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EMBEDDED BETAS AND BETTER BETS: FACTOR INVESTING IN EMERGING MARKET BONDS*

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We document novel empirical insights driving the prices of sovereign external emerging market bonds. In the time series, we examine the market portfolio's time-varying exposures to a broad set of macro factors (rates, credit, currency, and equity) and identify these embedded betas as key drivers of its excess returns. In the cross-section, we construct complementary value and momentum style factors and demonstrate their ability to explain country expected returns. Building off these insights, we introduce a simple risk-on versus risk-off framework to characterize the correlation structure spanning our macro and style factors. Lastly, we show how our style factors can be incorporated into an optimized long-only portfolio to generate outperformance relative to a value-weighted benchmark portfolio.

Sovereign external emerging market bonds (EMBs) are complex assets. While similar to traditional fixed-income instruments driven primarily by interest rate and credit risk factors, the unique dynamics of emerging markets (EM) suggest that additional factors may be necessary to understand this asset class in both the time series and the cross-section. As such, we argue that the EMB universe serves as an appealing empirical setting to explore the role of both macro and style factors.[1] Our paper attempts to answer several salient questions: What broad insights can macro factors provide to the time series of returns? What country-specific insights can style factors provide to the cross-section of expected returns? How can a factor-based investor systematically leverage these insights?

To motivate our paper, we begin by illustrating how macro factors have been a significant source of time-varying risk in the EMB universe. The top panel of Figure 1 decomposes the total risk of a value-weighted EMB portfolio between 2000 and 2017 in terms of macro risk factors. As expected, interest rate and credit risk factors appear to be

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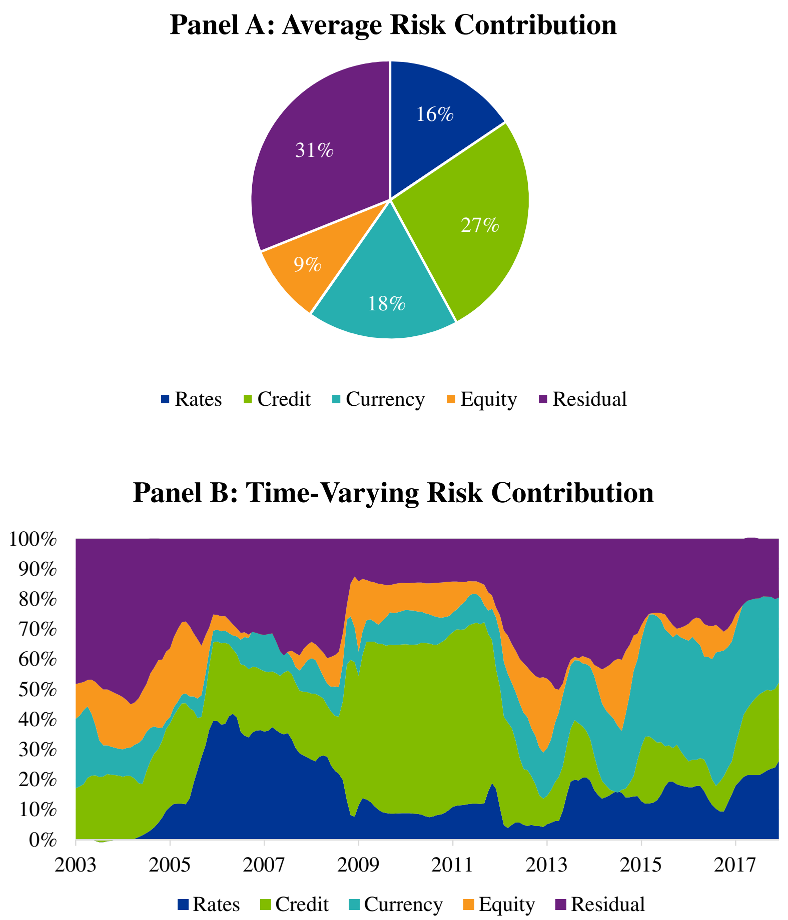

Figure 1 Macro Factors and Emerging Market Bonds (2000–2017).

The figures above illustrate macro factor risk contributions for a value-weighted portfolio of USD-denominated sovereign emerging market bonds. Macro factors are defined as the following indices: Rates (JP Morgan Government Bond Index Global), Credit (Bloomberg Barclays US High Yield Index), Currency (MSCI Emerging Market Currency Index), and Equity (MSCI World Index). Risk contributions are estimated and attributed following the risk decomposition methodology described in the Appendix.

the primary sources of risk, with relative risk contributions of 16% and 27%, respectively.[2] While the EMB universe only includes USD-denominated bonds with no explicit exposure to exchange rate fluctuations or global equity markets, our EM currency and global equity factors surprisingly account for 18% and 9% of the portfolio's risk, respectively. Moreover, the bottom panel of Figure 1 reveals that these relative risk contributions have not been static, but in fact varied significantly over time.

Given these observations, our empirical analysis begins with an examination of the time series relationship between macro factors and EMB returns. We first highlight the impressive performance of the EMB portfolio, which realized an annualized excess return of 7.5% with a volatility of 9.0% over this sample period, corresponding to a Sharpe ratio of 0.83. After controlling for its macro factor exposures, however, we find that the EMB portfolio realized no significant outperformance. We then examine the EMB portfolio's macro factor exposures, which we call embedded betas, finding the relative risk contributions from these macro factors to be well balanced on average.

Next, we investigate the ability of value and momentum style factors to explain the cross-section of country expected returns. We find that our risk-seeking value factor serves as an important source of risk-adjusted returns, while our momentum factor provides valuable defensive protection. We construct our value factor based on a measure we call default-adjusted spread, which corresponds to option-adjusted spread adjusted for expected sovereign default risk. On the other hand, our momentum factor exploits a simple cross-asset insight from currency markets to identify challenging sovereign credit conditions. Since a depreciating currency weakens a sovereign issuer's ability to service its external debt, we argue that negative currency momentum should forecast lower bond prices to the extent that bond markets underreact to movements in the foreign exchange market.

Comparing our macro and style factors, a particularly interesting observation is the balance between risk-on and risk-off characteristics. Consistent with this intuitive framing, our empirical analyses confirm the diversifying risk-seeking versus defensive correlation structure both within and across both types of factors. We argue that our analysis provides a valuable framework that practitioners can employ to help guide asset allocation decisions that aim for diversification across macro and style factors.

