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Emerging Market Sovereign Bond Spreads: Estimation and Back-testing

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Abstract

We estimate sovereign bond spreads of 28 emerging economies over the period January 1998-December 2011 and test the ability of the model in generating accurate in-sample predictions for emerging economies bond spreads. The impact and significance of country-specific and global explanatory variables on bond spreads varies across regions, as well as economic periods. During crisis times, good macroeconomic fundamentals are helpful in containing bond spreads, but less than in non-crisis times, possibly reflecting the impact of extra-economic forces on bond spreads when a financial crisis occurs. For some emerging economies, in-sample predictions of the monthly changes in bond spreads obtained with rolling regression routines are significantly more accurate than forecasts obtained with a random walk. Rolling regression-based bond spread predictions appear to convey more information than those obtained with a linear prediction method. By contrast, bond spreads forecasts obtained with a linear prediction method are less accurate than those obtained with random guessing.

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I. INTRODUCTION

Sovereign debt securities have become a key method of funding for many emerging market economies as well as an increasingly important asset class for investors. A relevant question for policymakers and investors is whether the difference between the yield of a given emerging market sovereign bond and the yield of a United States Treasury debt security of a comparable maturity – the sovereign bond spread – is appropriately priced in relation to the country-specific fundamentals of that particular emerging economy. If the sovereign bond spread stays at very low levels for long without reflecting the economy's fundamentals, sudden shifts in the investors' perception of risk may lead to sharp changes in the cost of external borrowing for that particular economy.

Against that background, many studies propose a wealth of empirical models to estimate sovereign bond spreads using country-specific and common explanatory variables. However, to our knowledge, the empirical literature has not always emphasized that the contribution of the variables explaining sovereign bond spreads may change across time and regions. In addition, the ability of empirical models in generating accurate in-sample bond spread predictions has not been extensively tested yet. In this context, this study attempts to answer the following questions. Does the contribution of country specific variables change when the time and country dimensions of the panel change? Can an empirical model – used to estimate sovereign bond spreads – generate in-sample predictions for sovereign bond spreads which are more informative than those obtained with random guessing?

Following Hartelius (2006), we estimate emerging economies sovereign bond spreads using a panel of 28 emerging economies, over the period January 1998–December 2011 and allow for the dimensions of the panel to change. After estimation, we back-test the model by generating bond spreads in-sample predictions with linear predictions and rolling regression routines. We are interested to establish (i) which of the methods is more successful at correctly predicting the direction of the monthly change in bond spreads, (ii) whether the forecasting accuracy of each method changes before and after the global financial turmoil of 2008, and (iii) to test whether the forecasting methods employed are more accurate than a random walk in predicting the monthly change in bond spreads.

In the first part of the paper, we find that better country-specific fundamentals are associated with lower bond spreads, although their impact on spreads varies across periods and regions. This implies that over time and across regions of emerging economies investors do not always assign the same importance to country-specific variables when investing in emerging economies' sovereign bonds. We also find that the impact of global explanatory variables, as well as their statistical significance, in explaining bond yield spreads changes with the economic period considered.[2] Specifically, US short and long-term interest rates are no longer significant if the time dimension of the panel includes only the period beginning with the latest global financial crisis. In addition, the model fails to explain well the rising bond

[2] The changing relative importance of country-specific and global explanatory variables over time is in line with the findings of Mauro et al. (2002, 2006).

spreads in observed in some of the emerging economies between 2010 and 2011. This could reflect concerns that international investors might have about the potential impact of the euro area economic downturn on emerging economies and on their borrowing costs. Finally, we find that during crisis times, good macroeconomic fundamentals are helpful in containing bond yield spreads, but less than in non-crisis times. This might reflect the likely impact of extra-economic forces on bond yield spreads when a financial crisis occurs.

In the second part of the paper, we assess the ability of the model to generate accurate predictions for bond spreads. For some emerging economies – Colombia, Mexico, and Poland – forecasts of the monthly changes in actual bond spreads obtained with rolling regression routines are significantly more accurate than forecasts obtained with a random walk model. The results enrich the literature because they suggest that rolling regression method can in some cases be more accurate than a random walk model in generating predictions for bond spreads, perhaps reflecting the fact that rolling regression routines allow to gradually enrich the information set available to investors.

This paper is structured as follows. Section II contains a review of the relevant literature for this study. Section III describes the data while section IV describes the empirical methodology employed. Section V presents the estimation results while the back-testing exercise of the model is presented in section VI. Concluding remarks are in Section VII.

II. LITERATURE

There are at least two branches of literature that are relevant for this study. On the one hand, there is the empirical work analyzing the determinants of emerging market bond spreads. On the other hand, some studies are concerned with the use of sovereign bond spreads in early warning systems. To our knowledge, the literature has not been testing sufficiently the ability of empirical models to generate accurate out-of-sample forecasts for sovereign bond spreads, which is the main goal of this study. This study proposes a forecasting method to predict sovereign bond spreads which was found to be superior to random guessing for some emerging market economies. Such a method could be useful for conducting scenario analysis that use sovereign bond spreads as one of the inputs.

The production of empirical studies analyzing the determinants of emerging market bond spreads was stimulated by the use of Brady bonds in the early 1990s, and the development of indices of secondary market bond spreads (see IMF 2004). While in theory it was expected that lower world interest rates would lead to higher demand of risky financial assets and lower bond spreads in emerging economies, Cline and Barnes (1997), Min (1998) and Kamin and von Kleist (1999) did not find significant relationships between U.S. Treasury yields and emerging market bond spreads. Then, the literature found evidence of significant relationships between emerging market sovereign bond spreads and country-specific macroeconomic indicators (pull factors) and indicators of external financing conditions (push factors). Eichengreen and Mody (1998), Kamin and von Kleist (1999), and Sy (2002) all found that improved credit ratings were associated with lower bond spreads. Other studies found a greater role for advanced economies interest rates in explaining emerging market bond spreads. Ferrucci (2003) finds that a steeper U.S. yield curve is associated with lower

EM bond spreads, a result he suggests may be attributable to the presence of leveraged investors, who borrow at short-term rates to lend at longer-term rates.

Other studies identified also the degree of investors risk aversion as an important factor to explain bond spreads. McGuire and Schrijvers (2003) found a significant role for a single common external factor underlying the variation of spreads across the constituents of the EMBI Global index. The authors find that the best fit for the common factor is investors' attitude toward risk as proxied by the VIX Index.

Models including country-specific fundamentals and indicators of external financing conditions became increasingly popular to estimate bond spreads. For example, Hartelius (2006) estimates emerging markets sovereign bond spreads using a set of country-specific and common external explanatory variables. The study found that the contraction of EMBIG spreads observed until 2006 could not be explained entirely by the improvements in emerging markets country-specific fundamentals. Rather, the low volatility environment of global financial markets has also played a role in explaining the tightening of EMBIG spreads since January 2003. Luengnaruemitchai and Schadler (2007) use a similar model and ask whether market participants underestimated or not the riskiness of holding sovereign bonds issued by new European Union Member States (Central and Eastern European Countries, CECs) relatively to other emerging markets sovereign bonds. They find that for CECs the residuals were systematically negative during the period included between mid-2002 and the end of 2006. This suggests that before the global financial crisis, market participants were systematically requiring lower yields to hold CECs sovereign bonds in their portfolio than those determined by the econometric analysis. Hartelius et al. (2008) model emerging market sovereign bond spreads as a function of domestic fundamentals and global liquidity conditions. They find that both domestic fundamentals and global liquidity conditions contribute significantly to explain the change in emerging market sovereign bond spreads over the period included between December 2002 and February 2007. González-Rosada and Levy Yeyati (2008) regress bond spreads over a set of country-specific and global factors for 33 emerging economies. They find that global factors are largely responsible for most of the variance of emerging market bond spreads. By contrast, they find that the contribution of the evolution of country-specific fundamentals to the variability of emerging market bond spreads is lower. Finally, Caceres et al (2010) analyze how much of the movements in euro area sovereign bond spreads reflected shifts in global risk aversion and country-specific risks. They find that earlier in the crisis, the increase in global risk aversion was a significant factor influencing euro area sovereign spreads, while more recently country-specific factors have started playing a more important role.

There is also a branch of the economic literature which is concerned with the use of sovereign bond spreads in early warning systems. Baldacci et at. (2011) propose an index of fiscal stress to provide early warning signals of fiscal sustainability problems in advanced and emerging economies. They use among other indicators also sovereign bond spreads to identify periods of fiscal crises. Schaecther et al 2012, propose a set of short-term and long-term indicators to assess fiscal vulnerabilities in advanced economies. Among the indicators to assess short-term financing pressures, they include measures of financial market perception of sovereign risks. Finally, Candelon et al. (2012) provide evidence that sovereign bond yield spreads in a number of emerging market economies turn out to be an important leading indicator for currency crises.

III. The Data

A. Emerging Market Sovereign Bond Spreads Data

We take monthly data for sovereign bond spreads for 28 emerging market economies, for the period January 1998 – December 2011, using the JP Morgan's Emerging Market Bond Index – Global (EMBIG) database. Bond spreads are defined as weighted averages of bond yield spreads over US government debt securities of external debt instruments issued by sovereign and quasi sovereign entities in emerging market economies, denominated in US$ (see Luengnaruemitchai and Schadler, 2007 and Kim, 2010). For those countries where US$ EMBIG spreads data are not available, we use Euro EMBIG spreads data, which are bond yield spreads over German government debt securities of external debt instruments issued by sovereign and quasi-sovereign entities, denominated in euros.[3]

The 28 economies considered are a subset of all the emerging market economies included in the JP Morgan EMBIG index, plus Romania: Argentina, Brazil, Bulgaria, Chile, China, Colombia, Croatia, Dominican Republic, Ecuador, Egypt, El Salvador, Hungary, Indonesia, Lebanon, Malaysia, Mexico, Pakistan, Panama, Peru, Philippines, Poland, Romania, Russia, South Africa, Turkey, Ukraine, Uruguay and Venezuela.[4] Countries have been chosen according to the following rules: for each emerging market economy, sovereign bond spreads monthly data must be available at least from January 1, 2005. Sovereign bond spreads are regressed on a set of push and pull factors.

B. Pull Factors Data

Pull factors monthly data for each economy in the sample are taken from the International Country Risk Guide (ICRG) database.[5] The ICRG database contains monthly data for a political risk rating (PRR), an economic risk rating (ERR) and a financial risk rating (FRR)[6]. Each risk rating is calculated as a weighted average of the scores assigned to a number of individual risk subcomponents. For example, the PRR includes twelve individual subcomponents that capture one given aspect of political risk, while the ERR and the FRR indices include five individual subcomponents each.

[3] This is the case of Romania.

[4] The countries in the J.P. Morgan EMBIG Index that have been excluded because of their shorter bond spread time series are Belarus, Cote d'Ivoire, Gabon, Georgia, Ghana, Iraq, Jamaica, Jordan, Kazakhstan, Lithuania, Namibia, Nigeria, Senegal, Serbia, Sri Lanka and Vietnam.

[5] These indices are taken from the International Country Risk Guide database. The methodology for calculating these risks is available at http://www.prsgroup.com/ICRG_Methodology.aspx#FinRiskRating

[6] The ICRG database is property of the PRS Group (www.prsgroup.com).

Political Risk Rating (PRR)

The PRR measures the degree of political stability in a given country. The sub-components included in the PRR are government stability, socioeconomic conditions, investment profile, internal conflict, external conflict, corruption, military in power, religious tensions, law and order, ethnic tensions, democratic accountability and bureaucracy quality. The PRR can assume any value included between 0 and 100. In each country, low scores signal high political risk, whereas high scores are associated to low risk.

Economic Risk Rating (ERR)

The ERR measures the soundness of the macroeconomic fundamentals of each emerging market economy. The ERR includes five components: per capita GDP, the real GDP growth rate, inflation, as well as fiscal and current account balances expressed as percentages of GDP. The ERR can assume any value between 0 and 50. Low scores signal weak macroeconomic fundamentals, while high scores are associated to sound fundamentals.

Financial Risk Rating (FRR)

The FRR assesses the ability of a country to pay its external debt obligations. Like the ERR, the FRR includes five sub-components: external debt as a percentage of GDP, external debt as a percentage of exports of goods and services, current account balance as a percent of exports of goods, the ratio between official reserve holdings and months of imports, and a measure of nominal exchange rate stability. The FRR can be interpreted as an index that measures the degree of external vulnerability of a given country. The FRR can assume any value between 0 and 50. Low scores signal a high degree of external vulnerability, while high scores are associated to low degrees of external vulnerability (or resilience to external shocks).

C. Push Factors Data

Following Hartelius et al. (2008) and Luengnaruemitchai and Schadler (2007), one of the push factors included in the regression is the CBOE volatility index (VIX), which measures the expected stock market volatility over the next 30 days from the prices of the S&P500 stick index options.[7] The CBOE Volatility Index (VIX) is frequently used as an indicator to quantify the degree of investors' risk appetite.[8] In addition, we include in the push factors the three-month and ten-year U.S. interest rates.

[7] See CBOE (2003) for further details.

[8] The VIX Index is regarded as one of the main indicators of investor's sentiment and market volatility (CBOE 2012).

IV. THE MODEL

Like Luengnaruemitchai and Schadler (2007), we follow Edwards (1986) to motivate the theoretical rationale behind the model used for obtaining estimates. Specifically, Edwards (1986) considers a one-period bond *i* where in case of default the lender will not recover anything:

$$p(X_{it}) * 0 + [1 - p(X_{it})]\left(1 + r_t^f + s_{it}\right) = \left(1 + r_t^f\right) \qquad (1)$$

where r_t^f is the world risk-free interest rate at time *t*, $p(X_{it})$ is the probability of default, X_{it} denote the country's fundamentals and s_{it} is the country's risk premium.

After rearranging (1), the country's risk premium s_{it} can be expressed as

$$s_{it} = \left[\frac{p(X_{it})}{1-p(X_{it})}\right]\left(1 + r_t^f\right) \qquad (2)$$

Assuming that the probability of default has a logistic form,

$$p(X_{it}) = \frac{\exp \sum \beta_i X_{it}}{1+\exp \sum \beta_i X_{it}} \qquad (3)$$

then the country risk premium (or spread) can be expressed as

$$s_{it} = \left[\exp \sum \beta_i X_{it}\right]\left(1 + r_t^f\right). \qquad (4)$$

Equation (4) shows that the bond spread at time *t* is influenced by the country's fundamentals X_{it} and by the risk-free interest rate. Expressing (4) in logs yields

$$\ln s_{it} = \sum \beta_i X_{it} + \ln\left(1 + r_t^f\right) + \varepsilon_{it} \qquad (5)$$

where a disturbance term ε_{it} has been added.

To perform regressions, we use a working specification of (5) whereby we expect that U.S. three-month and the ten-year nominal interest rates, and the VIX expected stock market volatility index all play a role in explaining the country spread. Specifically, bond spreads are regressed on country specific variables (ERR, FRR and PRR) and global variables (VIX, US long-term and short-term nominal interest rates):

$$\ln(\mathrm{embig}_{it}) = \alpha_{0i} + \alpha_1 \ln(\mathrm{err}_{it-1}) + \alpha_2 \ln(\mathrm{frr}_{it-1}) + \alpha_3 \ln(\mathrm{prr}_{it-1}) + \alpha_4 \ln(\mathrm{vix}_t) + \\ + \alpha_5 \ln(10\mathrm{y}_t) + \alpha_6 \ln(3\mathrm{m}_t) + \varepsilon_{it} \qquad (6)$$

In (6) embig_{it} denotes the bond spreads of country i at time t, err_{it-1}, frr_{it-1} and prr_{it-1} denote, respectively, the lagged economic, financial and political risk ratings of country i, vix_t is the VIX stock market volatility at time t, 10y_t and 3m_t denote respectively the U.S. ten year and three month nominal interest rate at time t, respectively. The explanatory variables are lagged in order to control for endogeneity.

Before choosing the technique for estimating (6), we check for panel unit roots and co-integration. Panel unit root tests show that the panel is potentially mixed as for a given variable stationarity is detected only in some of the countries of the panel.[9] We also performed the error-correction-based co-integration Westerlund (2007) test for panel data. The test failed to reject the null hypothesis of no co-integration among the variables used. We therefore estimate (6) with fixed effects.

V. Regression Results

We begin by estimating a baseline regression and check how the results change if the time dimension of the panel is modified. First, we run a baseline regression over the period January 1998-December 2011. Then, we run a regression for the period January 2003 –July 2007, labeled as Global Abundant Liquidity and one for the period August 2007–July 2011, labeled as Global Financial Crisis. We also divide the panel into three broad emerging market regions (Asia and Pacific, Eastern Europe, Middle East and Africa, henceforth EMEA, and Western Hemisphere). For each region, we run three separate regressions: one for the period January 1998–December 2011, one for the period of Global Abundant Liquidity and one for the Global Financial Crisis. Finally, we show how much each individual emerging economy included in the sample can benefit from an improvement in its country-specific fundamentals.

