

The model does a much better job in predicting the direction of individual country performance in these critical weeks than on average. The average hit rate rises to 59.0% from 51.4%. More important, nine of ten countries have a hit rate above 50%, and eight of ten have a higher hit rate in the high-return months than on average.

Finally, consider an analysis of excess return that would have been earned by using the SECM for leveraged spread positions. In a first exercise, I apply the most simple portfolio rule: Positions are built or liquidated at the beginning of a week and sustained throughout at least one week. If the estimated spread error at the end of the previous week is positive, i.e., the spread is wider than the fundamentals-based equilibrium, take a long position in the country.

This is a notional leveraged position, funding investment in the country's bonds by shortening the IGOV. In practice such trades are represented by over- and underweights of countries in a portfolio benchmarked against the IGOV. Profits on such positions are henceforth called excess returns. Yet, since these are leveraged positions that require little or no funding, the actual returns on capital are a high multiple of these excess returns. To put this differently, our excess returns are based on the excessively restrictive assumption that one has to hold 100% collateral for the face value of the leveraged position.

The second column in Exhibit 9 gives the excess returns earned by applying the rule to all countries for the full sample period investigated. Two findings are particularly noteworthy.

- First, the average excess return is positive. On each U.S. dollar put at risk according to the SECM-based rule, the average of positions would have earned an annual excess return of 5.0%. Some analysts might point out that for most of the sample period spreads had been narrowing for the ten investigated countries, and that simple long positions in all these countries would likewise have been possible. Yet, as the first column in Exhibit 9 shows, the excess return for this strategy would have earned less than one-twentieth of the SECM-based excess return.
- Second, the portfolio rule produces positive excess returns in eight of ten countries investigated, i.e., fairly consistently across the sample and even in countries where the simple forecast evaluation looks very unimpressive. For example, in Peru, where model-based forecasts failed to enhance accuracy and to exhibit association, the trading rule would have produced a 15.3% annual excess return.

EXHIBIT 9
Excess Return Over Market Portfolio (IGOV)

	% annualized, 2002-2004		% annualized, 2002-mid-2004 [a]			
	if always invested	position based on SECM spread error	if always invested	if positions had been taken based on SECM spread error	SECM and CDRF [b]	SECM and BDRF [c]
Brazil	7.7	3.6	6.2	7.2	21.1	13.4
Bulgaria	-5.6	5.2	-3.7	2.9	0.9	1.4
Colombia	-1.5	8.5	-1.6	8.8	8.1	2.5
Mexico	-4.7	-4.7	-3.8	-3.8	-3.8	-2.1
Peru	-1.1	15.3	-2.6	17.4	15.4	2.8
Philippines	-4.6	-0.8	-2.7	-1.2	0.8	0.0
Russia	4.7	4.7	5.9	5.9	5.9	5.2
South Africa	-4.2	11.8	-3.0	14.1	6.3	6.4
Turkey	2.1	5.8	1.5	4.3	1.7	2.8
Venezuela	8.9	0.8	8.3	1.9	-5.5	-0.2
Average	0.2	5.0	0.5	5.8	5.1	3.2

[a] *Data go only to mid-2004 since the analysis needs a 6-month lead for rating data; long (short) position is taken if SECM shows positive (negative) spread error.*

[b] *CDRF = Correct directional rating forecast; market is never surprised by the direction of rating change.*
Long (short) position is taken only if SECM shows positive (negative) spread error and there is no downgrade (no upgrade) over next 12 months.

[c] *BDRF = Basic directional rating forecast; market is able only to rule out upgrade 6 months prior to an actual downgrade and vice versa.*
Long (short) position is taken only if SECM shows positive (negative) spread error and there is an upgrade (downgrade) over next 6 months.

The portfolio rule is next investigated assuming that the market has a basic idea as to the direction of credit rating changes over the coming six months. Market knowledge is assumed to be of two kinds.

The first assumption is that the market always makes a *correct directional rating forecast* (CDRF assumption). This means investors are never surprised by the direction of rating change, although they might be by its timing. This is consistent with the common perception that rating changes tend to lag obvious economic changes and also with the common practice of rating agencies to comment on economic developments between rating announcements.

Under this assumption, I evaluate returns for an SECM-based portfolio rule with the additional restriction that investors should not take long (short) positions when they expect ratings biased toward a downgrade (upgrade). The restriction is implemented by assuming that investors could have guessed the directional bias of the rating six months prior to an actual rating action. Consequently, I exclude SECM signals for long (short) positions six months prior to a downgrade (an upgrade).

The excess return under this position is fairly close to that under the investment rule without economic knowledge. Once again eight of ten countries post a positive excess return. While the excess returns may be a touch lower, the economics-based rule is also less risky, since it avoids, for example, long positions in a country that was hit by a persistent negative shock and whose rating adjustment has been put off only because of a rating agency sluggish response.

A second and more conservative assumption as to the market's ability to anticipate rating changes is a *basic directional rating forecast* (BDRF assumption). This simply says that markets would not be expecting an upgrade (downgrade) six months before an actual deterioration (improvement) in the rating. In this case, we need to restrict position taking to long (short) positions when the SECM sends a signal *and* the market is convinced that a downgrade (an upgrade) is out of the question. For practical application, I assume that in the past the latter condition has been met six months prior to an actual upgrade (downgrade). This portfolio rule would mimic an extremely risk-averse strategy.

It is notable that even under this very conservative rule, SECM-based portfolio rules would have earned considerable excess returns—lower return than under the simple portfolio rule or under the CDRF rule, but still positive.