Finally, we empirically test how incorporating our style factors into a long-only portfolio can generate outperformance relative to the value-weighted EMB portfolio through improved country-selection bets. We do so by constructing and backtesting optimized long-only portfolios that incorporate realistic benchmark-relative constraints and trading frictions. We find that a multi-factor strategy that combines value and momentum insights outperforms its value-weighted benchmark by 60 basis points per annum net of transaction costs, resulting in a net information ratio of 0.82.

The remainder of this paper is organized as follows: Section 1 provides a review of related literature, Section 2 describes our data, Section 3 examines macro factors in the time series, Section 4 investigates style factors in the cross-section, Section 5 incorporates our style insights into a long-only optimized portfolio, and Section 6 concludes.

1 Literature review

Our paper attempts to contribute to a few areas of existing academic and practitioner research: emerging markets finance, asset pricing anomalies, and factor investing in fixed income markets. We argue that EMB returns are not only explainable in the time series by macro factors, but also predictable in the cross-section by style factors. Given our empirical findings and the growing interest in factor investing, our research aims to provide new perspectives on key drivers of EMB returns, along with practical insights for investors seeking to outperform traditional value-weighted indices.

A large body of research has explored the behavior of asset prices in emerging market countries. For example, Bekaert and Harvey (1997) demonstrate that the influence of global factors on EM equity markets varies over time depending on the degree of capital market integration. Moreover, they find that equity volatility varies significantly across countries depending on numerous country-specific factors. Their results are consistent with our examination of emerging market bonds in the time series as well as in the cross-section. Levy-Yeyati and Williams (2010) find that changes in EM bond spreads are related to interest rate and credit factors, but the sign of these relationships varies depending on risk-on and risk-off periods. Our results demonstrate how an even broader set of macro factors that includes equity and currency factors further contributes to the time-varying risk of EMB returns.

A number of studies within empirical asset pricing have identified several factors that are useful for explaining as well as predicting returns. Fama and French (1993) identify five broad risk factors from equity and corporate bond markets, which they use to explain the time series of returns in both asset classes. Asness *et al*. (2013) document robust empirical evidence for value and momentum style factors forecasting returns across several asset classes over a long history. In this paper, we propose EMB assets as an interesting setting to investigate similar insights, and we indeed find empirical evidence consistent with these seminal papers in the time series as well as in the cross-section.

Lastly, this paper relates to a topic of growing interest amongst investors – factor-based investment strategies in fixed income markets. Israel *et al*. (2018) define a rich set of carry, defensive, momentum, and value style factors that helps explain the cross-section of corporate bond returns. Kang *et al*. (2018) identify quality and value style factors motivated by the insight that corporate bond investors have an excessive preference to reach for yield within ratings groups. Staal *et al*. (2015) examine the role of macro risk factors in fixed income portfolios and demonstrate the risk-adjusted outperformance of a risk-balanced strategy. In relation to these papers, our paper not only furthers the investigation of style factors to a less studied fixed income market, but also highlights the significant role of macro factors in this setting.

2 Data

The bond dataset used in this paper consists of monthly pricing and security-level information for all USD-denominated bonds contained in the Bank of America Merrill Lynch Emerging Markets External Sovereign Index from January 2000 through December 2017. We further subset this dataset to form our universe by selecting bonds issued by the 25 countries that have historically been included in the JP Morgan EMBI Plus index over the sample period. Though other proxies for emerging markets external debt exist, we choose to use the EMBI Plus index as the basis for our universe due to its secondary market liquidity requirements and exclusion of quasi-sovereign issuers.

Table 1 reports performance statistics of a benchmark portfolio, which we call EMB, and individual country portfolios. The EMB portfolio is formed at the end of each month by value-weighting all bonds in our universe, while the individual country portfolios are similarly constructed by value-weighting all bonds issued by each country. As reported in Panel A, the EMB portfolio realized an average excess return of 7.5% with 9.0% volatility over our sample period, resulting in a Sharpe ratio of 0.83. For context, the JP Morgan EMBI Plus index earned an average excess return of 7.1% with 9.3% volatility, resulting in a Sharpe ratio of 0.77 over the same period. All excess returns are annualized figures calculated in excess of the 3-month USD LIBOR rate. We stress that the empirical tests and conclusions presented throughout this paper are robust to swapping EMB returns with JP Morgan EMBI Plus returns.

As shown in Panel B, the three largest countries over time were Brazil, Mexico, and Russia, representing on average 15.6%, 13.4%, and 12.5% of our universe by market capitalization, respectively. During this period, the best performing countries were Romania, Russia, and the Philippines, which realized Sharpe ratios of 1.09, 1.05, and 0.88, respectively. The worst performing country was Argentina, which saw

Table 1 Summary statistics (2000–2017).

	EMB	Rates	Credit	Currency	Equity
Panel A: Index Portfolios					
Return	7.5%	2.7%	5.5%	4.6%	3.2%
Volatility	9.0%	3.0%	9.5%	6.4%	15.2%
Sharpe Ratio	0.83	0.88	0.58	0.72	0.21
	Return	**Volatility**	**Sharpe ratio**	**% Market**	**# Bonds**
Panel B: Country Portfolios					
Argentina	5.6%	29.7%	0.19	5.4%	5.8
Brazil	9.0%	15.3%	0.59	15.6%	18.8
Bulgaria	5.5%	8.0%	0.68	1.1%	2.0
Colombia	7.8%	10.1%	0.77	10.6%	10.1
Croatia	4.4%	6.1%	0.72	1.2%	3.6
Ecuador	11.5%	24.0%	0.48	1.1%	2.5
Egypt	6.8%	9.5%	0.72	0.7%	2.4
Hungary	5.8%	9.8%	0.59	1.5%	3.1
Indonesia	8.1%	12.4%	0.66	5.2%	9.4
Malaysia	4.0%	5.0%	0.80	1.9%	2.4
Mexico	6.2%	8.0%	0.78	13.4%	16.0
Morocco	4.3%	7.0%	0.61	0.6%	1.4
Nigeria	11.8%	14.1%	0.84	1.0%	2.5
Panama	7.6%	9.3%	0.81	2.6%	7.2
Peru	8.2%	12.0%	0.68	2.7%	5.8
Philippines	7.4%	8.4%	0.88	6.6%	14.5
Poland	4.6%	5.8%	0.79	3.7%	4.9
Qatar	5.4%	6.8%	0.79	3.0%	5.5
Romania	7.7%	7.1%	1.09	1.3%	3.3
Russia	12.2%	11.7%	1.05	12.5%	7.4
South Africa	5.8%	8.1%	0.72	2.0%	5.0
South Korea	4.3%	6.0%	0.73	1.9%	3.9
Turkey	8.0%	12.3%	0.65	9.0%	15.4
Ukraine	12.3%	22.7%	0.54	1.6%	5.4
Venezuela	6.8%	23.3%	0.29	6.1%	12.1