Throughout this study, we run fixed effects regression with Driscoll and Kraay (1998) standard errors to control for heteroskdasticity, autocorrelation and possible correlation within groups in the panel. Following Driscoll-Kraay (1998), Driscoll and Kraay standard errors are robust to very general forms of cross-sectional ("spatial") and temporal dependence when the time dimension becomes large.

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[9] The Dickey-Fuller and Phillips-Perron panel unit root tests failed to reject the null hypothesis at the 5% confidence level that all panels contain unit roots, for most of the variables used in the regressions. To control for cross-sectional dependence, the variables were demeaned and a drift term was included. We also ran the Im-Pesaran-Shin test for panel unit roots, which in several cases rejects the null hypothesis of presence of unit roots in all panels. In addition, when we restricted the Im-Pesaran-Shin panel unit root test to individual countries, we found that a given variable was stationary only in some countries of the panel. These findings show that the panel is potentially mixed. We also performed the error-correction-based co-integration Westerlund (2007) test for panel data. The test failed to reject the null hypothesis of no co-integration among the variables used.

A. Baseline regression

The baseline regression shows that both the country-specific and global explanatory variables are statistically significant to explain emerging market bond spreads (table 1). Specifically, better country-specific fundamentals are associated with lower emerging market bond spreads while a higher degree of investors' risk aversion (as measured by the VIX index) and higher long term U.S. interest rates are associated with higher emerging market bond spreads.

Table 1. Sovereign Bond Spreads: Coefficient Estimates, All Emerging Market Economies

	Baseline (1)	Global Abundant Liquidity (2)	Global Financial Crisis (3)
	Jan 98–Dec 11	Jan 03–Jul 07	Aug 07–Dec 11
$\ln(\mathrm{err}_{it-1})$	–.67**	–.83**	–.30
	(.21)	(.25)	(.23)
$\ln(\mathrm{frr}_{it-1})$	–2.27**	–1.57**	–1.55**
	(.21)	(.35)	(.21)
$\ln(\mathrm{prr}_{it-1})$	–1.81**	–1.91**	–2.09**
	(.27)	(.33)	(.56)
$\ln(\mathrm{vix}_t)$	.87**	.25*	.81**
	(.06)	(.10)	(.13)
$\ln(10\mathrm{y}_t)$	.48*	–.05	–.14
	(.22)	(.30)	(.23)
$\ln(3\mathrm{m}_t)$	–.04	–.30**	–.03
	(.03)	(.05)	(.03)
Constant	21.6**	23.4**	19.5**
	(1.39)	(2.03)	(2.16)
R^2	.77	.88	.83
Root MSE	.43	.33	.29
Observations	4,294	1,551	1,484

**Significant at 5%; **significant at 1%. Driscoll-Kraay robust standard errors in parentheses.*
Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

A 10% increase in the log of long-term U.S. interest rates is associated with a 4.8% increase in the log of emerging markets bond spreads. An increase in the ten-year U.S. interest rate increases debt-servicing costs of external debt and may deteriorate the creditworthiness of emerging market borrowers. It also increases the rate at which the existing debt must be rolled over. In addition, an increase in U.S. interest rates may also be associated with lower risk tolerance of international investors, driving bond yield spreads wider. Finally, stock market volatility matters for bond spreads, as a ten percent increase in the log of the VIX raises emerging market bond spreads by 8.5%. An increase in risk aversion raises the yields requested by investors to hold emerging market sovereign debt securities.

B. Global Abundant Liquidity and Global Financial Crisis

The impact of push and pull factors on emerging market bond spreads changes depending on the economic period considered. During the Global Financial Crisis, while the indices for political risk (PRR) and external vulnerability (FRR) remain significant in explaining bond spreads, the index for macroeconomic variables (ERR) is no longer significant. By contrast, since the beginning of the Global Financial Crisis, the VIX index gained significance in explaining bond spreads.

Three-month U.S. interest rates were significantly negatively related with bond spreads only during the period of Global Abundant Liquidity. These findings are in line with Eichengreen and Mody (1998), as they found a negative relationship between U.S. Treasury yields and emerging market bond spreads, possibly motivated by supply and demand conditions of emerging market sovereign debt securities. The results in table 1 show that during the period of Global Abundant Liquidity, low short-term US interest rates constituted favorable financing conditions for the issuance of emerging markets debt securities, which ultimately might have led to excess supply of emerging market sovereign bonds and higher spreads. Conversely, a rise in US short-term interest rates tightened financing conditions, thereby reducing the supply of emerging market sovereign bonds. With the beginning of the crisis, however, this effect disappears: US three-month interest rates rapidly approached the zero bound without rebounding, while emerging market bond spreads became more volatile compared to the pre-crisis period.

Ten-year US interest rates are significant in explaining bond spreads neither in the Global Abundant Liquidity period nor in the Global Financial Crisis period. This suggests that from 2003 the demand of international investors for emerging market sovereign bonds tends to be more sensitive to country-specific explanatory variables rather than to US long-term interest rates. Put differently, long-term world interest rates appear to lose significance in explaining the creditworthiness of emerging market sovereign borrowers.

Summing up, the significance of country-specific and global factors in explaining bond yield spreads changes with the economic period considered, which is in line with the findings in Mauro et al. (2002, 2006). In addition, and differently from Gonzalez-Rosada and Levy Yeyati (2008), country-specific explanatory variables play systematically an important role in explaining emerging market sovereign bond spreads.[10]

C. Regional Subgroups

Table 2 reports the coefficients estimates across the different emerging market regions. The importance of country-specific factors in explaining bond spreads varies across emerging market regions and periods.

During the Global Abundant Liquidity period none of the country-specific explanatory variables is significant to explain bond spreads in emerging Asia. In addition, the economic risk rating index – a proxy for the macroeconomic fundamentals – is significant neither in Asia, nor in the Western hemisphere during the Global Abundant Liquidity and the Global Financial Crisis periods. By contrast, the economic risk rating index is always significant in the EMEA region. The financial risk rating index – a proxy for the degree of external vulnerability – always played a significant role in containing bond spreads in the Western Hemisphere region, while during the Global Abundant Liquidity period the financial risk rating was not found to be significantly related with bonds spreads in Asia and EMEA.

[10] Global factors might have greater impact on bond spreads in individual regressions. Zhang et al (2011) show that bond spreads in high risk countries tend to commove more with global variables such as the VIX and U.S. High Yield bond spreads.

Finally, the political risk rating index was not significant for the EMEA region during the Global Abundant Liquidity and Global Financial Crisis periods.

As regards the global factors, the degree of risk appetite – as proxied by the VIX index – is almost always significant to explain bond spreads across the three different regions of emerging economies. By contrast, the ten-year U.S. interest rates were not significant for bond spreads during the Global Abundant Liquidity and the Global Financial Crisis periods. U.S. short-term interest rates were significant in explaining bond spreads only during the Global Abundant Liquidity period.

Table 2. Sovereign Bond Spreads: Coefficient Estimates Across EM Regions.

	Baseline (1)				Global Abundant Liquidity (2)				Global Financial Crisis (3)			
	All	Asia	EMEA	WH	All	Asia	EMEA	WH	All	Asia	EMEA	WH
$\ln(\mathrm{err}_{it})$	–.67**	–1.46*	–.66*	–.61*	–.83**	–.08	–1.3**	–0.11	–.30	–.73	–.60*	–.02
	(.21)	(.42)	(.26)	(.24)	(.25)	(.81)	(.45)	(0.27)	(.23)	(.42)	(.28)	(.24)
$\ln(\mathrm{frr}_{it})$	–2.3**	–2.6**	–2.0**	–2.3**	–1.6**	–.71	–.13	–2.0**	–1.6**	–2.4**	–1.6**	–1.0**
	(.21)	(.54)	(.31)	(.29)	(.35)	(.73)	(.51)	(.44)	(.21)	(.47)	(.33)	(.23)
$\ln(\mathrm{prr}_{it})$	–1.8**	–2.0**	–1.3**	–2.0**	–1.9**	–.03	–1.4*	–2.9**	–2.1**	–1.9	–1.7	–2.2**
	(.27)	(.40)	(.47)	(.36)	(.33)	(.33)	(.51)	(.51)	(.56)	(1.0)	(1.1)	(.48)
$\ln(\mathrm{vix}_{t})$	.87**	0.76**	1.12**	.68**	.25*	.17*	.54**	.04	.81**	.70**	.75**	0.91**
	(.06)	(.08)	(.08)	(.09)	(.10)	(.08)	(.11)	(.12)	(.13)	(.17)	(.17)	(.11)
$\ln(10\mathrm{y}_{t})$	.48*	.08	.93**	.24	–.05	–.01	.13	–.28	–.14	–.31	–.49	.19
	(.22)	(.18)	(.31)	(.21)	(.30)	(.31)	(.30)	(.38)	(.23)	(.31)	(.32)	(.18)
$\ln(3\mathrm{m}_{t})$	–.04	–.01	–.10	–.01	–.30**	–.22**	–.25**	–.39**	–.03	.02	–.03	–.04
	(.03)	(.03)	(.05)	(.04)	(.05)	(.06)	(.05)	(.06)	(.03)	(.03)	(.04)	(.02)
Constant	21.6**	26.2**	15.9**	23.1**	23.4**	6.7**	13.2**	27.0*	19.5**	23.0**	18.7**	16.2**
	(1.39)	(2.94)	(2.43)	(.60)	(2.03)	(2.8)	(3.1)	(3.0)	(2.16)	(4.5)	(4.5)	(1.5)
R^2	.77	0.82	0.70	0.80	.88	0.91	0.82	0.87	.83	0.88	0.69	0.90
Root MSE	.43	0.32	0.50	0.38	.33	0.21	0.35	0.33	.29	0.26	0.34	0.22
Observations	4,294	723	1708	1863	1,551	263	616	672	1,484	265	583	636

**Significant at 5%; **significant at 1%. Driscoll-Kraay robust standard errors in parentheses.*
Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

D. How Do Fitted Bond Spreads Compare With Actual Bond Spreads?

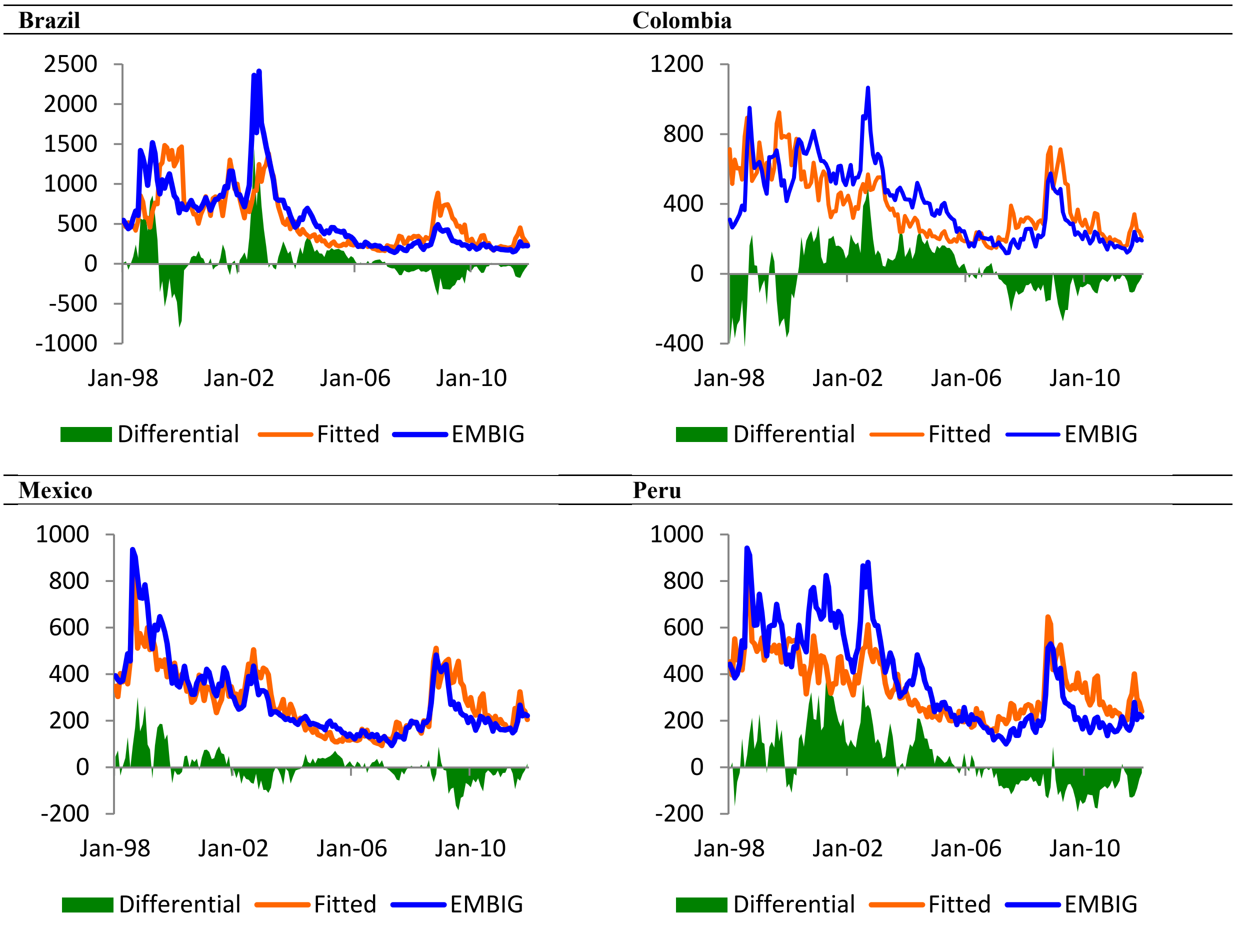
After having obtained estimates, the fitted bond spreads are compared with the actual ones. If the actual bond yield spread is higher than the fitted bond yield spread, then that particular bond trades at a lower price compared to what the model suggests. By contrast, if the actual bond yield spread is lower than the fitted spread, than that bond trades at a higher price compared to what implied by the model.[11]

Charts 1-4 plot the actual and fitted bond spreads, as well as the residuals, for selected Latin American economies. The charts show that since January 2006, a number of Latin American economies – Brazil, Colombia, Mexico and Peru – had most of times negative residuals, meaning that in those economies the actual spread was systematically lower than the fitted bond yield spread. Luengnaruemitchai and Schadler (2007) found a similar result for bonds issued by the New European Union (EU) Member States. They regressed emerging market

[11] Panel 1 in the Appendix contains the charts plotting the actual and fitted spreads as well as the residuals of all the emerging economies considered, from January 1998 until December 2011. The same data is also collected in the tables contained from Panel 2 until Panel 5.

sovereign bond spreads on a set of country-specific and global variables to determine whether the compression in bond spreads observed in the mid-2000s was justified or not by the fundamentals. They concluded that international investors tended to underestimate the risk of holding sovereign bonds issued by the New EU Member States, by requiring systematically lower yields compared to what suggested by their model. They interpreted this result by observing that as international investors expected a smooth entry of those new EU Member States into European Monetary Union (EMU), they were anticipating a steady decline in bond yields and spreads. The Authors labeled this phenomenon as the *Halo Effect*. With the Halo Effect, governments of the new EU Member States were able to borrow externally at a lower interest rate compared to other emerging markets governments.

Panel 1. Actual and Fitted Sovereign Bond Spreads *(basis points)*

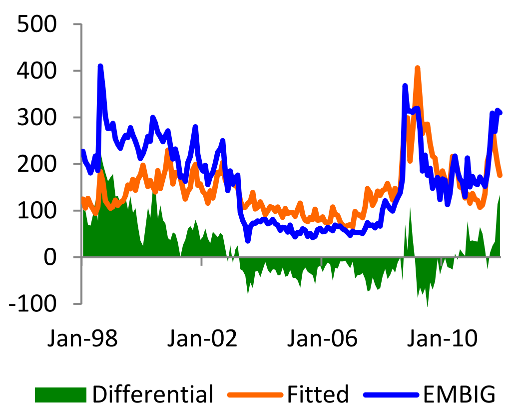


Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

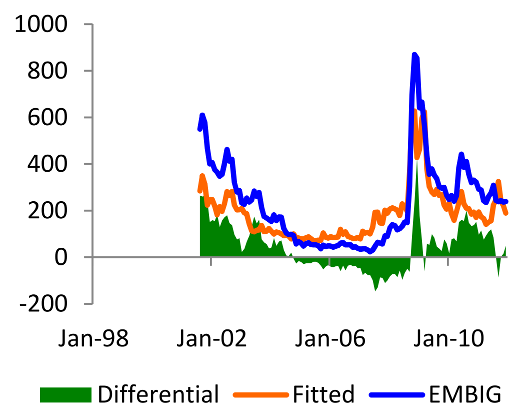
The results obtained by Luengnaruemitchai and Schadler (2007) appear to be broadly in line with the charts in Panel 1 and the tables in Panels 2–5 (see appendix), as they show that for most of the period between January 2003 and July 2007, in the New EU Member States (Bulgaria, Hungary, Lithuania, Poland and Romania) actual bond spreads were lower than the fitted bond spreads. However, with the beginning of the global financial crisis, those economies experienced bond flow reversals, their bond yields rose and the residuals became positive. Put differently, the results show that the global financial crisis removed the Halo Effect from the valuations of the New EU Member States sovereign bonds. By contrast, for most of the period after January 2006, in a number of Latin American countries – Brazil, Colombia, Mexico, Panama, Peru and Uruguay – sovereign bond yields compressed substantially and the difference between actual and model spreads became negative. Hence, the results suggest that following the latest financial crisis international investors reduced their holdings of sovereign bonds issued in New EU Member States possibly in favor of sovereign bonds issued in Latin America.