IV. CONCLUSION

Analysis of a basic framework for tracking the mispricing of sovereign emerging market bonds, relative to the overall market and the country's fundamental economic position, shows that (despite a short data series) a parsimoniously specified model produces coefficients that are broadly consistent with theory and intuition. Testing indicates the model provides a valuable basis for establishing trading and portfolio rules in the sovereign external credit market.

The examples illustrate merely the principles and the potential of the cointegration approach in credit markets. For practical purposes, a less rigid approach and a more flexible selection of what I call fast fundamentals will likely enhance the model's forecasting ability.

Extensions of this work would first build a theoretical bridge between the econometric model and fully fledged structural models. Second, empirical evaluation should become more fruitful with the growing maturity of sovereign credit markets. Beyond longer time series, market developments should in the future also allow for use of the cleaner risk pricing in the credit default swap market, where at present there is not yet a long enough history for analysis.

APPENDIX A

Merrill Lynch USD Emerging Markets Sovereign Plus Index (IGOV)

The IGOV is a sovereign bond index that tracks basic features of U.S. dollar-denominated sovereign debt of countries with BBB ratings or lower. Country weightings are based on prior month-end market capitalization. Country ratings over the sample period examined (1999-2004) are based on a composite of Moody's and Standard & Poor's. The calculation of the composite rating is simply an average with a bias toward the lower of the two ratings.[4]

Minimum requirements for inclusion in the index are an amount of USD300 million outstanding and one year remaining to maturity. Countries rated as in default may remain in the index, but individual bonds that are in default are excluded.

The IGOV is rebalanced on the last calendar day of each month. New bonds that have met the criteria during the month are added. Conversely, bonds that have ceased to meet all criteria are dropped. This can have a considerable impact on index dynamics.

For example, in December 1999, Greece, then 10% of the entire IGOV, was upgraded to A and taken out of the index. As a result, the overall credit quality of the index declined, and spreads narrowed. Another big jump occurred in early 2002, when Argentine bonds were beginning to be downgraded. The first downgrade resulted in the loss of about 8% of the index, improving IGOV credit quality and narrowing spreads. Importantly, however, revisions of the IGOV are always mirrored by revisions to the IGOV rating index, which means both are moving in a coordinated fashion, preserving their suitability for cointegration.

Merrill Lynch publishes subindexes that segment the IGOV by region (Latin America, Europe, and Asia); by type (Brady and non-Brady debt); and by individual country.

APPENDIX B

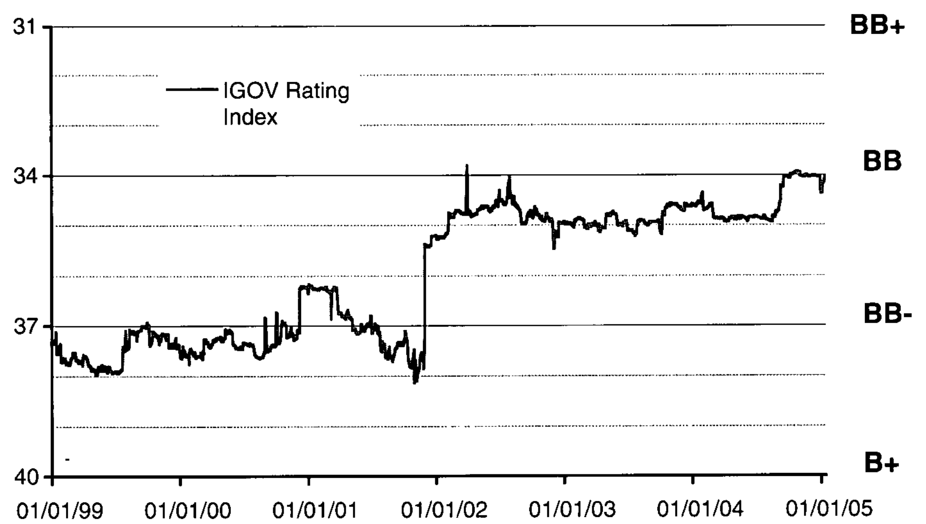
Merrill Lynch Sovereign Rating Index

The Merrill Lynch credit rating indexes are based on S&P and Moody's long-term foreign currency ratings. The rating scale runs from a minimum of 0 (AAA) to a maximum of 63 (selective default).

An index declines linearly when a credit rating improves. It also takes into consideration the rating outlook (positive, stable, or negative). Thus, each credit point denotes a shift in outlook by both agencies, e.g., BB+/positive to BB+/stable or BB+/positive to BBB+/negative. An outlook change by only one agency is worth half a point. A full rating change by both agencies would represent a three-point shift in the rating value.

Exhibit B shows that a BB/stable rating by both agencies corresponds to an index level of 34, a BBB/stable – to 25, and an A/stable – to 16 points.

EXHIBIT B
Merrill Lynch Emerging Markets Rating Index



Source: Merrill Lynch.

ENDNOTES

This article reflects the personal views of the author, not necessarily those of his employer.

[1]IGOV data are publicly available from Bloomberg under IND<Go> and on the web at www.mlindex.ml.com/gispublic. Performance and spreads are very similar to the EMBI.

[2]Trend and intercept are not generally identified in this specification, although one can argue that the average residual of the cointegrating relation was probably zero over the sample horizon. The intercept in the cointegrating relation is thus restricted so that it guarantees the zero mean of the residuals.

[3]For example, in Bulgaria the presence of callable bonds in the index has limited the downside for index spreads, since the government has an incentive to call if the price breaks a certain threshold, capping the upside for investors.

[4]As of January 1, 2005, country ratings in the Merrill Lynch indexes are based on a composite rating of Moody's, S&P, and Fitch.

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