This table reports summary statistics for the monthly dataset between January 2000 and December 2017. EMB corresponds to a value-weighted portfolio of USD-denominated sovereign emerging market bonds. Country portfolios are formed similarly. Macro factors are defined as the following indices: Rates (JP Morgan Government Bond Index Global), Credit (Bloomberg Barclays US High Yield Index), Currency (MSCI Emerging Market Currency Index), and Equity (MSCI World Index). Returns are reported in annualized terms and in excess of the 3-month USD LIBOR rate.

a return of 5.6% with 29.7% volatility, resulting in a Sharpe ratio of 0.19. We also note that our sample includes historical issuer defaults in Argentina, Ecuador, Nigeria, Russia, Ukraine, and Venezuela.[3]

In addition to bond data, we augment our dataset with pricing information for each country's credit and currency markets. We source credit default swap (CDS) data from Markit for each sovereign reference entity based on 5-year CDS spreads. Since not all countries have tradable instruments for all markets at each point in time, we note that some of our empirical analyses exclude countries with missing data. We also obtain foreign exchange (FX) spot rates from Bloomberg to calculate FX returns for each country. Note that countries with official or unofficial currency pegs during our sample period are also excluded from our empirical analyses.

Finally, we obtain a ratings transition matrix from the Standard & Poor's Sovereign Ratings Performance 2002 report. This table presents the 1-year probability of ratings migration for sovereign foreign currency bonds computed using data from 1975 to 2002. We compute the cumulative average probability of default by rating and time-to-maturity by iteratively multiplying this transition matrix with itself and extracting the column corresponding to default. Since our value measure utilizes data from this table, all empirical tests involving style factors begin in 2003 to prevent look-ahead bias.

3 Macro factors

We identify four key macro factors (rates, credit, currency, and equity) that drive EM bond returns and proxy their returns using well-known global market indices. Our choices are primarily motivated by the fact that the chosen indices are investable, track reasonably liquid securities, and possess historical coverage spanning our sample period. We furthermore emphasize that our empirical results are robust to different index choices and replacing them with alternative specifications does not materially affect our conclusions.[4] While we acknowledge the importance of commodities to emerging markets, we do not include commodities as a macro factor since exposures are very heterogeneous across countries. Our universe not only includes countries that are net exporters of commodities, but also countries that are net importers. Moreover, commodities include multiple subsectors with varying degrees of impact on different countries – some countries may be exporters of metals, while others may be importers of oil. As such, we exclude commodities as a macro factor to avoid confounding results.[5]

We proxy the rates factor with the USD-hedged version of the JP Morgan Government Bond Index Global, which tracks a global portfolio of government bonds. This measure essentially aims to capture interest rate risk and inflation risk in the global economy.[6] Note that we minimize any FX risk embedded in foreign government bonds that may interfere with our analysis by using the USD-hedged version of the index.

Our credit factor is represented by the Bloomberg Barclays US Corporate High Yield Index, which consists of global high-yield corporate bonds denominated in USD. While this return series primarily captures corporate default risk, we also exploit its properties as a proxy for sovereign credit risk, drawing inspiration from the results of Longstaff *et al.* (2011), who find that changes in US high-yield spreads contain significant power in explaining changes in EM sovereign CDS spreads. We further justify the selection of this index by emphasizing its rich history versus alternatives like the CDX High Yield index.

Our currency factor is represented by the MSCI Emerging Market Currency Index, which captures the USD performance of 25 EM currencies weighted by each country's weight in the MSCI Emerging Markets Index. Although our bonds are denominated in USD and thus do not have direct exposure to currency fluctuations, we employ this series to capture several closely related, yet arguably inseparable risk factors. In particular, we stress that changes in exchange rates induce an asset-liability mismatch that affects the debt burden of sovereign issuers and their ability to service their USD-denominated debt.[7] We also contend that EM currency fluctuations reflect global trade activity, especially with respect to commodity cycles and capital flows between developed and emerging markets.

Our equity factor is represented by the USD-hedged version of the MSCI World Index, which reflects the performance of a market-capitalization-weighted basket of stocks from developed market countries. We interpret this series not only as a measure of the global equity risk premium, but also as a proxy for economic growth and changes in investor risk appetite.

Panel A of Table 1 reports performance statistics for each of the macro factors, along with the benchmark EMB portfolio. Over our sample period, the rates, credit, currency, and equity factors realized Sharpe ratios of 0.88, 0.58, 0.72, and 0.21, respectively. We particularly draw attention to the result that the EMB portfolio delivered excess returns greater than all four macro factors and a Sharpe ratio higher than the credit, currency, and equity factors.

In Table 2, we report the results of time series regressions of monthly excess returns of the EMB benchmark portfolio onto excess returns of our macro factors over the sample period of January 2000 through December 2017. Regressions (1) through (4) each include one macro factor and an intercept while regression (5) is a multivariate regression that evaluates the joint explanatory power of all four macro factors. The credit factor appears to have the most standalone explanatory

Table 2 Macro factors and EMB (2000–2017).

	(1)	(2)	(3)	(4)	(5)
Intercept	0.45%	0.34%	0.31%	0.54%	0.04%
	[2.6]	[2.5]	[2.1]	[3.6]	[0.3]
Rates	0.76				1.11
	[3.9]				[8.5]
Credit		0.62			0.42
		[12.8]			[7.3]
Currency			0.83		0.31
			[10.7]		[3.6]
Equity				0.33	0.11
				[9.7]	[2.7]
Adj. Rsq.	0.06	0.43	0.35	0.30	0.62
Num. Obs.	216	216	216	216	216

This table reports time-series regressions of monthly EMB portfolio returns regressed onto each of the macro factors. Note these are explanatory regressions as all variables are contemporaneous. Returns are reported in annualized terms and in excess of the 3-month USD LIBOR rate.

power, with $R^2 = 0.43$, followed by the currency factor with $R^2 = 0.35$ and the equity factor with $R^2 = 0.30$. The rates factor, while significant, surprisingly has the lowest standalone explanatory power among our macro factors, with $R^2 = 0.06$. Taken more generally, the univariate regressions (1) through (4) show that while the macro factors each have significant power in explaining the returns of these bonds, the significant intercept suggests that the EMB portfolio generates a premium over passive exposure to any one of these factors. In comparison, the multivariate specification in regression (5) produces significant loadings on all four macro factors and an insignificant intercept with adjusted $R^2 = 0.62$. In other words, combining all of these macro factors allows us to fully explain the performance of the EMB portfolio over this sample period.