Panel 2. Actual and Fitted Sovereign Bond Spreads: ***(basis points)***

Poland



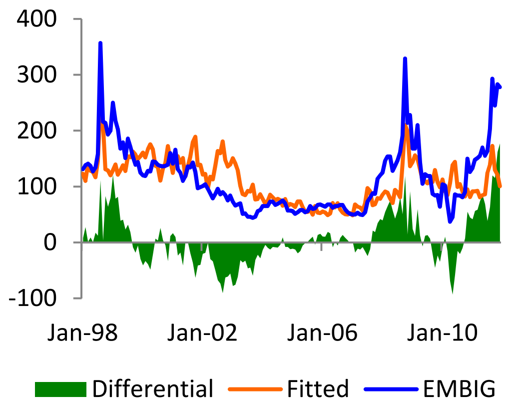
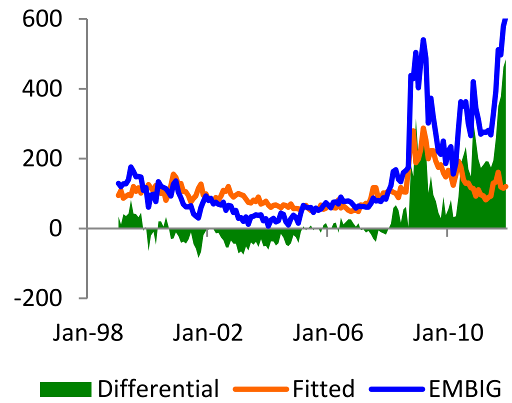
Romania



Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

Finally, charts 7-8 plot actual and fitted bond spreads for China and Hungary. The charts show that in 2010 and 2011, as the economic downturn and debt sustainability concerns in some advanced economies became more acute, actual sovereign bond spreads in China and Hungary increased considerably. This increase in risk perceptions could be related to concerns that market participants might have about the potential impact of economic downturn of some advanced economies on the Chinese and Hungarian economies. Put differently, the rising residuals in 2010 and 2011 suggest the possible presence of contagion from the euro area toward emerging market economies.

Panel 3. Actual and Fitted Sovereign Bond Spreads *(Basis points)*

China	Hungary
	

Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

E. Robustness Checks

In this session we perform some robustness checks of the coefficient estimates obtained so far. Specifically, we are interested to assess the extent to which the coefficient estimates change if the dimensions of the panel change as follows. First, we remove Argentina from the list of the countries in the panel, de facto omitting a major financial crisis after which the sovereign spreads remained stubbornly high before the debt-rescheduling with private creditors in 2005. Second, we change the time dimension of the panel by restricting it to the period included between 2003 and 2011. In this way, we exclude from the panel those observations relative to the financial crises originating in emerging economies between 1998 and 2002.

Table 3. Sovereign Bond Spreads: Coefficient Estimates, Robustness Checks.

	Baseline 1998–2011	Excluding Argentina 1998–2011	Excluding Crises btw. 1998–2002
$\ln(\mathrm{err}_{it})$	–.67**	–.76**	–.83*
	[.21]	[.22]	[.23]
$\ln(\mathrm{frr}_{it})$	–2.3**	–2.1**	–2.9**
	[.21]	[.23]	[.32]
$\ln(\mathrm{prr}_{it})$	–1.8**	–1.6**	–1.9*
	[.27]	[.28]	[.37]
$\ln(\mathrm{vix}_{t})$	.87**	.91**	.57**
	[.06]	[.06]	[.11]
$\ln(10\mathrm{y}_{t})$	.48*	.52*	–.27
	[.22]	[.22]	[.25]
$\ln(3\mathrm{m}_{t})$	–.04	–.04	–.02
	[.03]	[.03]	[.03]
Constant	21.6**	19.0**	27.2**
	[1.4]	[1.6]	[2.1]
R^2	.77	.77	.80
Root MSE	.43	.42	.39
Observations	4,294	4,126	3,008

***Significant at 1%, *significant at 5%. Driscoll-Kraay robust standard errors in parentheses.*
Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

Table 3 shows that most of the coefficient estimates of the country-specific explanatory variables maintain the sign and the degree of statistical significance even if the dimensions of the panel change. The coefficient of the country-specific explanatory variables that varies the most of is the one associated to the economic risk rating, which becomes more important in containing sovereign bond yield spreads if the crisis observations are omitted from the panel. Overall, the results suggest that the impact of having good economic indicators on bond yield spreads is stronger when the panel does not include observations relative to the 1998-2002 emerging market financial crises. The implication is that during tranquil times, having good economic fundamentals may be quite effective in containing external borrowing cost. In crisis times, good macroeconomic fundamentals are still helpful in containing bond spreads, but less than during crisis times. Perhaps this is because extra-economic forces are also responsible for the movement in bond spreads during crisis times.

F. Simulating an Improvement in Country-specific Variables on Bond Spreads

After having established that the impact of country-specific factors on emerging market bond spreads varies across regions and periods, we now turn to simulate the impact of potential changes in country-specific explanatory variables on bond spreads of all the emerging economy included in the panel.

Emerging economies sovereign bond spreads have been regressed over a set of country-specific factors, all expressed as indices. For each emerging economy in the panel we calculate the percent change in the estimated bond spread provoked by a one-standard deviation change in each country-specific explanatory variable, holding everything else constant.

The results are reported in table 4 and panel 1. An improvement in country-specific explanatory variables lowers bond spreads, while a deterioration in country-specific factors increases it. The impact is asymmetric, as the increase in the model spread provoked by deteriorating fundamentals tends to be larger than the decline in the bond spread provoked by improving fundamentals. For example, a one-standard deviation improvement in the economic risk rating leads to a decline of the average model spread of 6.1%.[12]

Conversely, a one-standard deviation deterioration in the economic risk rating is estimated to increase the external cost of borrowing by 7.5%. The financial risk rating, a proxy for the degree of external vulnerability, is the country fundamental with the strongest estimated impacts on the cost of external borrowing. A one-standard deviation improvement in the financial risk rating lowers the average model spread by 18.1%, while a one-standard deviation deterioration in the financial risk rating increases the average model spread by 26.6%. The impact of a change in the political risk rating is asymmetric as well. A one-

[12] It should be clarified that because the coefficient on the country-specific explanatory variables is the same for all countries, the heterogeneity in the responses of bond spreads shown in table 4 and panel 1 comes from different countries having different standard deviations in their country-specific explanatory variables.

standard deviation improvement in the political risk rating index lowers the average model bond spread by 10%, while a deterioration increases it by 12.3%.

Summing up, changes in the economic risk rating have the smallest impact on the estimated spreads, while the financial risk rating is the country-specific fundamental that affects the estimated bond spread the most.

Table 4. Impact of one-standard deviation change on the model spread *(Percent)*

	Improvement			Deterioration		
	ERR	FRR	PRR	ERR	FRR	PRR
Argentina	-7.8	-34.4	-13.4	9.7	74.1	16.8
Brazil	-5.7	-28.8	-6.7	6.6	50.1	7.5
Bulgaria	-6.8	-21.9	-7.5	8.1	32.3	8.5
Chile	-5.1	-9.6	-8.0	5.8	11.1	9.1
China	-2.3	-7.2	-8.7	2.4	8.0	10.1
Colombia	-5.3	-13.2	-14.2	6.0	16.3	18.1
Croatia	-4.9	-11.4	-7.8	5.5	13.7	8.9
Dom. Rep.	-5.1	-14.6	-9.0	5.8	18.6	10.4
Ecuador	-9.3	-28.8	-10.4	12.0	51.9	12.3
Egypt	-5.2	-12.5	-11.0	6.0	15.2	13.2
El Salvador	-2.7	-15.4	-8.4	2.9	19.9	9.6
Hungary	-4.0	-12.5	-8.0	4.4	15.3	9.1
Indonesia	-9.5	-23.8	-19.6	12.3	36.3	27.9
Lebanon	-9.3	-17.1	-7.6	12.0	22.7	8.7
Malaysia	-5.6	-13.5	-8.6	6.4	16.7	9.8
Mexico	-5.3	-17.1	-6.6	6.0	22.8	7.3
Pakistan	-5.5	-22.5	-12.8	6.3	33.5	15.8
Panama	-2.9	-9.5	-3.1	3.1	11.0	3.2
Peru	-4.1	-12.7	-6.7	4.5	15.6	7.5
Philippines	-3.5	-17.3	-11.4	3.8	23.1	13.8
Poland	-3.4	-14.4	-8.2	3.7	18.2	9.3
Romania	-3.4	-25.0	-7.2	3.7	39.1	8.0
Russia	-12.9	-26.5	-16.2	19.3	43.8	21.6
S. Africa	-4.3	-11.9	-7.3	4.8	14.4	8.2
Turkey	-9.9	-20.2	-16.3	13.0	28.6	21.8
Ukraine	-9.6	-22.1	-11.5	12.6	32.5	13.9
Uruguay	-6.3	-22.4	-6.9	7.5	33.4	7.7
Venezuela	-11.1	-19.3	-18.3	15.3	26.7	25.5
Average	**-6.1**	**-18.1**	**-10.0**	**7.5**	**26.6**	**12.3**
Min	-12.9	-34.4	-19.6	2.4	8.0	3.2
Max	-2.3	-7.2	-3.1	19.3	74.1	27.9

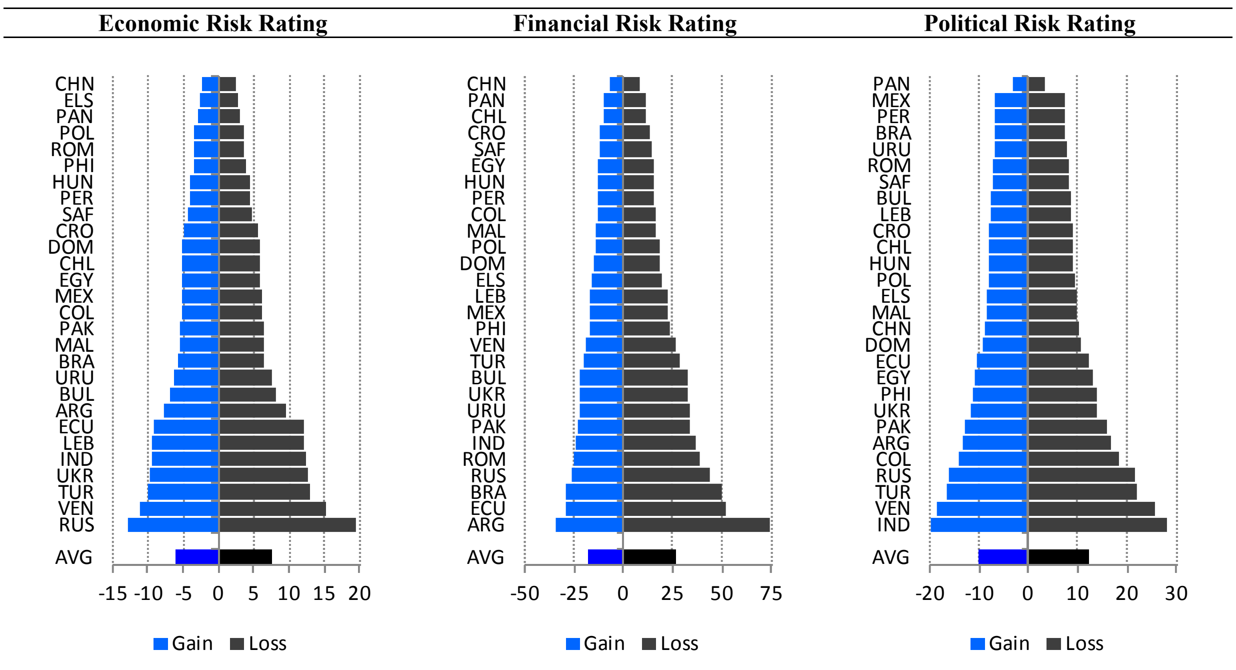
Sources: J.P. Morgan, Bloomberg, ICRG Database and author's calculations.

The countries that benefit most from an improvement in the economic risk rating are Russia and Venezuela. A one-standard deviation improvement in the economic risk rating in Russia and Venezuela would have lowered the model spread by 12.9% and 11% respectively.

Improvements in financial risk rating – a proxy for the risk of experiencing sudden capital outflows – would have lowered considerably (e.g. by more than 20%) the model spread in Argentina, Brazil, Bulgaria, Ecuador, Indonesia, Pakistan, Romania, Russia, Turkey, Ukraine and Uruguay. Considerable reductions (e.g. by more than 10%) in the model spread provoked by improvements in political risk rating would have been observed in Argentina, Colombia, Ecuador, Egypt, Indonesia, Pakistan, Philippines, Russia, Turkey, Ukraine and Venezuela.

In Brazil, Russia and South Africa, the country-specific factor affecting the most the model spread is the financial risk rating. In Brazil and Russia, a deterioration of a one-standard deviation in the financial risk rating index can be very costly, as the model spreads would increase by 50% and 43% respectively. By contrast, a similar deterioration in the financial risk rating leads to a more contained (but still considerable) increase in the model spread of South Africa (14.4%). On the other hand, gains would also be considerable for the three countries. A one-standard deviation improvement in the financial risk rating lowers the model spread by 29% in Brazil, 27% in Russia and 12% in South Africa.

Panel 4. Impact on the Model Spread Provoked by a One-standard Deviation Change in Country-specific Factors *(Percent)*



Sources: J.P. Morgan, ICRG and Author's calculations.

China is the country where the model spread declines the least following a one-standard deviation improvement in the economic rating, as the model spread declines by only 2.3%. By contrast improvements in China's financial risk rating and in the political risk rating are more powerful in reducing the model spread. A one-standard deviation improvement in China's financial risk rating index lowers the model spread by 7.2%, while a one-standard deviation improvement in China's political risk rating lowers the model spread by 8.7% (almost three times the decline in the model spread following a similar improvement in the economic risk rating). On the other hand, a one-standard deviation deterioration in China's economic risk rating increases the model spread by 2.4%. A similar deterioration in the political risk rating increases the model spread by 10.1%, more than four times the increase following a deterioration in the economic risk rating.

Summing up, changes in the degree of external vulnerability are estimated to provoke the largest changes in the cost of external financing. Improvements in the degree of external vulnerability are estimated to be three times more effective than improvements in the economic risk rating and almost twice more effective than improvements in the political risk rating in lowering the cost of external debt finance for emerging market economies. In addition, improvements in the degree of political risk are estimated to be twice as more powerful than improvements in the economic risk rating in lowering the cost of external borrowing.

VI. Back-testing the Model

Thus far, we have estimated emerging markets bond spreads and asked whether the estimates changed across different periods and regions. We now turn to back-test the model by generating in-sample predictions for bond spreads, which will be compared with the actual bond spreads. We follow the idea developed in Berg and Pattillo (1998) and Kumar et al. (2003) among others. We proceed as follows. The time dimension of our panel consists of T observations. We re-estimate the model using the data in a subsample made of $t<T$ observations (the estimation sample) to generate bond spreads forecasts in the remaining part $(T-t)$ of the whole sample (the forecasting sample).

In terms of our study, we re-estimate emerging market bond spreads for the periods January 1998–December 2006, January 1998–December 2007 and January 1998–December 2008 (the estimation samples) in order to forecast bond spreads in the periods January 2007–December 2011, January 2008–December 2011 and January 2009–December 2011, respectively (the forecasting samples). The purpose of this exercise is to ask whether the model can predict accurately bond spreads in periods that are not included in the estimation sample. We use different estimation samples because we are interested to assess whether the in-sample forecasting ability of the model changes with the beginning of the global financial crisis.