We present an alternative way of understanding this insight in Figure 1, which illustrates the relative risk contributions of our macro factors to the overall risk of the EMB portfolio. Drawing inspiration from the methodology of Ang and Kristensen (2012), we calculate the time-varying factor exposures of the EMB portfolio by performing rolling 36-month regressions onto our macro factors. We then take the coefficients β_i from these regressions and measure relative risk contribution (RRC) for each factor as follows[8]:

$$RRC_i = \beta_i \frac{cov(EMB, x_i)}{\sigma^2_{EMB}} \qquad (1)$$

$$RRC_{Resid} = \frac{\sigma^2_{\epsilon}}{\sigma^2_{EMB}}. \qquad (2)$$

Panel A of Figure 1 presents the relative risk contribution of each macro factor averaged over the entire sample period. This chart reveals the average risk contribution across time to be surprisingly balanced across factors, suggesting that the EMB portfolio embeds risk parity-like properties. While both Panel A and the results of Table 2 ostensibly show that the EMB portfolio has exposure to all four macro factors simultaneously, the heterogeneity and dynamic nature of emerging markets suggest that these exposures are unlikely to be static. Ang *et al.* (2017) stress the importance of analyzing time-varying factor exposures, noting that return attribution using full-sample regressions can be misleading. We explore this idea further in Panel B of Figure 1, which presents the relative risk contribution of each macro factor to the total risk of the EMB portfolio at each point in time. From this perspective, the risk composition of the EMB portfolio appears to vary dramatically over time, with the credit factor dominating the period around the 2008 Global Financial Crisis and the currency factor playing a larger role in later parts of the sample. We argue that since the EMB portfolio has no active mechanism to diversify its macro factor exposures, it experiences relatively large volatility shocks from macro events. In other words, EMB's dynamic factor exposures might be considered a form of embedded leverage (Frazzini and Pedersen, 2012).

4 Style factors

Having established that macro factors explain EMB returns in the time series, we next assess the ability of style factors to predict the cross-section of country returns. We define intuitive measures of value and momentum, constructing factor portfolios that correspond to each style factor, and demonstrate that these style factors predict returns in a complementary manner.

Our measure of value, which we refer to as default-adjusted spread, aims to identify bonds with an attractive spread relative to their default risk. In order to recognize these relative opportunities, we first compute a model spread using historical default probabilities. For each bond, we use the table described earlier to estimate its expected cumulative probability of default (CPD) based on its time-to-maturity (TTM) and credit rating. We calculate the annualized probability of default (PD) as the geometric average of CPD such that $PD = 1 - (1 - CPD)^{\frac{1}{TTM}}$. It then follows that the model spread can be calculated as $PD(1 - R)$, where R is the expected recovery rate. For the purpose of our analysis, we simplistically assume $R = 50\%$ and aggregate model spreads to the country level with market-value weights. Note that since this model spread is calculated within a risk-neutral framework without accounting for investors' risk preferences, it is not directly comparable to spreads observed in the market. To avoid making assumptions about time-varying risk preferences, we perform monthly cross-sectional regressions of the log of option-adjusted spread (OAS) onto a constant and the log of model spread:

$$ln(oas_{i,t}) = \alpha_t + \beta_t \ln(Model\ Spread_{i,t}) + \epsilon_{i,t}. \tag{3}$$

The intercept controls for variables driving the general level of credit spreads, while the slope controls for the price of default risk across different countries. We estimate default-adjusted spread by taking the residuals from this regression. A high (low) residual indicates a country trading at a relatively low (high) price compared to its default risk, thereby indicating that its bonds are cheap (expensive).

We also consider an alternative value measure that exploits differences between bonds and their related CDS contract by regressing the log of OAS onto the log of the CDS spread:

$$ln(oas_{i,t}) = \alpha_t + \beta_t \ln(CDS\ Spread_{i,t}) + \epsilon_{i,t}. \tag{4}$$

We then take the residuals from this regression as a proxy for the bond–CDS basis. While the law of one price suggests that this basis should theoretically not exist, Chan-Lau and Kim (2004) argue that market frictions in emerging markets produce short-term differences between CDS and sovereign bond spreads, though a strong cointegrating relationship exists between the two. If we interpret the basis as a measure of bonds' relative cheapness to their related asset, we can identify cheap (rich) issuers as those with a high (low) option-adjusted spread relative to the CDS spread. Compared to the value measure using model spreads computed from historical default probabilities, we interpret this alternative specification as incorporating forward-looking default probabilities. Although we examine the explanatory power of both specifications, we use the measure based on model spread for our final value factor due to the limited coverage of CDS data.

Our momentum factor capitalizes upon the tendency of recent past asset returns to persist in the future and utilizes information from currency markets. We define our momentum measure as the ratio of past returns to realized volatility, both measured over a 6-month horizon:

$$Momentum_{i,t} = \frac{r_{t:t-6}^{FX_i}}{\sigma_{t:t-6}^{FX_i}}. \tag{5}$$

While we observe that short-term bond returns are somewhat predictive, we find that past returns from currency markets possess even greater explanatory power. Greater liquidity in currency markets compared to bond markets may contribute to a difference in the speed at which prices incorporate country-specific information. Viewed from a more fundamental perspective, we argue that FX momentum captures an element of credit quality. Since fluctuations in the exchange rate can create asset–liability mismatches for sovereign issuers, FX momentum may identify credit deterioration before this information is reflected in bond spreads. As for the choice of the return horizon, our regression results are robust to alternative specifications, but we choose an intermediate horizon of 6 months to balance

Table 3 Style factors and EMB country returns (2003–2017).