We use three methods to generate in-sample predictions for bond spreads. With the first method we re-estimate the model in the estimation sample and obtain the coefficients estimates.[13] Then, in the forecasting sample we multiply the explanatory variables by the estimated coefficients to generate bond spread forecasts for all the emerging economies included in the panel. With the second method – the rolling regression method – we predict

[13] We calculate the linear prediction from the fitted model. The model can be thought of as estimating a set of parameters $b_1, b_2, :::, b_k$, and the linear prediction is $y^p_j = b_1x_{1j} + b_2x_{2j} + ::: + b_kx_{kj}$ where j=t+1, t+2, : : : , T. The values y^p_j are the out-of-sample predictions; $x_{1j}, x_{2j}, :::, x_{kj}$ are the values of the explanatory variables in the forecasting period and have not been used to fit the model (hence to obtain $b_1, b_2, :::, b_k$).

bond spread forecasts using a rolling regression routine. We run a regression over the first $t<T$ observations of the sample. Then, the regression is run again adding the following periods $t+1, t+2, \ldots,$ one at a time, until the full original sample T has been employed (see Baum 2006). This routine adds gradually the latest observations in the sample. The third method is another rolling regression method where we begin running a regression over the full sample T. Then the regression is run again removing the first $t<T$ observations of the sample, one at a time, until all the first t observations have been removed from the full sample. This routine eliminates the oldest observations in the sample. With both rolling regression methods, bond spread forecasts are generated only for some of the emerging economies included in the database.[14]

How do we assess the model ability to generate informative in-sample bond spread predictions? We proceed in three steps. First, in each month of the forecasting sample, we assign a value of *one* if actual and predicted bond spreads change in the *same* direction (e.g. they both increase or decrease). Otherwise, if actual and predicted spreads change in *opposite* directions, we assign a value of *zero*. We then calculate the probability that each forecasting method correctly predicts the direction of monthly changes in actual bond spreads. Second, within the set of correct calls on the direction of monthly changes in bond spreads, we calculate the probability that each forecasting method correctly predicts upward or downward movements in bond spreads. Finally, we assess the accuracy of the two forecasting methods by running the Diebold and Mariano (1995) test.

A. Linear Prediction Method

Table 5 shows for each emerging economy the probability that the linear prediction (LP) method correctly predicts the direction of the monthly change in actual bond spreads. We consider LP to perform well in predicting the direction of the monthly change in bond spreads if for a given country the probability is above 0.7 in every forecasting period. The countries having a probability above 0.7 in all the forecasting periods are Colombia, Dominican Republic, Indonesia, Peru, Philippines, and Uruguay. By contrast, the model is considered to perform poorly if for a given country the probability is below 0.6 in any of the forecasting periods. By this criterion, the model performs poorly for Argentina, Chile, China, Ecuador, Egypt, Hungary, Lebanon, Malaysia, and Pakistan.

The table also shows that in two of the three forecasting samples (January 2007–December 2011 and January 2008 – December 2011), on average the model predicts equally well downward and upward movements in bond spreads. However, if the forecasting sample is restricted to the period January 2009–December 2011, the number of emerging market economies for which the model predicts downward movements in bond spreads better than upward movements rises to thirteen (from ten in the forecasting sample January 2007–December 2011 and twelve in the sample January 2008–December 2011). These results suggest that if the estimation sample includes the year 2008 the model's ability to forecast declining bond spreads improves. This result is in line with the notion that following the

[14] This is because the routine works only with a balanced panel.

global financial turmoil in 2008, investors preferred to gain exposure to emerging market sovereign debt securities, as they were anticipating a deterioration in credit quality of (sovereign and corporate) debt securities issued in advanced economies.

Table 5. Probabilities that the linear prediction method correctly predicts (i) the direction of monthly changes in bond spreads (M), (ii) upward movements in bond spreads (U), and (iii) downward movements in bond spreads (D) *Probabilities*

	Forecasting period								
	Jan 07 – Dec 11			Jan 08 – Dec 11			Jan 09 – Dec 11		
	M	U	D	**M**	U	D	**M**	U	D
Argentina	0.68	0.51	0.53	0.68	0.48	0.52	0.57	0.43	0.44
Brazil	0.86	0.73	0.76	0.79	0.68	0.66	0.74	0.60	0.61
Bulgaria	0.68	0.57	0.54	0.79	0.63	0.61	0.71	0.52	0.57
Chile	0.63	0.44	0.53	0.60	0.41	0.45	0.57	0.38	0.40
China	0.59	0.46	0.46	0.68	0.62	0.48	0.74	0.57	0.60
Colombia	0.76	0.58	0.65	0.79	0.56	0.65	0.74	0.56	0.63
Croatia	0.71	0.60	0.56	0.68	0.59	0.59	0.69	0.57	0.52
Dom. Rep.	0.75	0.58	0.61	0.83	0.71	0.70	0.74	0.57	0.62
Ecuador	0.46	0.27	0.41	0.43	0.32	0.26	0.37	0.24	0.21
Egypt	0.59	0.45	0.38	0.62	0.50	0.43	0.54	0.40	0.39
El Salvador	0.75	0.59	0.60	0.68	0.52	0.50	0.63	0.48	0.42
Hungary	0.58	0.46	0.43	0.70	0.55	0.53	0.80	0.65	0.64
Indonesia	0.73	0.65	0.69	0.87	0.73	0.74	0.83	0.74	0.71
Lebanon	0.59	0.41	0.42	0.53	0.39	0.41	0.54	0.36	0.33
Malaysia	0.58	0.43	0.41	0.64	0.47	0.50	0.60	0.45	0.48
Mexico	0.70	0.57	0.51	0.70	0.52	0.55	0.66	0.55	0.50
Pakistan	0.68	0.55	0.51	0.64	0.50	0.52	0.54	0.35	0.42
Panama	0.78	0.66	0.66	0.70	0.59	0.57	0.63	0.55	0.46
Peru	0.73	0.51	0.59	0.81	0.65	0.70	0.77	0.58	0.67
Philippines	0.76	0.55	0.63	0.77	0.59	0.65	0.71	0.52	0.58
Poland	0.69	0.59	0.54	0.72	0.64	0.57	0.80	0.65	0.64
Romania	0.64	0.51	0.56	0.64	0.50	0.47	0.60	0.38	0.54
Russia	0.68	0.58	0.49	0.72	0.55	0.50	0.66	0.52	0.45
S. Africa	0.64	0.48	0.49	0.72	0.55	0.58	0.74	0.52	0.54
Turkey	0.75	0.62	0.61	0.72	0.52	0.60	0.69	0.52	0.57
Ukraine	0.73	0.63	0.52	0.62	0.53	0.40	0.60	0.46	0.48
Uruguay	0.73	0.56	0.59	0.72	0.55	0.60	0.74	0.52	0.61
Venezuela	0.66	0.50	0.49	0.68	0.48	0.52	0.66	0.45	0.46
Average	**0.68**	**0.54**	**0.54**	**0.70**	**0.55**	**0.54**	**0.67**	**0.50**	**0.52**

Legend: M: monthly change in bond spreads; U: upward change in bond spreads; D; downward change in bond spreads.
Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

B. Rolling Regression Method

Table 6 shows for each country the probability that the rolling regression (RR1) method correctly predicts the direction of the monthly change in actual bond spreads. As for the bond spread forecasts obtained with LP, we consider RR1 to perform well in predicting the direction of the monthly change in bond spreads if, for a given country, the probability is above 0.7 in every forecasting period. The countries with a probability above 0.7 in all the forecasting samples are Brazil, Peru, Philippines, Russia, Turkey and Venezuela. By contrast, the model performs less well for Ecuador and Malaysia, where the probability is lower than 0.6. Finally, similarly to the linear prediction method, in each forecasting period the model appears on average to be more successful in predicting downward than in predicting upward movements in bond spreads.

Table 6. Probabilities that the rolling regression (RR1) method correctly predicts (i) the direction of monthly changes in bond spreads (M), (ii) upward movements in bond spreads (U), and (iii) downward movements in bond spreads (D) *Probabilities*

	Forecasting period								
	Jan 07 – Dec 11			Jan 08 – Dec 11			Jan 09 – Dec 11		
	M	U	D	**M**	U	D	**M**	U	D
Argentina	0.66	0.50	0.47	0.60	0.44	0.45	0.63	0.39	0.52
Brazil	0.78	0.67	0.69	0.77	0.63	0.63	0.77	0.58	0.65
Bulgaria	0.63	0.45	0.50	0.68	0.50	0.53	0.71	0.55	0.63
China	0.61	0.49	0.42	0.62	0.50	0.43	0.66	0.55	0.55
Colombia	0.75	0.53	0.66	0.70	0.40	0.62	0.69	0.39	0.61
Ecuador	0.54	0.34	0.41	0.55	0.38	0.41	0.54	0.29	0.41
Malaysia	0.54	0.36	0.42	0.57	0.33	0.47	0.54	0.30	0.46
Mexico	0.69	0.58	0.55	0.68	0.52	0.55	0.66	0.53	0.52
Panama	0.78	0.64	0.70	0.77	0.63	0.63	0.66	0.45	0.56
Peru	0.75	0.61	0.69	0.77	0.58	0.63	0.74	0.53	0.64
Philippines	0.76	0.56	0.66	0.74	0.50	0.65	0.71	0.44	0.65
Poland	0.69	0.57	0.55	0.79	0.52	0.53	0.80	0.63	0.70
Russia	0.71	0.57	0.55	0.70	0.50	0.52	0.71	0.55	0.58
S. Africa	0.66	0.47	0.53	0.66	0.43	0.47	0.71	0.45	0.58
Turkey	0.80	0.64	0.58	0.79	0.63	0.68	0.74	0.58	0.63
Venezuela	0.71	0.59	0.56	0.74	0.57	0.58	0.74	0.57	0.61
Sample Average	**0.69**	**0.53**	**0.57**	**0.70**	**0.50**	**0.55**	**0.69**	**0.49**	**0.58**

Legend: M: monthly change in bond spreads; U: upward change in bond spreads; D; downward change in bond spreads.
Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

To check the robustness of the results obtained with RR1, we also run another regression routine (RR2) to forecast bond spreads and calculate the probabilities of correctly predicting the direction of the monthly change in bond spreads. This time we assess whether *removing* observations – instead of adding them – affects the ability of the model to correctly predict the direction of the monthly change in bond spreads. We proceed as follows. We begin running a regression over the full sample T. Then the regression is run again removing the first $t<T$ observations of the sample, one at a time, until all the first t observations have been removed from the full sample. This routine eliminates the oldest observations in the sample. We intend to check if for each country and in each month of the forecasting period, actual and predicted bond spreads change in the same direction. In addition to that, we are interested to check whether the model forecasts better upward or downward monthly changes in bond spreads. The results are summarized in table A1 (see Appendix). The RR2 method obtains the best results for Brazil, Bulgaria, Colombia, Mexico, Panama, Philippines, South Africa and Turkey, while it performs less well for China, Ecuador and Malaysia. Finally the results confirm that the model on average predicts downward movements better than upward movements in bond spreads.

Summing up, judging by the probability to correctly predict the direction of the monthly changes in bond spreads, all the forecasting methods used – LP, RR1 and RR2 – appear to be successful. The results also show that all methods are better in predicting downward than upward movements in bond spreads. However, this does not constitute sufficient information to assess which of the forecasting methods is the most accurate in predicting the direction of monthly change in bond spreads. In the next section, we run the Diebold and Mariano (1995) test for forecasting accuracy.

C. Comparing Competing Forecasts

We perform the Diebold–Mariano (1995) test for each emerging economy for which we have generated bond spread predictions with both forecasting methods.[15] Given actual bond spreads, the Diebold Mariano test is a measure to establish which of the two competing methods has the highest predictive accuracy in forecasting bond spreads. The Diebold-Mariano test outcomes are reported in table 7.

Table 7. Measuring the accuracy of bond spread forecasts with the Diebold-Mariano test

	Rolling Regression (RR1) – Linear Prediction (LP)		
	Better forecast	Test statistics	p-value
Argentina	**RR1**	**-4.41**	**0.00**
Brazil	**RR1**	**-2.00**	**0.04**
Bulgaria	RR1	-1.65	0.09
China	RR1	-1.62	0.10
Colombia	**RR1**	**-2.82**	**0.00**
Ecuador	RR1	-1.53	0.24
Malaysia	**RR1**	**-0.94**	**0.34**
Mexico	**RR1**	**-2.12**	**0.03**
Peru	**RR1**	**-4.17**	**0.00**
Philippines	**RR1**	**-4.09**	**0.00**
Poland	LP	0.94	0.34
Russia	RR1	-0.49	0.13
S. Africa	RR1	-0.56	0.57
Turkey	RR1	-1.54	0.12
Venezuela	**RR1**	**-4.14**	**0.00**

Significant test outcomes in bold.
Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

The test outcomes show that in most cases bond spread forecasts obtained with the rolling regression method (RR1) are significantly more accurate than those obtained with the linear prediction method (LP). This result can be motivated by observing that the rolling regression method involves adding one observation at a time to the original estimation sample, hence it is possible to enrich by one observation at a time the information set available to market participants. By contrast, with the linear prediction method, the information set is fixed at time $t<T$. Intuitively, if market participants have a richer information set available, then they will formulate more accurate predictions for bond spreads.

For robustness, we also ran the Diebold-Mariano test to compare the forecast accuracy of the other method involving a rolling regression routine (RR2) with the linear prediction method. Table A2 (in the Appendix) shows also that RR2 produces more accurate forecasts compared to LP. It also shows that RR2 generates more accurate bond spread forecasts compared to RR1. These results imply that gradually removing the initial (oldest) $t<T$ observations from

[15] The Diebold-Mariano test calculates a measure of predictive accuracy proposed by Diebold and Mariano (1995). Given an actual series and two competing predictions, the test applies a loss criterion (such as squared error, mean absolute error, or mean absolute percentage error) to each competing prediction. Then, the procedure tests that the mean difference between the loss criteria for the two competing predictions is zero. Hence, under the null, the two competing predictions have equal forecasting accuracy. Rejection of the null implies that it is possible to distinguish the competing predictions for their forecasting accuracy.

the estimating sample produces better bond spread forecasts then gradually adding the last (newest) *T-t* observations to the estimation sample. In addition, for both rolling regression methods (RR1 and RR2) we calculated other measures for forecasting accuracy, such as the mean squared error (MSE), the mean absolute error (MAE) and Theil's U-Statistics (see tables A3 and A4 in the Appendix).[16] The tables show that the bond spread predictions generated with the RR2 method tend to have lower MSE and MAE. The tables also show that, as opposed to the RR1 method, the U-Statistics associated to the bond spread predictions generated with the RR2 method are frequently lower then unity, particularly when the forecasting period is set between January 2008 and December 2011.

We now turn to test whether the forecasting methods used so far – linear prediction and rolling regressions – are significantly more accurate in predicting the monthly changes in bond spreads than a naïve forecasting method (e.g. a random walk model). Following Diebold and Mariano (1995), the series to be forecast is the monthly change in emerging market bond spreads from January 2007 until December 2011. We assess four forecasts: the change in bond spread prediction associated with a random walk model (RW), the predicted monthly changes in bond spreads obtained with the rolling regression methods – RR1 and RR2 – and with the linear prediction method (LP). The Diebold-Mariano (1995) test outcomes are reported in table 8.

Table 8. Measuring the accuracy of predicted monthly changes in bond spreads with the Diebold-Mariano test

Competing forecasts	Rolling Regression 1 (RR1) – Random Walk (RW)			Rolling Regression 2 (RR2) – Random Walk			Linear Prediction (LP) – Random Walk (RW)		
	Better forecast	Test statistics	p-value	Better forecast	Test statistics	p-value	Better forecast	Test statistics	p-value
Argentina	RW	1.30	0.19	RR2	-0.04	0.97	**RW**	**2.78**	**0.00**
Brazil	RW	1.19	0.06	RR2	-0.58	0.56	**RW**	**3.29**	**0.00**
Bulgaria	RW	1.64	0.10	**RW**	**2.54**	**0.01**	**RW**	**1.49**	**0.05**
China	RR1	-1.62	0.10	RW	1.49	0.13	LP	-1.12	0.26
Colombia	RR1	-0.80	0.42	**RR2**	**-2.43**	**0.01**	**RW**	**3.14**	**0.00**
Ecuador	RR1	-0.57	0.56	RR2	-0.34	0.73	RW	0.88	0.37
Malaysia	RR1	-1.10	0.27	RR2	-1.26	0.20	LP	-0.71	0.47
Mexico	RW	0.79	0.42	**RR2**	**-2.42**	**0.01**	**RW**	**4.52**	**0.00**
Peru	RR1	-1.69	0.09	RR2	-0.09	0.92	**RW**	**3.74**	**0.00**
Philippines	RR1	-0.61	0.54	RW	0.72	0.48	**RW**	**2.48**	**0.01**
Poland	**RR1**	**-2.63**	**0.00**	RR2	-0.54	0.58	LP	-0.87	0.06
Russia	RW	1.72	0.20	RW	0.49	0.61	**RW**	**1.99**	**0.04**
S. Africa	RW	1.09	0.27	RR2	-0.92	0.35	RW	0.32	0.74
Turkey	RW	0.33	0.73	RR2	-1.46	0.14	Near positive definite matrix		
Venezuela	**RW**	**2.57**	**0.01**	RW	1.83	0.07	**RW**	**3.68**	**0.00**

Significant test outcomes in bold (95% confidence level).
Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

[16] Theil's U-Statistics allows comparing the rolling regression forecasting method with a random walk approach (Markidakis, Wheelwright and McGee, 1983). Theil's U-Statistics can be expressed as $U = \sqrt{\frac{\sum_{i=1}^{n-1}\left(\frac{F_{i+1}-X_{i+1}}{X_i}\right)^2}{\sum_{i=1}^{n-1}\left(\frac{X_{i+1}-X_i}{X_i}\right)^2}}$ where F is the forecast and X the actual observation. The numerator is the predicted (squared) relative change, while the denominator is the actual (squared) change. If U is lower than unity, then the forecasting technique being used to generate F_{i+1} produces more accurate predictions than the naïve forecasting method (i.e. random walk). The smaller the U-Statistics, the better the forecasting technique is relative to the naïve method.