	(1)	(2)	(3)	(4)	(5)
Duration	−0.02	−0.01	−0.02	−0.01	−0.11
	−[0.4]	−[0.2]	−[0.4]	−[0.3]	−[0.7]
Rating	0.29	0.22	0.28	0.21	0.23
	[4.8]	[3.8]	[4.5]	[3.3]	[2.9]
Value		0.27		0.28	0.27
		[6.4]		[6.4]	[4.9]
Momentum			0.03	0.06	0.05
			[1.5]	[3.1]	[2.0]
Adj. Rsq.	0.011	0.034	0.012	0.035	0.029
Num. Obs.	2,582	2,582	2,582	2,582	1,438

This table reports relationships between country portfolio returns and style factors. Note these are predictive panel regressions as all independent variables are lagged by one month. Value and momentum style factors are defined in the text. In Column (5), value is measured using CDS spreads for those countries with liquid CDS markets (as described in the text). All regressions include time and country fixed effects with standard errors clustered by country.

the trade-off between statistical significance and portfolio turnover.

For all of the measures defined above, we construct standardized factor scores as follows. For a given set of values on a given month, we standardize by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. This methodology aids the interpretability and comparability of factor scores for different cases, both in the cross-section and in the time series. For each factor, we also construct a self-financing factor portfolio whose long and short sides each sum to one by taking its standardized factor scores (z) and calculating portfolio weights (f):

$$f_{i,t} = 2\frac{z_{i,t}}{\sum_i |z_{i,t}|}. \tag{6}$$

We first use these factors in panel regressions to judge their ability to explain returns and then proceed to incorporate them into a portfolio optimization framework in an attempt to outperform our value-weighted benchmark.

Table 3 reports the results of panel regressions of country portfolio returns onto lagged value and momentum factor scores. Across all regression specifications, we include duration and rating as controls while also incorporating time and country fixed effects. Ratings are mapped to numeric values at the bond level, with a higher number representing a lower rating, and then aggregated to the country level using market-value weights.

Regression (1) shows that rating, rather than duration, is the more significant factor among our control variables in explaining the cross-sectional variation in returns. On the other hand, regression (2) reveals the country-selection ability of our value measure, which has a t-statistic of 6.4. While the results of regression (3) suggest that our momentum measure has little forecasting ability, regression (4) reveals that it is in fact significant once value is included. As will be shown later, momentum is quite negatively correlated with value as well as other risk factors. Regression (5) uses our forward-looking measure of value based on CDS spreads instead of model spreads

Table 4 Macro and style factors (2003–2017).

	Rates	Credit	Currency	Equity	Val	Mom	ValMom
Panel A: Performance Statistics							
Return	2.4%	7.3%	4.7%	8.2%	7.6%	1.2%	4.4%
Volatility	3.1%	9.3%	6.8%	14.4%	6.1%	4.7%	3.1%
Sharpe Ratio	0.77	0.78	0.69	0.57	1.24	0.25	1.43
Panel B: Factor Correlations							
Rates	1.00	−0.12	−0.07	−0.21	−0.13	0.06	−0.09
Credit		1.00	0.63	0.75	0.51	−0.16	0.39
Currency			1.00	0.74	0.45	−0.22	0.28
Equity				1.00	0.45	−0.11	0.36
Val					1.00	−0.38	0.70
Mom						1.00	0.39
ValMom							1.00

This table reports performance statistics and correlations of macro and style factor returns. Long-short style portfolios are constructed as described in the text. ValMom corresponds to an equal-weighted combination of value and momentum. Returns are reported in annualized terms and in excess of the 3-month USD LIBOR rate.

for the subset of countries with CDS markets. Overall, these results highlight the significance of our value and momentum style factors as well as the importance of carry as expressed through our rating variable.

We next consider interactions within and across our macro and style factors, with a particular focus on their correlation structure. Panel A of Table 4 reports performance statistics for our style factors and macro factors. Our value factor outperforms the EMB portfolio and all the four of our macro factors with a Sharpe ratio of 1.24. In contrast, momentum seems to be a weak factor with a Sharpe ratio of 0.25, paralleling the result presented in Table 3. Despite its weak standalone performance, momentum appears to be additive to value, as reflected in the 1.43 Sharpe ratio of the ValMom factor, which equally combines value and momentum. Panel B of Table 4 includes a correlation matrix of EMB along with all our macro and style factors. Value appears to be positively correlated to the three risk-on macro factors, whereas momentum has a negative correlation to all our risk-on factors and almost no correlation to the risk-off rates factor. We view this correlation structure in the context of a risk-on and risk-off frameworks, as presented in Panel A of Figure 2. This framework allows us to interpret value as a risk-seeking factor that drives performance during risk-on periods and momentum as a defensive factor that provides stability during risk-off periods. Panel B of Figure 2 visualizes this parallelism by presenting correlations both within and across macro and style factors. We emphasize that this correlation structure underlines the additivity of momentum as a defensive factor that is not only complementary to the risk-seeking value factor and risk-on macro factors, but also orthogonal to the standard defensive rates factor.

We examine the robustness of our style factors by considering alternative constructions in Table A.1. Panel A reports performance statistics for the baseline value factor (V1) and momentum factor (M1), along with alternative constructions. For value, we decompose our default-adjusted

Panel A: Risk-On vs. Risk-Off Matrix

	Macro Factors	Style Factors
Risk-On	Equity Credit Currency	Value
Risk-Off	Rates	Momentum

Panel B: Correlation Estimates

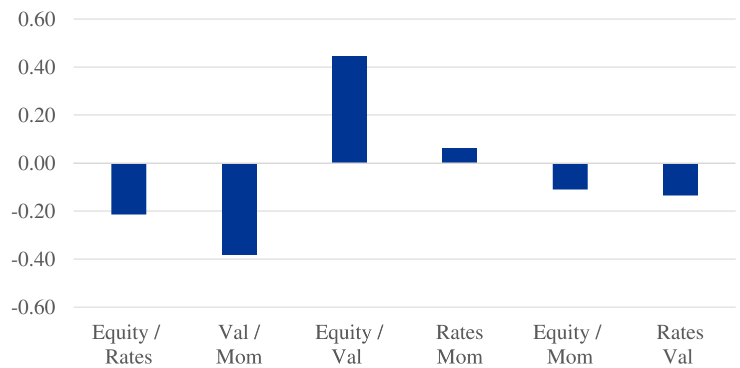

Figure 2 Factor Correlations.