Table 8 shows that in most cases, when the rolling regression methods are compared with the random walk, it turns out that most of the times the test outcomes are not significant. In the cases of Colombia, Mexico and Poland, the shows that rolling regression methods are *significantly more accurate* than random walk models in generating in-sample bond spread predictions. In other cases (Ecuador, Malaysia and Peru), rolling regression methods dominate the random walk model, but the test outcomes lack of statistical significance. By contrast, in the cases of Bulgaria and Venezuela, the random walk forecasts of the monthly changes in bond spreads are significantly more accurate than the corresponding rolling regression forecasts. Finally, the random walk forecasts appear significantly more accurate in most of the cases when compared with the linear prediction forecasts. Overall, the results suggest that while the linear prediction method does not deliver more information compared to a random walk model, rolling regression methods can in some cases be more accurate than a random walk models to generate predictions for bond spreads.

VII. Concluding Remarks

This study was divided into two parts. In the first part, in a baseline regression we estimated sovereign bond yield spreads for 28 emerging market economies using a set of country-specific and global factors, over the period January 1998 – December 2011. We also ran the same regression while allowing for the dimensions of the panel to change, and calculated the improvement in the fitted bond spreads following a hypothetical improvement in the country-specific explanatory variables.

The second feature of this study was to back-test the model to assess the ability of the model to generate accurate in-sample forecasts for bond spreads. We generated bond spread forecasts with three competing forecasting methods: linear prediction and two rolling regression routines. For each method used, we checked whether actual and predicted bond spreads changed in the same direction during each month of the forecasting period. Then, we compared the forecasting accuracy of both methods by running the Diebold-Mariano (1995) test. Finally, we compared the accuracy of each forecasting method against that of random walk model in predicting bond spreads.

A number of conclusions can be drawn from this study.

First, the results show that the coefficient estimates and statistical significance of country-specific and global explanatory variables on bond spreads may vary across time and regions. One possible reason for this finding is that over time and across different emerging economies, investors do not always assign the same weight to country-specific and global factors when selecting which sovereign bonds to hold in their portfolios. From an econometric perspective, the results imply that the coefficient estimates of the explanatory variables and their statistical significance may be sensitive to the dimensions of the panel. Changing the dimensions of the panel may lead to different coefficient estimates and may change the degree of statistical significance for the explanatory variables. However, from a policymaking perspective, despite country-specific explanatory variables may not always be significant to explain bond spreads the results show that good country-specific fundamentals tend to reduce the external cost of borrowing.

Second, the model fails to fully explain the increase in sovereign bond spreads observed in 2010 and 2011 in some emerging economies. The increase in sovereign bond spreads, hence yields, could be related to concerns that international investors might have about the potential impact of the euro area economic downturn on emerging economies and on their borrowing costs. Related to this result, we also find that during crisis times, good macroeconomic fundamentals are helpful in containing bond yield spreads, but less than in non-crisis times. Perhaps this is because extra-economic forces are also responsible for the movement in bond yield spreads when a financial crisis occurs.

Third, changes in the degree of external vulnerability are estimated to cause the largest changes in the cost of external borrowing for emerging economies. Improvements in the degree of external vulnerability are three times more effective than improvements in the economic risk rating and twice more effective than improvements in the political risk rating in lowering the cost of external borrowing. Improvements in the degree of political risk are estimated to be twice as more powerful than improvements in the economic risk rating to lower the cost of external borrowing. The results of these simulations imply that a low degree of external vulnerability and a high degree of political stability can substantially reduce the cost of external borrowing. From a policy perspective, the simulations results underscore the importance for emerging economies to adopt measures aiming to reduce their degree of external vulnerability such as, for example, developing local currency bond markets in order to reduce the reliance on external debt financing. In addition, the simulations results highlight the importance of having in place (or building) strong institutions to achieve and maintain political stability. Failure to do so may have negative implications for the cost of external borrowing.

Finally, we generated in-sample bond spread predictions with two competing forecasting methods. We ran the Diebold-Mariano (1995) test for forecasting accuracy to rank the three competing forecasting methods. Bond spread predictions obtained with rolling regression routines tend to be more accurate than those obtained with linear prediction, possibly reflecting that rolling regression routines allow to gradually enriching in every period the information set available to market participants, unlike in the case of the linear prediction forecasting method. We also tested whether the three forecasting methods used were significantly more accurate in predicting the monthly changes in bond spreads than a naïve forecasting method (e.g. a random walk model). For some countries – Colombia, Mexico and Poland – forecasts of the monthly changes in bond spreads obtained with rolling regression routines were significantly more accurate than forecasts obtained with a random walk model. The findings suggest that the rolling regression method can in some cases be more accurate than a random walk model to generate predictions for bond spreads. By contrast, the linear prediction method does not deliver more information compared to a random walk model. An implication of this finding is that rolling regression routines can be useful when forecasts for bond spreads are needed for scenario analyses to simulate the path of sovereign bond spreads and to measure the degree of fiscal distress.

This study can be extended in a number of directions.

As regards the estimation part of this study, we use indices for political, economic and financial risk from the International Country Risk Guide (ICRG) as country-specific controls in the regression for spreads. While these indices allow for a range of variables to be taken into account and introduced in the model in a parsimonious way, it would be interesting to check how the results look like when these indices are “unbundled” (e.g. use external debt/GDP, external debt/exports, current account/GDP and reserve adequacy indicators as controls rather than the ICRG Financial Risk Rating index). Similarly, it would be interesting to include to the country-specific explanatory variables data for real GDP growth, inflation, current account balance, and industrial production in emerging economies instead of the ICRG Economic Risk Rating index. It would also be interesting to consider other global explanatory variables such as the slope of the U.S. yield curve, as well as other panel estimation techniques that allow estimating the short-term dynamics of bond yield spreads. Another interesting extension would be running separate regressions for each country and compare the forecast performance of the panel regression (where variables such as the VIX have a common coefficient for all countries), with one where it is ran separately for each country (where all variables have a country-specific coefficient).

As regards the forecasting part of the study, another line of work could be to conduct more experiments to see whether sovereign bond spread forecasts have desirable properties for being used as a leading indicator of financial crises. Finally, if would be interesting to back-test a model where the panel includes also advanced economies in addition to emerging ones.

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APPENDIX

A. Tables

Table A1. Probabilities that the rolling regression (RR2) method correctly predicts (i) the direction of monthly changes in bond spreads (**M**), (ii) upward movements in bond spreads (U), and (iii) downward movements in bond spreads (D).
Probabilities

	Forecasting period								
	Jan 07 – Dec 11			Jan 08 – Dec 11			Jan 09 – Dec 11		
	M	U	D	**M**	U	D	**M**	U	D
Argentina	0.64	0.50	0.43	0.62	0.47	0.58	0.60	0.46	0.39
Brazil	0.72	0.61	0.57	0.76	0.58	0.63	0.79	0.65	0.70
Bulgaria	0.73	0.58	0.61	0.79	0.62	0.67	0.77	0.58	0.67
China	0.58	0.52	0.41	0.60	0.50	0.41	0.66	0.55	0.48
Colombia	0.73	0.55	0.59	0.70	0.52	0.64	0.80	0.56	0.68
Ecuador	0.59	0.39	0.45	0.57	0.39	0.42	0.54	0.29	0.39
Malaysia	0.56	0.39	0.44	0.57	0.39	0.50	0.60	0.38	0.40
Mexico	0.73	0.63	0.58	0.74	0.62	0.63	0.77	0.67	0.70
Panama	0.78	0.60	0.62	0.72	0.59	0.60	0.77	0.67	0.65
Peru	0.76	0.56	0.64	0.72	0.56	0.66	0.74	0.53	0.68
Philippines	0.75	0.65	0.57	0.72	0.57	0.59	0.80	0.60	0.65
Poland	0.75	0.60	0.59	0.79	0.64	0.63	0.80	0.68	0.73
Russia	0.61	0.50	0.44	0.62	0.48	0.47	0.69	0.52	0.58
S. Africa	0.78	0.60	0.65	0.74	0.54	0.63	0.74	0.53	0.64
Turkey	0.73	0.59	0.59	0.77	0.63	0.65	0.80	0.67	0.70
Venezuela	0.69	0.56	0.60	0.68	0.53	0.53	0.79	0.52	0.50
Average	**0.70**	**0.55**	**0.54**	**0.70**	**0.54**	**0.57**	**0.72**	**0.55**	**0.60**

Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

Table A2. Comparing rolling regression and linear prediction forecasts with the Diebold-Mariano test

Competing forecasts	Rolling Regression 2 (RR2) – Linear Prediction (LP)			Rolling Regression 1 (RR1) – Rolling Regression 2 (RR2)		
	Better forecast	Test statistics	p-value	Better forecast	Test statistics	p-value
Argentina	**RR2**	**-3.91**	**0.00**	RR2	0.89	0.37
Brazil	**RR2**	**-2.42**	**0.01**	RR2	1.88	0.06
Bulgaria	**RR2**	**-2.61**	**0.00**	**RR2**	**2.04**	**0.04**
China	RR2	-1.31	0.19	RR2	0.81	0.41
Colombia	**RR2**	**-3.55**	**0.00**	**RR2**	**3.05**	**0.00**
Ecuador	RR2	-1.26	0.21	RR1	-1.42	0.15
Malaysia	RR2	-1.28	0.20	Non-positive definite matrix		
Mexico	**RR2**	**-2.31**	**0.03**	RR2	1.42	0.15
Peru	**RR2**	**-4.16**	**0.00**	RR2	1.76	0.07
Philippines	**RR2**	**-3.63**	**0.00**	**RR2**	**2.20**	**0.03**
Poland	LP	0.22	0.82	RR2	1.26	0.21
Russia	**RR2**	**-1.95**	**0.05**	RR2	1.39	0.16
S. Africa	RR2	-1.81	0.07	**RR2**	**2.17**	**0.03**
Turkey	**RR2**	**-2.51**	**0.01**	**RR2**	**2.25**	**0.02**
Venezuela	**RR2**	**-3.92**	**0.00**	RR2	0.89	0.37

Significant test outcomes are in bold.
Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

Table A3. Mean Square Error, Mean Absolute Error and Theil's U Statistics for the rolling regression (RR1) method

	Forecasting period								
	Jan 07 – Dec 11			Jan 08 – Dec 11			Jan 09 – Dec 11		
	MSE	MAE	U-STAT	MSE	MAE	U-STAT	MSE	MAE	U-STAT
Argentina	0.52	0.65	6.78	0.58	0.68	7.41	0.46	0.61	7.39
Brazil	0.23	0.39	4.79	0.14	0.30	3.37	0.07	0.21	2.15
Bulgaria	0.31	0.45	3.76	0.21	0.38	2.23	0.17	0.29	2.12
China	0.16	0.34	1.50	0.18	0.35	1.35	0.15	0.30	1.27
Colombia	0.20	0.40	3.20	0.15	0.35	2.43	0.13	0.32	2.72
Ecuador	0.14	0.32	1.44	0.16	0.35	1.40	0.17	0.36	3.71
Malaysia	0.03	0.13	**0.85**	0.03	0.13	**0.78**	0.02	0.12	1.01
Mexico	0.04	0.16	1.40	0.03	0.15	1.21	0.03	0.14	1.35
Panama	0.10	0.26	2.34	0.09	0.23	2.11	0.08	0.21	2.08
Peru	0.05	0.17	1.17	0.04	0.14	**0.88**	0.04	0.14	1.08
Philippines	0.15	0.36	3.06	0.12	0.32	2.71	0.12	0.31	2.81
Poland	0.13	0.30	1.30	0.16	0.33	1.26	0.15	0.33	1.47
Russia	0.20	0.38	2.93	0.19	0.35	2.50	0.22	0.38	3.39
S. Africa	0.09	0.24	1.72	0.07	0.22	1.30	0.06	0.20	1.53
Turkey	0.12	0.30	2.85	0.09	0.26	2.00	0.07	0.23	2.01
Venezuela	0.06	0.21	1.93	0.06	0.21	2.04	0.05	0.16	2.81

Legend: MSE: mean square error; MAE: mean absolute error; U-STAT: Theil's U Statistics.
Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

Table A4. Mean Square Error, Mean Absolute Error and Theil's U Statistics for the rolling regression (RR2) method

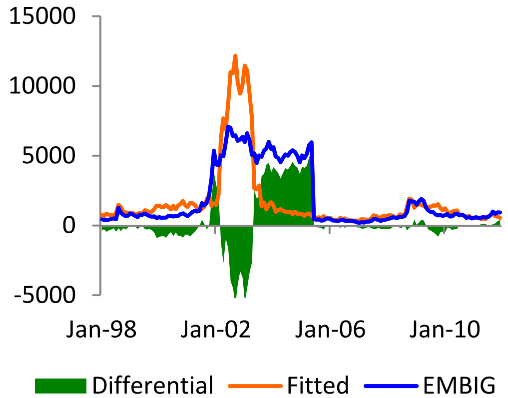
	Forecasting period								
	Jan 07 – Dec 11			Jan 08 – Dec 11			Jan 09 – Dec 11		
	MSE	MAE	U-STAT	MSE	MAE	U-STAT	MSE	MAE	U-STAT
Argentina	0.12	0.30	2.13	0.11	0.28	1.99	0.13	0.31	2.99
Brazil	0.04	0.17	1.56	0.03	0.14	1.18	0.03	0.14	1.42
Bulgaria	0.12	0.28	1.73	0.11	0.26	1.52	0.09	0.20	1.96
China	0.12	0.29	1.72	0.14	0.30	1.70	0.14	0.29	1.81
Colombia	0.04	0.16	1.06	0.03	0.15	**0.96**	0.03	0.15	1.16
Ecuador	0.16	0.33	1.35	0.18	0.34	1.24	0.16	0.31	2.79
Malaysia	0.03	0.14	**0.82**	0.03	0.13	**0.73**	0.02	0.14	1.06
Mexico	0.02	0.11	1.00	0.01	0.08	**0.65**	0.01	0.08	**0.74**
Panama	0.05	0.17	1.54	0.03	0.13	1.10	0.01	0.10	**0.84**
Peru	0.04	0.15	1.00	0.03	0.14	**0.87**	0.04	0.15	1.12
Philippines	0.03	0.13	1.06	0.02	0.11	1.00	0.03	0.13	1.15
Poland	0.08	0.23	1.17	0.09	0.25	1.18	0.11	0.28	1.60
Russia	0.05	0.18	1.11	0.05	0.17	**0.96**	0.04	0.15	1.17
S. Africa	0.05	0.19	1.22	0.04	0.17	**0.95**	0.04	0.16	1.15
Turkey	0.03	0.15	1.20	0.03	0.14	**0.97**	0.03	0.15	1.31
Venezuela	0.06	0.20	1.74	0.06	0.21	1.84	0.06	0.17	2.83

Legend: MSE: mean square error; MAE: mean absolute error; U-STAT: Theil's U Statistics.
Sources: J.P. Morgan, Bloomberg, ICRG database, author's calculations.

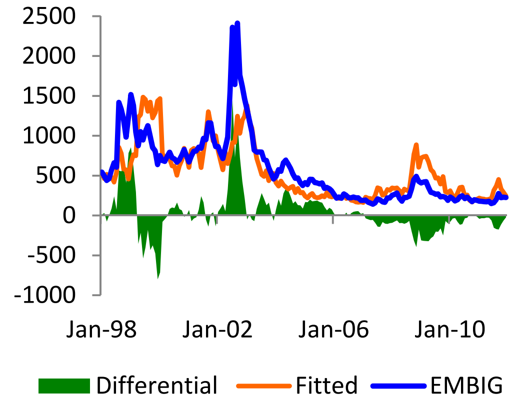
B. Charts

Panel A1. Emerging Market Sovereign Bond Spreads: Actual, Fitted and Residuals *Basis Points*

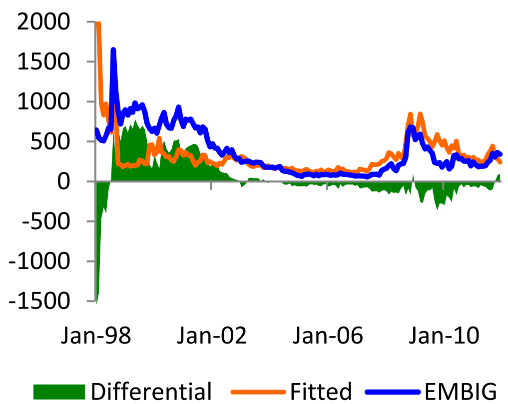
Argentina



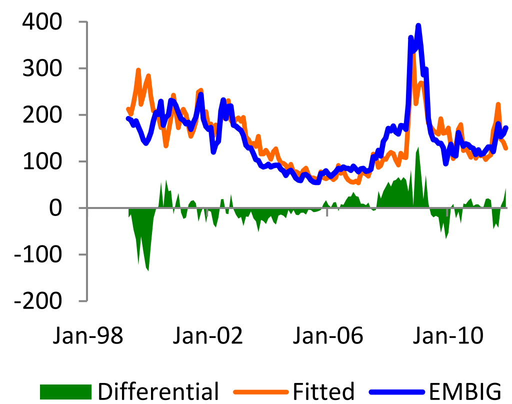
Brazil



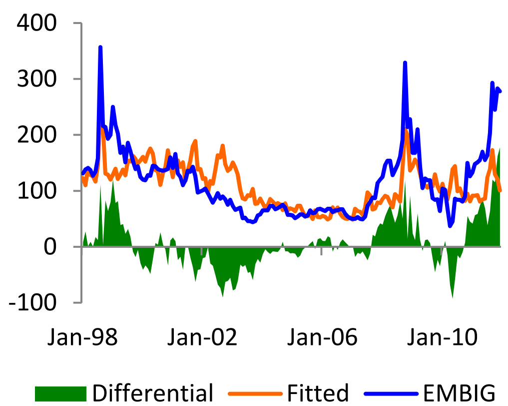
Bulgaria



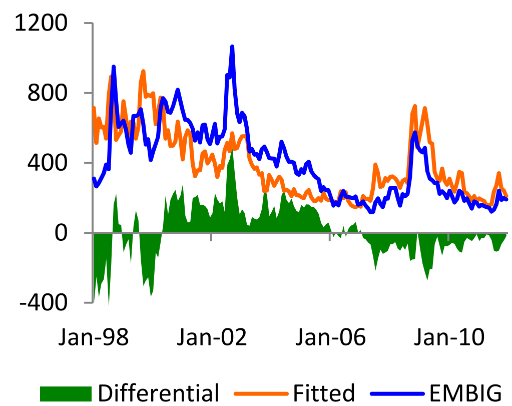
Chile



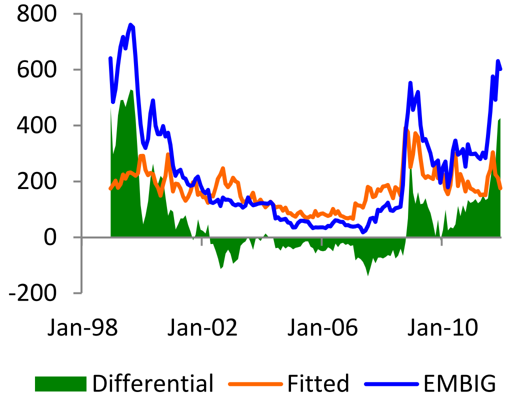
China



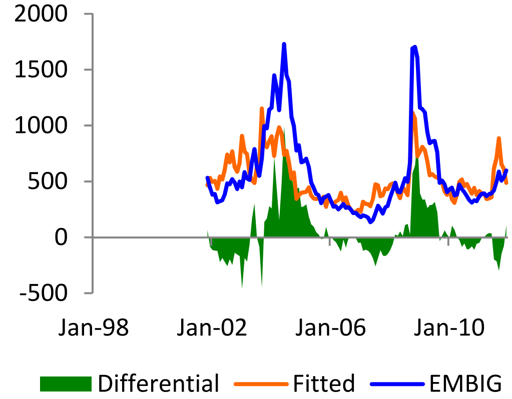
Colombia



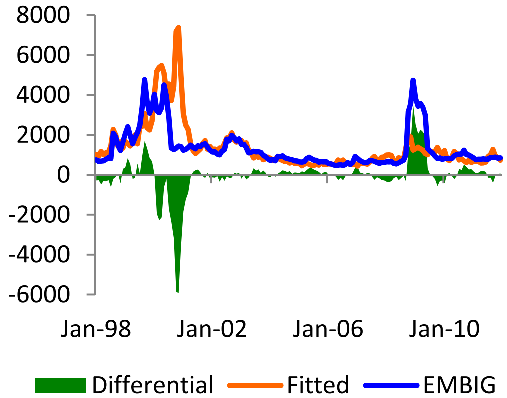
Croatia



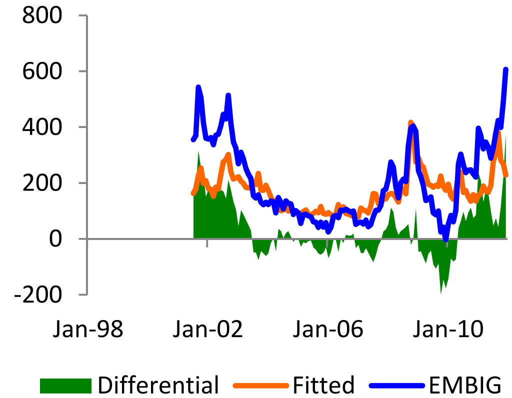
Dominican Republic



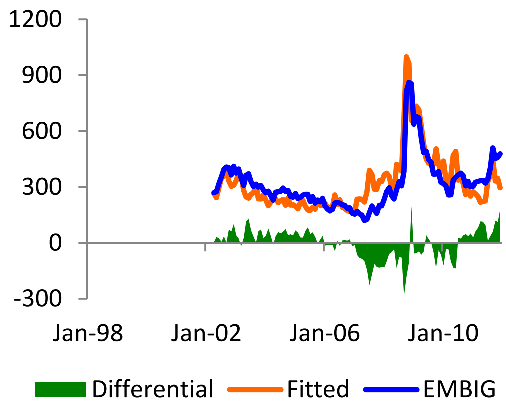
Ecuador



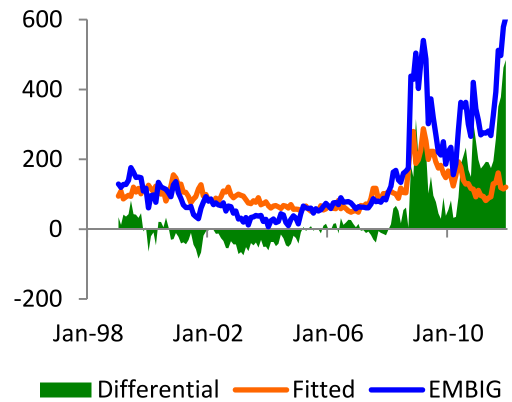
Egypt



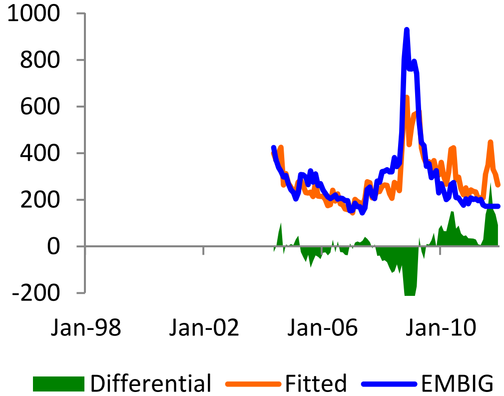
El Salvador



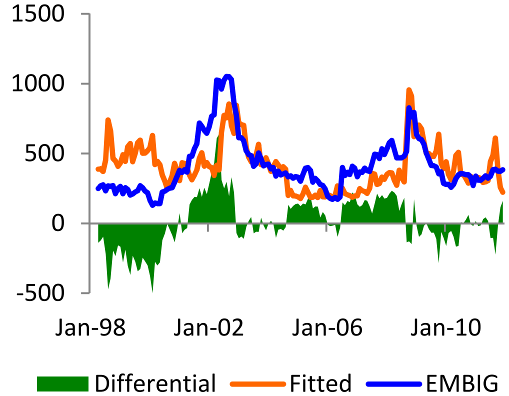
Hungary



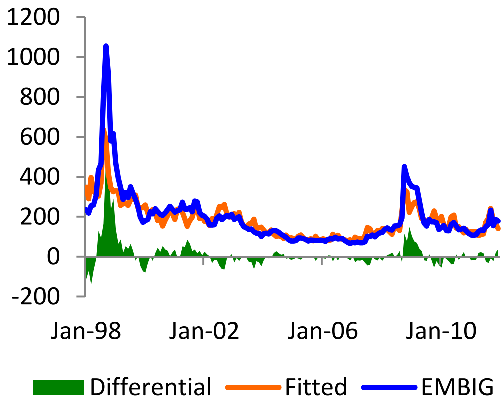
Indonesia



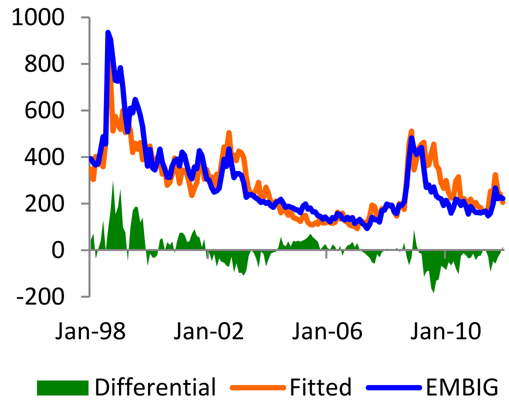
Lebanon



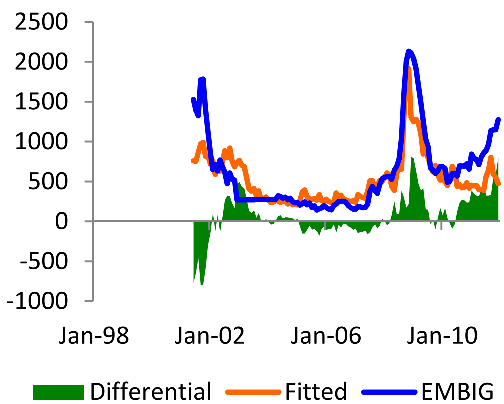
Malaysia



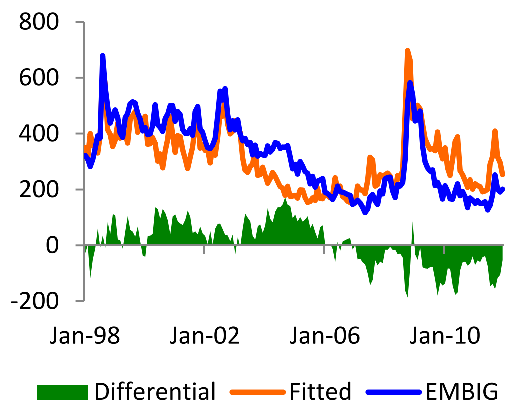
Mexico



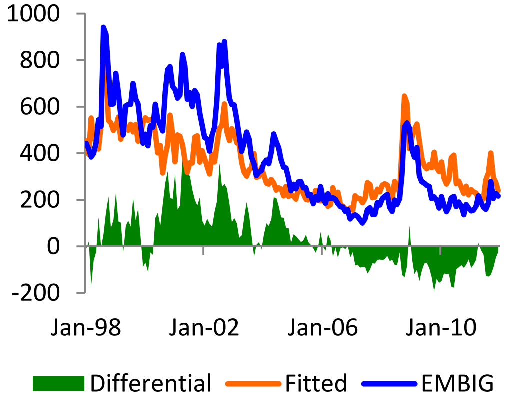
Pakistan



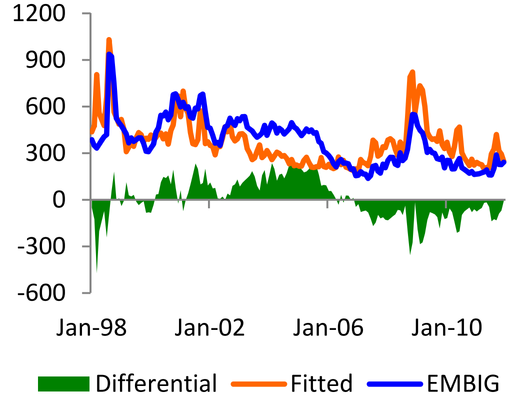
Panama



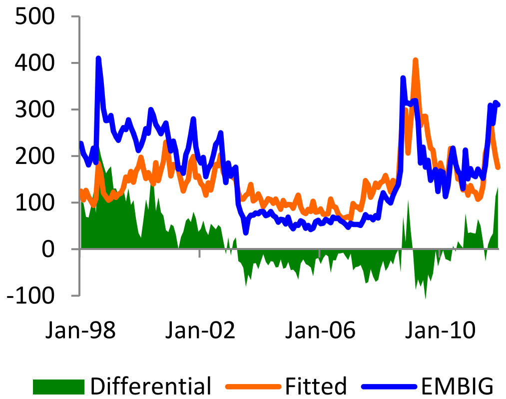
Peru



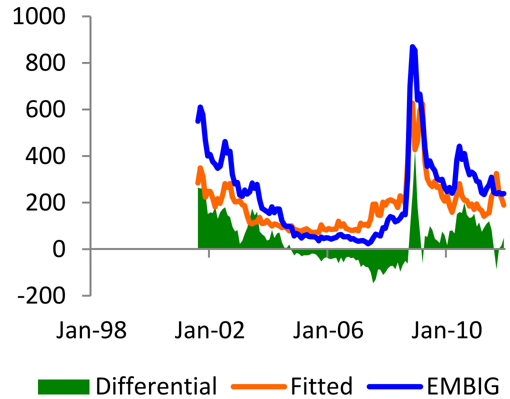
Philippines



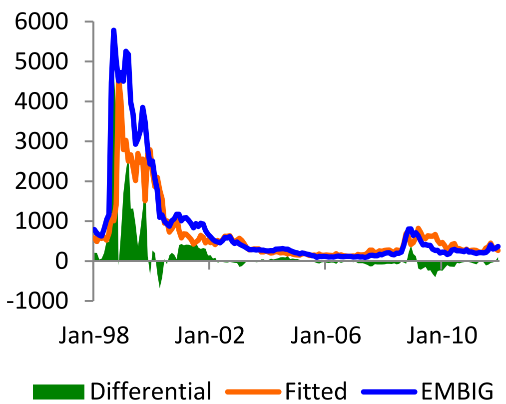
Poland



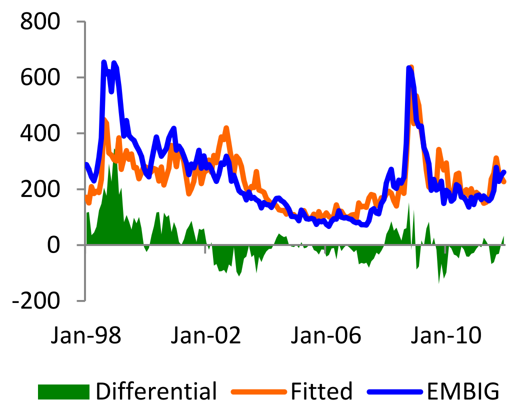
Romania



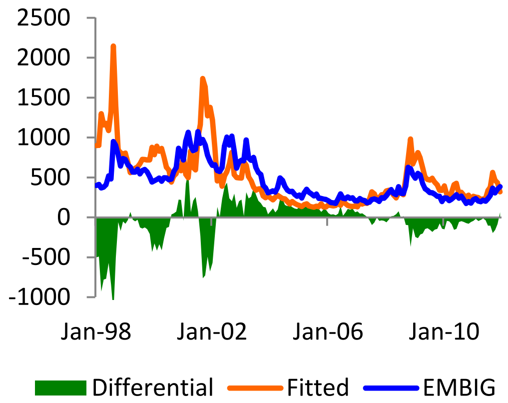
Russia



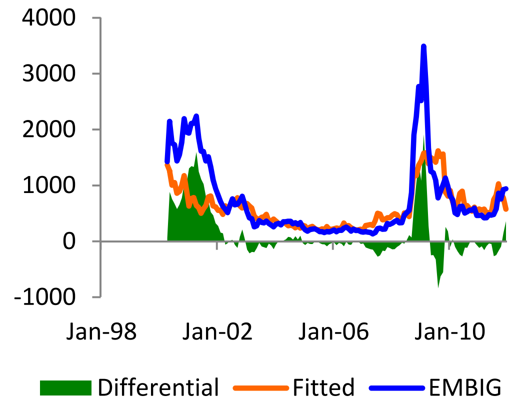
South Africa



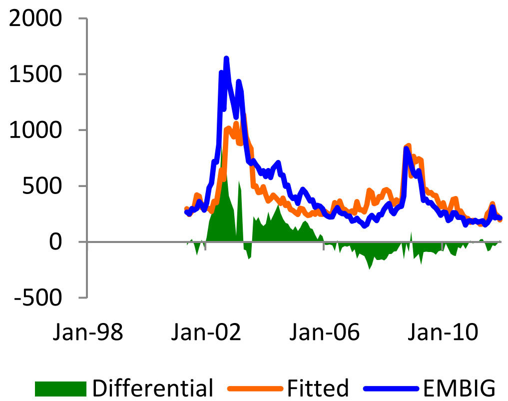
Turkey



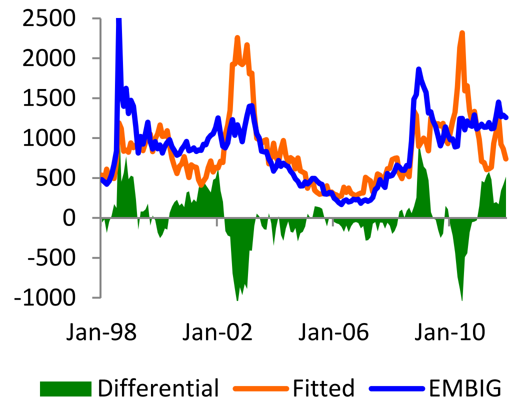
Ukraine



Uruguay



Venezuela



Sources: J.P. Morgan, ICRG Database, Bloomberg and Author's calculations.