The figures above provide illustrations of macro and style factor correlations. Panel A provides a risk-on versus risk-off framework for considering these correlations. Panel B reports historical correlations estimated between January 2003 and December 2017.

spread measure into its constituent components and assess their standalone performance as factors. The V2 specification uses only OAS in its construction, essentially corresponding to a carry factor. Specifications V3 and V4 continue to utilize the cross-sectional regression methodology, with V3 assuming a recovery rate of 0% and V4 replacing model spread with a numeric ratings variable. For momentum, we consider different return horizons and examine the importance of volatility scaling. M2 uses a 3-month horizon for returns and volatility, whereas M3 uses a 9-month horizon. Finally, M4 uses a 6-month horizon for returns without volatility scaling. The strong performance of all our value specifications demonstrates the additivity of each subcomponent in our baseline value factor, while the negative performance of the momentum specification based purely on past returns highlights the importance of exchange rate volatility in return predictability. Panel B presents a correlation matrix that includes each variant, revealing that the alternative specifications are not only highly correlated with each other, but also preserve the negative correlation structure between value and momentum.

5 Long-only portfolio optimization

We conduct backtests on long-only portfolios determined using an optimization methodology that incorporates our factor insights as well as a set of practical investment constraints. Our optimization problem is specified as follows:

$$\max_{w} \sum_{i} w_{i,t} z_{i,t}$$

$$\textit{subject to} \quad w_{i,t} \geq 0 \; \forall i$$

$$\omega^{L} \leq w_{i,t} - b_{i,t} \leq \omega^{U} \; \forall i$$

$$\sum_i w_{i,t} = 100\%$$

$$\sum_i |w_{i,t} - w_{i,t-1}| \leq \tau$$

$$DUR^L \leq \sum_i w_{i,t} dur_{i,t} \leq DUR^U$$

$$DTS^L \leq \sum_i w_{i,t} dts_{i,t} \leq DTS^U.$$

Every month, we solve for the vector of portfolio weights (w) that maximizes exposure to a vector of factor scores (z) subject to position, trading, and risk constraints. The first constraint limits position weights for all assets in the portfolio to a minimum of 0%. The second constraint limits the portfolio's active weights to a minimum of -5% (ω^L) and a maximum of 5% (ω^U). The third constraint is a full-investment constraint that ensures that the portfolio weights sum to 100%. The fourth constraint limits monthly portfolio turnover based on a parameter (τ), which we set to be 3% monthly, or about 1% higher than the turnover of the value-weighted benchmark. The fifth constraint sets upper and lower bounds on portfolio duration exposure, which we set to be within $+/-10\%$ of the benchmark's duration. The sixth constraint similarly limits duration-times-spread exposure to be within $+/-10\%$ of the benchmark's exposure.[9] While all of these parameter choices represent our baseline specifications, we will also show robustness tests that vary these choices.

It is worth noting that for the sake of simplicity, we do not incorporate a risk model or transaction cost model into our optimization problem. While a risk model could help improve portfolio diversification, risk management, and risk-adjusted performance, building such a risk model would introduce additional parameters and choices. We instead utilize the duration and duration-times-spread constraints to help control key systematic risk factor exposures relative to the benchmark. Likewise, using a transaction cost model with an ex-ante transaction cost aversion term could help improve net returns, but we exclude this in favor of only applying transaction cost estimates ex post to all trades. These transaction costs are approximated at the country level, using the average of historical bid–ask spreads for sovereign emerging market bonds from an internal database. Estimated average one-way transaction costs range from 31 basis points for Argentina to 81 basis points for Turkey, with a mean of 47 basis points. Furthermore, given that many sovereign issuers have multiple external bonds, another practical consideration is to construct the portfolio at the bond level. Since country selection is the principal determinant of relative value performance, we choose not to incorporate bond selection into the modeling process.

In Table 5, we delineate the results of following the long-only portfolio optimization methodology described above to construct optimized portfolios that incorporate our style factors. We report performance statistics as before, but also include these figures net of estimated transaction costs along with standard fixed income portfolio characteristics (yield, option-adjusted spread, and duration). This table compares the benchmark portfolio against portfolios that incorporate only the value factor, only the momentum factor, and a blend of both factors. The benchmark portfolio, after accounting for transaction costs, has a net Sharpe ratio of 0.87. By comparison, the value and momentum portfolios outperform the benchmark with net information ratios of 0.56 and 0.14, respectively. Consistent with prior results, the value portfolio appears to be slightly more risk-seeking than the momentum portfolio, with a higher yield (5.4% vs. 5.1%) and higher OAS (252 vs. 215). The final optimized portfolio, labeled ValMom, demonstrates the

Table 5 Optimized portfolios (2003–2017).

	Return	Net return	Volatility	Sharpe ratio	Net S.R.	Net alpha	Volatility	Net I.R.	yield	oas	duration	turnover
EMB	7.1%	7.0%	8.0%	0.89	0.87				5.2	226	7.0	21%
Val	7.8%	7.7%	8.2%	0.95	0.93	0.5%	0.9%	0.56	5.4	252	6.7	38%
Mom	6.9%	6.7%	7.6%	0.91	0.88	0.1%	0.7%	0.14	5.1	215	7.1	37%
ValMom	7.8%	7.6%	8.0%	0.97	0.94	0.6%	0.7%	0.82	5.4	244	6.8	38%

This table reports performance statistics and characteristics of long-only portfolios. EMB corresponds to a value-weighted benchmark portfolio. Val, Mom, and ValMom portfolios are constructed following a monthly optimization methodology incorporating portfolio-level and asset-level constraints (as described in the text). Returns are reported in annualized terms and in excess of the 3-month USD LIBOR rate. Information ratios are estimated using alphas defined as risk-adjusted returns from regressing portfolio excess returns against EMB excess returns. Net returns and alphas incorporate estimated transaction costs (as described in the text).

Table 6 Optimized portfolio return decomposition (2003–2017).