Panel A2: Emerging Markets Sovereign Bond Spread Tracker: January 1998 – December 2001
(Basis points)

	Jan-98	Feb-98	Mar-98	Apr-98	May-98	Jun-98	Jul-98	Aug-98	Sep-98	Oct-98	Nov-98	Dec-98	Jan-99	Feb-99	Mar-99	Apr-99	May-99	Jun-99	Jul-99	Aug-99	Sep-99	Oct-99	Nov-99	Dec-99
Asia																								
CHN	6	27	-3	11	0	14	6	114	28	77	62	79	119	77	81	33	31	13	32	11	-24	-2	-7	-31
MAL	-97	-97	-116	-60	-28	122	64	120	433	534	212	293	151	87	85	19	17	36	55	7	8	17	-45	-81
PHI	-148	-284	-290	-157	-132	-139	-210	-41	111	193	-1	15	56	98	108	6	9	26	-43	-7	-16	-4	-62	-88
Eastern Europe, Middle East and Africa																								
BUL	-1682	-259	-459	-505	-300	154	22	649	818	651	524	665	697	614	722	675	750	671	668	742	631	300	212	306
CRO												462	292	323	432	486	486	461	494	523	520	417	278	104
HUN													30	21	42	36	33	70	58	35	37	39	1	-3
LEB				-144	-141	-101	-227	-492	-416	-207	-236	-160	-200	-308	-273	-319	-313	-239	-366	-364	-302	-223	-281	-311
POL	109	107	71	79	94	130	75	228	190	185	164	177	174	126	132	119	101	125	112	116	102	93	62	21
RUS	222	209	4	24	218	447	452	3294	3623	-392	-294	1861	1427	2120	2447	1516	1196	313	378	558	2025	699	-209	47
SAF	120	108	41	41	58	122	110	163	140	281	216	368	274	251	185	60	90	102	104	104	90	96	44	9
TUR	-666	-674	-1009	-866	-841	-635	-917	-723	-376	-116	-260	-58	56	-11	49	-44	-185	-14	-211	-144	-233	-123	-380	-346
Latin America																								
ARG	-311	-243	-431	-325	-265	-221	-434	-186	-467	-187	-246	-116	37	-50	-93	-262	-106	-190	-188	-100	-406	-463	-741	-837
BRA	19	87	-75	-16	118	221	83	535	494	594	493	613	789	489	-159	-390	-722	-393	-297	-308	-417	-389	-628	-811
CHL																	-45	-13	-84	-111	-80	-69	-120	-142
COL	-295	-271	-420	-316	-265	-291	-195	-204	168	154	-47	-113	5	-64	-120	-175	26	112	-232	-246	-297	-275	-260	-388
ECU	-324	-224	-427	-387	-440	-306	-570	-191	-138	-252	-223	66	599	749	310	-399	60	-60	6	371	2098	1584	465	-581
MEX	48	59	-48	-17	37	105	-69	90	156	198	134	232	214	104	45	2	121	177	208	162	143	136	25	-74
PAN	-27	-6	-120	-50	-12	69	-10	29	-31	78	55	112	77	12	26	-4	37	71	42	46	59	63	18	-34
PER	-15	-30	-145	-77	-17	108	-39	55	120	187	61	123	217	123	77	-27	23	139	114	185	127	156	4	-96
VEN	-30	-10	-163	-21	23	107	125	1293	401	522	746	435	668	374	247	-76	67	107	45	187	46	-51	-53	-242

	Jan-00	Feb-00	Mar-00	Apr-00	May-00	Jun-00	Jul-00	Aug-00	Sep-00	Oct-00	Nov-00	Dec-00	Jan-01	Feb-01	Mar-01	Apr-01	May-01	Jun-01	Jul-01	Aug-01	Sep-01	Oct-01	Nov-01	Dec-01
Asia																								
CHN	-44	-49	-41	-52	-24	14	3	25	8	-6	-32	9	14	7	-25	-44	-31	-7	-6	-16	-45	-63	-39	-39
MAL	-55	-40	-2	-24	18	45	22	52	33	27	5	10	27	-14	-10	65	59	72	64	24	24	13	25	5
PAK																		-853	-617	-532	-812	-677	-623	-308
PHI	-80	-39	31	9	63	132	122	138	110	172	-97	-15	16	14	-25	126	111	205	241	112	110	192	202	72
Eastern Europe, Middle East and Africa																								
BUL	275	60	354	425	488	419	347	455	487	490	479	374	388	440	406	503	487	453	447	333	363	340	276	177
CRO	37	72	124	208	260	204	189	217	205	138	70	95	89	25	42	66	68	79	45	20	-13	6	63	26
EGY																			195	187	300	243	220	162
HUN	-63	-10	-19	-43	13	14	20	32	-6	-35	-41	-16	0	-20	-45	-40	-26	-13	-43	-58	-94	-69	-19	-1
LEB	-510	-288	-275	-302	-277	-58	-66	-2	-49	-92	-132	-23	30	-72	-48	-5	118	170	191	188	226	141	242	186
POL	35	86	102	88	129	107	86	116	78	69	36	50	63	47	25	11	27	34	67	61	50	70	68	35
ROM																				258	297	273	224	116
RUS	330	-196	-32	-684	-48	-4	20	185	187	99	270	458	444	371	411	413	430	396	455	330	358	308	254	149
SAF	-18	-17	38	56	109	80	55	124	99	88	19	79	62	7	18	61	81	71	85	39	31	44	26	18
TUR	-521	-368	-349	-364	-281	-79	-74	40	77	87	193	-127	280	452	139	208	128	-101	-40	-598	-713	-908	-633	-751
UKR				6	847	727	646	555	632	747	984	1013	1289	1323	1305	1584	1232	1104	1012	780	693	493	446	309
Latin America																								
ARG	-799	-752	-796	-814	-681	-658	-789	-502	-700	-618	-734	-809	-620	-798	-638	-281	-220	-9	413	-123	-520	251	1833	3679
BRA	-86	-41	-41	-19	24	129	85	142	71	52	-34	13	-1	-125	-113	-50	151	105	39	-142	27	-126	-7	-76
CHL	-114	-49	-13	-6	-12	59	14	57	26	30	-10	11	41	-26	-32	-11	4	18	16	-10	-28	-11	-8	-21
COL	-222	-202	-214	-86	92	169	60	258	243	232	184	236	240	26	10	191	213	201	247	138	153	70	119	-13
DOM																							29	-106
ECU	-1770	-2386	-2336	-2285	-724	-613	-1910	-2548	-5541	-4990	-4446	-2386	-815	-1080	-348	157	110	228	281	110	-168	-187	17	-208
MEX	18	-23	-38	-32	33	42	6	72	24	38	-13	48	85	76	53	55	53	68	97	45	41	-5	18	-46
PAN	35	36	33	42	138	120	85	124	115	89	48	101	127	83	99	81	79	114	99	40	30	24	65	19
PER	-108	-120	-11	-10	118	128	137	168	272	290	217	250	286	152	174	421	403	307	340	217	209	166	176	94
URU																	-15	11	21	-56	-93	-46	13	-51
VEN	-162	-189	-120	-3	88	296	169	252	209	250	199	368	320	219	208	342	391	444	480	418	324	278	457	434

Panel A3: Emerging Markets Sovereign Bond Spread Tracker: January 2002 – December 2005
(Basis points)

	Jan-02	Feb-02	Mar-02	Apr-02	May-02	Jun-02	Jul-02	Aug-02	Sep-02	Oct-02	Nov-02	Dec-02	Jan-03	Feb-03	Mar-03	Apr-03	May-03	Jun-03	Jul-03	Aug-03	Sep-03	Oct-03	Nov-03	Dec-03
Asia																								
CHN	-23	-10	-1	-36	-37	-53	-71	-77	-96	-67	-63	-59	-82	-69	-67	-29	-37	-34	-45	-43	-60	-31	-23	-29
MAL	24	2	0	-36	-18	-23	-57	-52	-77	-17	1	8	-32	-40	-29	-7	-10	-12	-32	-27	-69	-30	-21	-50
PAK	-86	45	-120	58	-148	65	206	350	329	224	204	445	488	441	456	187	120	111	48	52	93	-3	0	18
PHI	119	76	67	-6	20	17	14	32	18	76	93	123	45	106	102	123	185	191	105	95	43	140	186	87
Eastern Europe, Middle East and Africa																								
BUL	251	191	224	131	112	105	103	40	34	25	9	-7	-87	-40	-30	35	41	40	40	40	1	26	-4	-26
CRO	22	13	46	-25	-25	-51	-80	-120	-115	-64	-49	-65	-101	-93	-84	-34	-24	-18	-1	-20	-49	-8	-7	-16
EGY	182	187	187	178	183	174	152	159	216	179	133	117	47	105	45	45	39	27	-40	-56	-78	-41	-52	-62
HUN	-4	1	-3	-14	-8	-25	-35	-55	-56	-35	-48	-41	-75	-67	-91	-52	-64	-42	-42	-38	-57	-33	-49	-47
LEB	287	362	430	603	475	299	234	279	169	313	22	94	-164	-129	-135	-31	27	32	-83	-69	-74	33	-23	-59
POL	49	60	37	33	53	46	37	48	40	13	-15	24	-11	13	14	-29	-35	-42	-86	-57	-70	-36	-32	-46
ROM	185	159	185	130	163	160	183	157	138	94	78	89	25	33	63	108	132	176	144	160	63	63	55	36
RUS	125	52	66	-48	11	-21	-53	10	-48	-43	-78	-60	-142	-59	-79	10	-11	-2	-16	15	-22	46	47	5
SAF	-31	-21	4	-79	-66	-79	-103	-93	-146	-49	-27	-53	-115	-104	-124	-51	-40	-9	-42	-60	-110	-39	-42	-35
TUR	-247	111	110	141	188	406	294	154	330	265	122	227	-56	15	282	209	312	429	260	252	174	156	124	37
UKR	263	145	133	-80	-45	-3	5	-88	-141	67	194	26	-171	-236	-207	-204	-133	-37	-102	-114	-131	-48	-80	-148
Latin America																								
ARG	2142	-3456	-1593	-3055	-1795	-2942	-5256	-5373	-7418	-5251	-4627	-5431	-6988	-3978	-4818	1869	2328	1674	3597	3449	3756	3979	4449	3847
BRA	157	98	45	118	327	767	1382	490	1077	391	369	139	31	24	-145	-8	144	311	299	206	91	99	41	-1
CHL	-13	-10	-28	-42	-17	27	19	-16	-19	18	-10	-7	-32	-38	-48	-36	-14	-2	-16	-30	-57	-25	-26	-40
COL	151	236	187	131	142	143	407	367	453	275	153	101	71	80	21	9	87	89	108	122	148	247	154	79
DOM	-120	-121	-134	-239	-168	-242	-207	-212	-260	-155	-221	-355	-385	-189	-230	-68	168	199	-13	-478	-499	169	161	95
ECU	-155	-161	-78	-433	-133	-332	-175	-209	-242	16	5	171	-153	-164	-279	-165	237	293	265	266	83	172	95	-135
MEX	-18	-47	-23	-77	-50	-58	-58	-100	-72	-84	-70	-75	-130	-96	-131	-75	-12	9	-28	-32	-73	-23	-41	-76
PAN	24	-2	50	2	55	58	65	44	11	21	8	20	-49	22	-19	62	106	94	72	26	13	63	70	40
PER	126	95	83	81	148	195	323	218	257	234	130	146	119	82	-4	39	126	181	120	33	-54	1	6	-22
URU	50	169	228	339	310	320	932	271	331	314	366	197	130	497	-207	-47	-74	-84	192	283	75	207	150	155
VEN	546	233	31	-417	-218	-570	-830	-1051	-1341	-1121	-1041	-995	-748	-549	-377	55	5	108	-164	-44	-114	-38	-193	-284

	Jan-04	Feb-04	Mar-04	Apr-04	May-04	Jun-04	Jul-04	Aug-04	Sep-04	Oct-04	Nov-04	Dec-04	Jan-05	Feb-05	Mar-05	Apr-05	May-05	Jun-05	Jul-05	Aug-05	Sep-05	Oct-05	Nov-05	Dec-05
Asia																								
CHN	-14	-4	-14	-13	-9	-9	-9	-4	9	-8	-12	-13	-12	-12	-15	-16	-3	-1	2	13	9	-4	15	16
IND					-6	34	118	-5	-24	35	-6	11	26	40	47	5	-40	-56	-44	-91	-57	-42	-41	-62
MAL	-21	3	-12	7	21	28	18	7	13	-12	-10	-16	-14	-7	-9	-16	-5	2	-5	-1	2	-22	-4	-2
PAK	-10	-55	-34	8	69	70	32	53	62	44	35	21	-43	-117	-156	-123	-109	-55	-94	-87	-123	-160	-91	-65
PHI	157	232	193	108	152	168	144	168	234	230	243	230	202	194	170	173	202	237	229	204	158	99	97	83
Eastern Europe, Middle East and Africa																								
BUL	-12	24	-3	-4	6	-29	-46	-41	-29	-60	-47	-63	-58	-61	-58	-67	-41	-34	-50	-46	-44	-61	-41	-49
CRO	-2	12	0	-3	-2	-40	-39	-50	-32	-41	-33	-36	-43	-38	-36	-33	-21	-14	-14	-33	-39	-58	-42	-48
EGY	-46	17	6	-24	40	31	-10	22	29	9	-9	4	6	-27	-10	-14	-12	-13	-30	-38	-49	-50	-45	-30
HUN	-62	-37	-33	-49	-42	-21	-27	-51	-50	-41	-19	-27	-41	-8	4	-5	2	8	-6	2	-1	-12	6	10
LEB	-4	12	-13	-111	-51	-51	-51	130	132	102	128	138	141	123	102	132	191	189	106	126	119	45	81	51
POL	-24	-12	-30	-41	-28	-34	-32	-43	-26	-52	-43	-32	-44	-45	-58	-57	-29	-21	-35	-36	-40	-53	-23	-20
ROM	40	82	60	67	72	30	11	6	15	-7	-25	-16	-22	-23	-24	-30	-25	-20	-15	-26	-46	-53	-37	-35
RUS	29	67	33	55	81	100	103	97	123	53	82	55	48	28	29	-1	16	23	0	-15	-44	-58	-31	-23
SAF	-35	7	-2	3	31	49	32	26	36	-1	-5	0	-3	-10	9	-8	-8	-3	-6	-8	-19	-33	-20	-21
TUR	69	97	59	106	239	240	184	150	157	118	133	114	138	107	153	193	170	170	141	156	108	84	104	78
UKR	-61	-4	-19	10	30	81	73	33	91	34	100	-35	-67	-26	-41	-46	-6	-1	-28	-48	-53	-84	-46	-27
Latin America																								
ARG	4506	3909	3736	3389	3759	4121	3966	4267	4550	4247	4137	3670	4273	4128	4286	4947	5345	-86	-128	-105	-166	-286	-28	-15
BRA	66	172	193	275	333	302	208	183	176	126	119	123	177	169	193	183	167	175	167	160	113	58	103	79
CHL	-26	-25	-28	-23	-13	-10	-15	-25	-2	-12	-4	-14	-13	-10	-9	-11	-3	-5	-1	-9	-5	-4	12	18
COL	109	145	74	112	260	242	190	161	195	141	125	119	152	146	162	168	148	144	132	110	59	23	54	66
DOM	299	585	388	106	596	958	737	769	575	576	394	401	235	331	280	196	101	92	63	35	20	19	-7	80
ECU	-118	23	-106	106	124	313	153	133	190	59	116	115	168	183	134	190	357	326	260	213	148	29	126	139
MEX	-31	12	-12	-6	36	46	28	9	46	16	46	38	41	38	48	62	54	71	57	47	37	3	16	27
PAN	65	132	89	77	117	160	135	143	170	145	140	87	110	85	112	83	91	98	62	76	46	24	65	62
PER	43	122	87	114	219	204	167	118	120	76	69	13	49	35	29	15	23	47	16	19	-7	-29	1	60
URU	160	275	180	227	271	375	195	218	205	157	134	117	141	89	150	175	181	162	125	116	73	24	72	39
VEN	-171	-88	-266	-157	-84	-92	-179	-169	-152	-257	-173	-181	55	43	-7	98	142	164	155	99	-8	-66	-4	35

Panel A4: Emerging Markets Sovereign Bond Spread Tracker: January 2006 – December 2009
(Basis points)

	Jan-06	Feb-06	Mar-06	Apr-06	May-06	Jun-06	Jul-06	Aug-06	Sep-06	Oct-06	Nov-06	Dec-06	Jan-07	Feb-07	Mar-07	Apr-07	May-07	Jun-07	Jul-07	Aug-07	Sep-07	Oct-07	Nov-07	Dec-07
Asia																								
CHN	11	13	19	17	-14	3	-6	12	13	8	4	-1	2	-18	-10	-10	-7	-17	-21	-4	22	19	35	42
IND	-31	-42	-40	-28	26	-18	21	-20	-33	-34	-37	3	-11	21	19	9	21	38	38	11	-8	1	-39	-38
MAL	-8	-8	7	8	-28	3	-21	0	1	-4	-9	-9	2	-28	-17	-20	-15	-31	-42	-40	-1	-12	-17	-10
PAK	-84	-94	-80	-55	-134	-38	-85	-26	-35	-58	-71	-103	-87	-144	-121	-133	-124	-158	-160	-104	-49	-95	-58	25
PHI	67	52	31	8	-35	30	-21	22	20	3	8	-47	-29	-78	-72	-71	-87	-130	-168	-141	-105	-127	-120	-153
Eastern Europe, Middle East and Africa																								
BUL	-52	-55	-43	-52	-85	-36	-69	-42	-39	-38	-39	-55	-44	-89	-77	-68	-71	-90	-128	-184	-125	-142	-136	-113
CRO	-50	-47	-35	-40	-49	-22	-34	-22	-19	-26	-23	-31	-28	-83	-73	-78	-88	-109	-141	-110	-76	-94	-76	-75
EGY	-64	-45	-1	-6	-47	2	-8	15	12	14	20	-32	-19	-49	-47	-30	-51	-67	-85	-58	-18	-6	27	32
HUN	4	-4	19	16	-1	33	6	24	27	21	17	5	16	-7	-11	-12	-10	-15	-35	-31	-6	-12	-17	-16
LEB	-12	-20	-17	-10	-97	-35	140	129	152	157	221	179	155	117	132	166	177	108	62	138	210	176	209	168
POL	-23	-23	-9	-18	-56	-11	-26	-5	-9	-13	-14	-23	-14	-45	-39	-38	-36	-47	-70	-76	-52	-61	-66	-65
ROM	-40	-47	-36	-37	-59	-34	-54	-35	-32	-40	-36	-47	-45	-74	-71	-76	-80	-112	-154	-125	-81	-119	-104	-102
RUS	-37	-43	-24	-32	-49	-14	-43	-22	-13	-8	-3	-27	-10	-47	-52	-65	-68	-91	-137	-122	-75	-86	-73	-82
SAF	-31	-34	-14	-10	-50	16	-27	-4	-8	-15	-11	-20	-26	-62	-67	-70	-62	-45	-58	-50	-26	-33	-20	-3
TUR	56	38	43	43	52	102	33	81	109	100	112	67	74	62	37	26	1	-42	-79	-49	-16	-42	-42	-65
UKR	-19	-66	-25	-41	-87	-6	-53	-61	3	-7	-4	-42	-34	-104	-125	-139	-146	-209	-272	-252	-165	-173	-100	-119
Latin America																								
ARG	39	-33	-22	-73	-177	-63	-128	-70	-29	-49	-31	-135	-127	-222	-219	-147	-116	-194	-263	-243	-154	-262	-261	-250
BRA	30	-8	21	16	10	45	-11	30	50	53	61	17	26	-35	-48	-55	-62	-94	-141	-128	-90	-115	-104	-98
CHL	6	5	12	12	-4	12	7	24	26	25	36	27	26	5	13	7	13	-1	-3	-3	36	21	37	47
COL	12	-26	4	-17	-35	32	-12	38	42	48	57	0	16	-26	-40	-55	-87	-168	-183	-139	-98	-123	-107	-101
DOM	17	-63	-41	-38	-111	-15	-78	17	13	-11	-11	-47	-43	-119	-108	-117	-140	-186	-264	-183	-113	-161	-169	-150
ECU	5	11	-19	-82	-305	-155	-240	-70	43	-14	90	454	391	111	81	37	111	130	-235	-260	-119	-179	-301	-304
MEX	10	2	26	16	-6	13	-17	7	27	27	45	16	31	5	-3	-14	-20	-28	-50	-55	-15	-31	-4	-2
PAN	3	5	5	-14	-61	23	-20	15	18	23	26	-17	2	-51	-48	-62	-68	-101	-145	-89	-54	-72	-61	-50
PER	-8	4	54	20	-44	-5	-33	-9	-4	-11	1	-50	-24	-86	-79	-86	-65	-82	-115	-99	-68	-73	-51	-64
URU	-19	-26	-21	-33	-81	-20	-102	-50	-38	-43	-34	-94	-65	-96	-105	-116	-127	-183	-245	-203	-133	-159	-166	-181
VEN	-46	-50	-69	-107	-171	-102	-169	-91	-58	-75	-58	-152	-146	-284	-258	-120	-62	-43	-163	-126	-82	-144	-77	-148

	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08	Jul-08	Aug-08	Sep-08	Oct-08	Nov-08	Dec-08	Jan-09	Feb-09	Mar-09	Apr-09	May-09	Jun-09	Jul-09	Aug-09	Sep-09	Oct-09	Nov-09	Dec-09
Asia																								
CHN	35	53	60	73	57	42	56	80	47	113	7	84	13	6	55	8	-10	9	4	5	-25	-51	-26	-40
IND	-60	-47	-58	-81	-110	-97	-72	-117	-75	-104	-260	-239	-196	-172	-44	-21	-43	-52	29	-15	23	90	19	103
MAL	-19	-7	-4	7	17	-3	7	26	-38	97	61	118	80	46	54	48	22	-20	-25	-23	-27	-68	-36	-53
PAK	-63	-71	31	75	181	-64	31	263	323	-107	106	835	755	558	365	447	307	169	204	9	29	-135	44	118
PHI	-143	-132	-119	-105	-67	-73	-96	-44	-225	-470	-318	-137	-267	-333	-297	-156	-130	-100	-106	-107	-126	-192	-101	-141
Eastern Europe, Middle East and Africa																								
BUL	-203	-176	-155	-156	-140	-132	-102	-57	-195	-325	-222	61	-179	-389	-329	-240	-185	-126	-69	-191	-289	-433	-294	-309
CRO	-80	-75	-68	-71	-48	-80	-70	-44	-74	-31	50	286	142	101	143	104	112	132	96	76	36	-12	50	-25
EGY	52	105	82	35	15	11	32	41	45	-44	-18	92	-22	-56	-79	-101	-61	-48	-105	-113	-95	-210	-154	-184
HUN	-2	12	41	66	50	21	41	66	-4	131	138	302	176	160	235	240	60	127	117	81	59	9	80	29
LEB	171	191	222	213	175	118	134	99	-144	-162	-187	136	-65	-130	-98	-43	-27	-58	-75	-138	-153	-179	-68	-116
POL	-44	-48	-59	-38	-14	-32	-30	10	-35	43	-1	42	-14	-128	-88	-51	-120	-90	-77	-41	-37	-58	-11	-47
ROM	-86	-80	-110	-92	-56	-103	-75	-70	-118	2	203	380	35	-27	103	62	56	86	50	52	67	13	64	52
RUS	-83	-81	-78	-73	-50	-79	-70	-22	-84	-7	175	346	61	-197	-244	-228	-199	-280	-261	-289	-298	-396	-238	-235
SAF	31	55	82	50	58	14	14	66	35	-60	-47	21	-55	-23	2	20	109	78	-16	8	-103	-170	-78	-125
TUR	-63	-35	15	21	53	55	-16	17	-104	-439	-412	-206	-317	-259	-222	-193	-145	-163	-192	-163	-63	-160	-121	-170
UKR	-144	-142	-104	-73	-26	-45	17	107	47	575	997	1306	983	1818	1087	189	-365	-351	-429	-969	-751	-686	190	121
Latin America																								
ARG	-261	-230	-128	-66	-65	-184	-151	-100	-380	-218	-230	239	-16	88	208	177	-158	-401	-544	-564	-560	-868	-477	-485
BRA	-83	-99	-92	-97	-72	-108	-120	-69	-194	-510	-432	-294	-322	-388	-382	-348	-287	-221	-219	-148	-188	-133	-94	-96
CHL	53	43	55	57	70	62	55	60	29	6	-4	82	126	59	17	77	7	-19	-21	-23	-29	-63	-55	-65
COL	-65	-69	-90	-94	-70	-104	-112	-57	-150	-256	-168	-67	-161	-318	-264	-280	-229	-73	-32	-28	-95	-133	-86	-87
DOM	-115	-63	20	9	62	23	108	124	-91	544	606	842	360	308	310	272	246	275	317	211	66	0	52	15
ECU	-344	-394	-210	-167	-111	-278	-203	-57	-370	1088	1679	3415	2463	2012	2075	2079	1929	40	-34	-157	-282	-657	-363	-383
MEX	7	-7	-4	-3	7	-10	-3	31	-34	-162	-42	43	-25	-65	-118	-95	-121	-174	-229	-125	-75	-142	-84	-89
PAN	-20	-21	-9	-20	-20	-39	-91	-48	-174	-210	-109	59	-53	-80	-34	-116	-85	-94	-92	-91	-140	-199	-145	-157
PER	-62	-62	-53	-70	-63	-76	-79	-49	-134	-155	-111	37	-84	-189	-118	-163	-89	-86	-101	-103	-148	-212	-167	-173
URU	-174	-157	-115	-114	-35	-88	-55	-13	-171	-101	-122	-85	-101	-221	-238	-41	-127	-88	-106	-92	-39	-145	-81	-83
VEN	-207	-211	-4	74	149	-1	75	124	39	93	181	918	739	604	568	-260	5	-83	-99	-227	-151	-280	60	24

Panel A5: Emerging Markets Sovereign Bond Spread Tracker: January 2010 – December 2011
(Basis points)

	Jan-10	Feb-10	Mar-10	Apr-10	May-10	Jun-10	Jul-10	Aug-10	Sep-10	Oct-10	Nov-10	Dec-10	Jan-11	Feb-11	Mar-11	Apr-11	May-11	Jun-11	Jul-11	Aug-11	Sep-11	Oct-11	Nov-11	Dec-11
Asia																								
CHN	-16	6	-20	-72	-99	-65	-21	-20	-15	2	51	39	34	50	54	67	82	64	29	54	101	105	156	166
IND	129	67	67	120	156	162	88	74	66	54	62	46	47	45	38	17	8	46	164	210	312	182	160	107
MAL	-63	-9	3	-28	-46	-46	3	-19	-1	17	-13	-2	-26	-24	-16	13	18	6	-35	-45	-28	-33	9	25
PAK	31	145	46	-47	-37	-63	108	217	193	242	212	223	361	311	303	297	410	446	292	277	266	513	552	764
PHI	-156	-71	-93	-161	-238	-201	-63	-87	-74	-71	-92	-65	-84	-72	-61	-34	-16	-56	-154	-157	-174	-111	-87	-25
Eastern Europe, Middle East and Africa																								
BUL	-355	-179	-229	-144	-189	-193	-46	-98	-95	-35	-72	-98	-56	-82	-101	-70	-86	-52	-127	-120	-97	-20	54	77
CRO	14	90	18	27	16	29	103	64	104	81	122	115	121	130	114	122	142	125	126	190	245	250	401	413
EGY	-149	-78	-85	-79	29	49	90	64	88	101	67	72	220	165	113	172	129	82	23	42	-2	82	194	352
HUN	18	90	26	33	107	148	219	213	163	160	306	239	206	171	178	183	187	174	199	257	340	366	426	465
LEB	-174	-71	-49	-102	-179	-176	12	-7	18	42	-16	-31	-15	-29	-36	21	32	4	-126	-134	-51	84	95	144
POL	-51	13	-20	-34	-19	-72	33	-6	12	5	72	22	38	30	29	57	25	2	-37	-7	-38	40	94	91
ROM	1	83	75	79	103	89	173	169	137	139	119	137	102	112	74	80	102	112	71	-35	-115	-11	-2	35
RUS	-294	-84	-109	-136	-158	-161	-56	-66	-55	-34	-19	-31	-62	-70	-87	-14	-11	-16	-102	-109	-75	-52	-8	70
SAF	-55	-4	-10	-34	-41	-59	-15	-57	-50	-51	-40	-34	-20	-1	-14	19	1	-11	-76	-70	-100	-48	-35	6
TUR	-129	-51	-52	-95	-170	-168	-75	-52	-66	-82	-87	-73	-53	-26	-63	-39	-19	-32	-122	-203	-311	-188	-48	17
UKR	-169	-11	-136	-202	-278	-312	-138	-145	-55	-11	-48	-92	-144	-113	-183	-106	-63	-73	-307	-304	-253	-37	201	322
Latin America																								
ARG	-516	-162	-203	-177	-272	-287	-18	-18	-27	-98	-28	-23	-28	24	-15	76	139	99	-89	-26	7	125	274	339
BRA	-93	-31	-45	-77	-116	-125	-43	15	10	-7	-47	-16	-45	-37	-55	-35	-34	-75	-187	-186	-213	-111	-80	-49
CHL	-59	17	4	-21	-16	-41	4	1	9	17	-2	5	4	-5	-6	11	16	10	-54	-39	-35	-9	-2	42
COL	-109	-57	-62	-81	-96	-125	-40	-36	-44	-53	-36	-11	-50	-29	-27	-11	-17	-46	-122	-119	-119	-83	-60	-37
DOM	-11	99	62	-4	-37	-261	-69	-126	-119	-95	-128	-67	-62	-19	-8	16	28	-50	-256	-258	-367	-190	-72	78
ECU	-251	5	78	-107	-124	-116	235	234	503	339	226	279	101	50	84	171	151	112	-195	-218	-511	-122	-91	68
MEX	-116	-64	-32	-55	-96	-118	-31	-33	-31	-47	-42	-21	-39	-30	-31	-6	-9	-35	-72	-79	-97	-52	-29	-13
PAN	-150	-92	-92	-128	-191	-185	-75	-71	-67	-81	-75	-45	-80	-61	-76	-48	-46	-82	-161	-165	-212	-138	-127	-74
PER	-177	-129	-91	-134	-183	-195	-109	-100	-91	-102	-89	-65	-100	-86	-64	9	-17	-37	-140	-154	-152	-110	-73	-44
URU	-96	-22	-67	-92	-119	-139	-53	-49	-31	-37	-25	11	-18	5	-6	22	18	-29	-92	-78	-49	-48	-19	8
VEN	-668	-578	-527	-853	-1161	-1275	-622	-376	-291	-126	-152	151	353	426	402	493	537	421	67	164	77	266	345	504

Legend	x: actual bond spread - fitted bond spread (BPs)				
			x	≤	-300
	-300	<	x	≤	-200
	-200	<	x	≤	-100
	-100	<	x	≤	-1
			x	=	0
	1	≤	x	<	100
	100	≤	x	<	200
	200	≤	x	<	300
	300	≤	x		