	(1)	(2)	(3)	(4)
Panel A: Time-Series Regressions				
Intercept	0.05%	0.06%	0.00%	0.00%
	[3.0]	[3.5]	[0.0]	−[0.3]
Benchmark	1.00	1.02	0.97	0.96
	[143.2]	[76.7]	[171.2]	[92.6]
Rates		−0.06		0.02
		−[2.3]		[1.0]
Credit		−0.02		−0.01
		−[1.6]		−[1.8]
Currency		0.00		0.01
		−[0.3]		[0.9]
Equity		0.01		0.01
		[1.6]		[1.3]
Value			0.10	0.11
			[12.5]	[11.9]
Momentum			0.08	0.08
			[8.7]	[8.6]
Adj. Rsq.	0.991	0.992	0.996	0.996
Num. Obs.	178	178	178	178
Panel B: Return Contributions				
Intercept	0.6%	0.7%	0.0%	0.0%
Benchmark	7.0%	7.1%	6.8%	6.7%
Rates		−0.1%		0.0%
Credit		−0.1%		−0.1%
Currency		0.0%		0.0%
Equity		0.1%		0.1%
Value			0.7%	0.8%
Momentum			0.1%	0.1%
Total	7.6%	7.6%	7.6%	7.6%

This table reports a return decomposition of the optimized long-only ValMom portfolio following the methodology of Israel and Ross (2017). Panel A reports time-series regressions for the portfolio regressed onto the benchmark portfolio as well as various specifications of macro and style factors. Panel B uses these regression estimates to estimate annualized return contributions.

efficacy of combining both value and momentum insights, realizing a net information ratio of 0.82 with portfolio characteristics that generally fall between the two other factor-optimized portfolios.

Table 6 decomposes the return of our optimized ValMom portfolio from Table 5 following the methodology of Israel and Ross (2017). In Panel A, we perform time series regressions of ValMom returns onto the benchmark

EMB portfolio, macro factors, and style factors. Panel B utilizes the regression coefficients from Panel A to decompose returns in terms of macro and style factors. The significant intercept in regression (1) highlights that the ValMom portfolio generates outperformance over the value-weighted benchmark, while the corresponding return decomposition shows that the optimized ValMom portfolio produces an alpha of 60 basis points per year. Regression (2) and its corresponding return decomposition show that exposures to macro factors do not explain this outperformance. Similarly, regressions (3) and (4) confirm that the outperformance of our ValMom portfolio can be attributed to style factor insights and not any unintended macro factor bets. The cumulative performance net of transaction costs for both the long-only optimized portfolio and the EMB market portfolio are presented in Figure 3.

Table A.2 examines the robustness of the combined long-only optimized portfolio to different constraint specifications. In specifications (1) and (2), we consider variations in the duration and duration-times-spread constraints by allowing them to be 5% tighter or 5% wider compared to the baseline, respectively. We then examine different turnover constraints, targeting 1% lower monthly turnover in specification (3) and 1% higher monthly turnover in specification (4). Tighter constraints on turnover appear to improve net information ratio significantly, most likely by reducing transaction costs. Finally, we consider 2% tighter asset bounds in specification (5) and 2% wider asset bounds in specification (6). The use of wider asset bounds results in an improved information ratio due to a higher transfer coefficient, while tighter asset bounds detract from performance based on the same reasoning.

Overall, our backtest results demonstrate that our optimized portfolios, leveraging style factor insights, outperform the EMB benchmark portfolio even after incorporating practical constraints and accounting for estimated transaction costs. In addition, our sensitivity analysis emphasizes the robustness of these results to variations in optimization constraints, while our regression

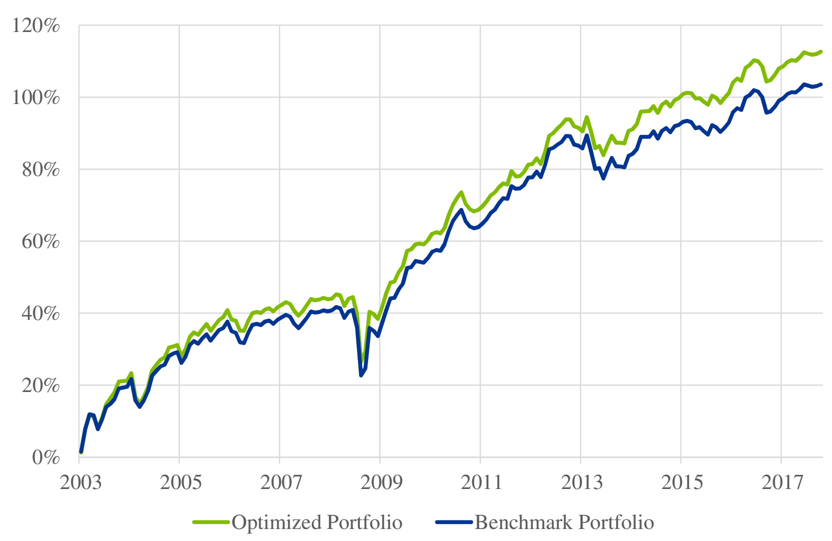

Figure 3 Historical Performance (2003–2017).

The plot above shows the historical cumulative performance of long-only optimized and benchmark portfolios. The optimized portfolio corresponds to the ValMom portfolio reported in Table 6. The benchmark portfolio is constructed by value-weighting all bonds in the universe. All returns are net of estimated transaction costs (as described in the text).

analysis confirms that this outperformance cannot be attributed to unintended factor bets.

6 Conclusion

In this paper, we demonstrate the importance of macro and style factors in developing a better understanding of the drivers of risk and return within sovereign emerging market bonds. In the time series, we show how the value-weighted EMB portfolio has historically exhibited significant and time-varying embedded betas to macro factors. We reveal that these embedded betas are not only time-varying, but also well balanced over time. In the cross-section, we show how value and momentum style factors can explain expected returns at the country level. Given their predictive power, we then demonstrate how our style factors can be used to develop better bets within a long-only portfolio that seeks to outperform a value-weighted benchmark.

Factor-based investment strategies, particularly within fixed income markets, are an exciting and growing area of research yielding new investment insights. As we have demonstrated in this paper, jointly analyzing the empirical properties of macro and style factors can lead investors towards a deeper understanding of factors and their correlation structure (e.g., risk-on versus risk-off). Such ideas may ultimately inspire new ways for contemplating portfolio construction—perhaps within an existing asset allocation framework, or an alternative factor allocation framework—thus leading to better diversified long-term investment portfolios.

Appendix A: Risk Decomposition

We present a regression-based methodology for decomposing factor exposures and attributing overall portfolio risk to individual factor contributions. This methodology can be

Table A.1 Factors with alternative specifications (2003–2017).

	V1	V2	V3	V4	M1	M2	M3	M4
Panel A: Performance Statistics								
Return	7.6%	8.9%	7.6%	6.2%	1.2%	1.1%	1.7%	−0.1%
Volatility	6.1%	7.3%	6.1%	5.5%	4.7%	5.8%	4.7%	5.4%
Sharpe Ratio	1.24	1.22	1.25	1.11	0.25	0.19	0.36	−0.03
Panel B: Factor Correlations								
V1	1.00	0.93	1.00	0.91	−0.38	−0.27	−0.52	−0.39
V2		1.00	0.93	0.82	−0.32	−0.30	−0.51	−0.34
V3			1.00	0.91	−0.38	−0.27	−0.52	−0.39
V4				1.00	−0.38	−0.25	−0.50	−0.40
M1					1.00	0.68	0.80	0.65
M2						1.00	0.67	0.52
M3							1.00	0.46
M4								1.00

This table reports performance statistics of value and momentum factors with alternative specifications. The different measures for value include: baseline (V1), no default adjustment, or essentially carry (V2), zero recovery assumption (V3), and ratings adjustment (V4). The different measures for momentum include: baseline (M1), 3-month lookback (M2), 9-month lookback (M3), and no volatility scaling (M4). Long-short style portfolios are constructed as described in the text. Returns are reported in annualized terms and in excess of the 3-month USD LIBOR rate.

Table A.2 Optimized portfolios with alternative specifications (2003–2017).

	Return	Net return	Volatility	Sharpe ratio	Net S.R.	Net alpha	Volatility	Net I.R.	yield	oas	duration	turnover
(1)	7.7%	7.5%	8.0%	0.96	0.94	0.5%	0.7%	0.76	5.3	240	6.8	38%
(2)	7.8%	7.6%	8.1%	0.97	0.94	0.6%	0.8%	0.79	5.4	244	6.8	38%
(3)	7.6%	7.5%	7.9%	0.96	0.95	0.6%	0.7%	0.91	5.3	239	6.8	26%
(4)	7.9%	7.6%	8.2%	0.96	0.93	0.5%	0.8%	0.64	5.4	246	6.8	49%
(5)	7.6%	7.4%	8.1%	0.93	0.91	0.3%	0.5%	0.67	5.3	239	6.9	37%
(6)	7.9%	7.7%	7.9%	1.00	0.98	0.9%	1.0%	0.90	5.3	244	6.7	39%

This table reports performance statistics and characteristics of long-only portfolios with alternative optimization specifications. Alternatives to the ValMom optimized portfolio in Table 6 include: (1) tighter linear constraints, (2) wider linear constraints, (3) lower turnover, (4) higher turnover, (5) tighter asset bounds, and (6) wider asset bounds. Returns are reported in annualized terms and in excess of the 3-month USD LIBOR rate. Information ratios are estimated using alphas defined as risk-adjusted returns from regressing portfolio excess returns against EMB excess returns. Net returns and alphas incorporate estimated transaction costs (as described in the text).

understood as a multivariate extension of the portfolio risk decomposition methodology presented in the Appendix section of Israel and Ross (2017). It also captures similar insights and intuition to the methodology of Menchero and Davis (2011). As will be shown, a convenient dual property of this decomposition is that risk contributions are equivalent whether measured in either variance or volatility terms.

We decompose portfolio returns (y) into factors (x_i) by performing a multivariate regression with the following form:

$$y = \beta_0 + \sum_i \beta_i x_i + \epsilon. \qquad \text{(A.1)}$$

The variance of portfolio returns can be calculated as:

$$\begin{aligned} var(y) &= cov(y, y) \\ &= cov\left(y, \beta_0 + \sum_i \beta_i x_i + \epsilon\right) \\ &= cov(y, \beta_0) + \sum_i \beta_i cov(y, x_i) \\ &\quad + cov(y, \epsilon) \\ &= \sum_i \beta_i cov(y, x_i) + \sigma_\epsilon^2. \qquad \text{(A.2)} \end{aligned}$$

We can then interpret $\beta_i cov(y, x_i)$ as the variance contribution of factor i to the portfolio and σ_ϵ^2 as the residual unexplained variance. Dividing both sides by σ_y allows us to view this decomposition in volatility terms:

$$\sigma_y = \sum_i \beta_i corr(y, x_i)\sigma_i + \frac{\sigma_\epsilon^2}{\sigma_y}. \qquad \text{(A.3)}$$

In this form, $\beta_i corr(y, x_i)\sigma_i$ represents the volatility contribution of factor i to the portfolio, while $\frac{\sigma_\epsilon^2}{\sigma_y}$ represents the residual unexplained volatility.

One might be interested in measuring relative contributions to portfolio variance (or portfolio volatility) from each of the individual factors as well as the unexplained residual component. As it turns out, these contributions are mathematically equivalent whether in variance or volatility terms. By dividing both sides of Equation (A.3) by σ_y, we arrive at relative contributions to volatility:

$$100\% = \sum_i \beta_i \frac{cov(y, x_i)}{\sigma_y^2} + \frac{\sigma_\epsilon^2}{\sigma_y^2} \qquad \text{(A.4)}$$

Note this is equivalent to dividing Equation (A.2) through by σ_y^2.

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Notes

1 Macro factors such as market returns (Fama and French, 1993) help explain the time series of returns. Style factors such as value and size (Fama and French, 1992) help explain the cross-section of expected returns.

2 Risk contributions are measured following the methodology presented in Appendix A.

3 We define issuer defaults as countries with foreign currency bonds in default based on the Bank of Canada's Database of Sovereign Defaults.

4 Alternative specifications using 10-year Treasury futures for rates, CDX High Yield for credit, the US Dollar Index (DXY) for currency, and S&P 500 for equity produce similar results.

[5] Regressing EMB returns onto our four macro factors and a commodities factor, as represented by the S&P GSCI index, results in an insignificant loading on commodities.

[6] Kang and Pflueger (2014) provide theoretical and empirical evidence documenting the significance of inflation risk factors in global corporate credit markets.

[7] This intuition shares similarities with the approach of Gray *et al*. (2007), who use exchange rate volatility as a component in measuring sovereign credit risk.

[8] See Appendix A for the derivation of these formulas.

[9] Ben Dor *et al.* (2007) demonstrate that duration-times-spread (DTS) is a useful measure to forecast systematic and idiosyncratic risk exposures for bond portfolios.

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