# Empirical determinants of emerging market economies' sovereign bond spreads

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**Abstract**

This paper investigates the empirical determinants of emerging market sovereign bond spreads, using a ragged-edge panel of JP Morgan EMBI and EMBI Global secondary market spreads and a set of common macro-prudential indicators. The panel is estimated using the pooled mean group technique due to Pesaran, Shin and Smith (1999). This is essentially a dynamic error correction model where cross-sectional coefficients are allowed to vary in the short run but are required to be homogeneous in the long run. This allows a separation of short-run dynamics and adjustment towards the equilibrium. The model is used to benchmark market spreads and assess whether sovereign risk was 'overpriced' or 'underpriced' during different periods over the past decade. The results suggest that a debtor country's fundamentals and external liquidity conditions are important determinants of market spreads. However, the diagnostic statistics also indicate that the market assessment of a country's creditworthiness is more broad based than that provided by the set of fundamentals included in the model. We also find that the generalised fall in sovereign spreads seen between 1995 and 1997 cannot be entirely explained in terms of improved fundamentals.

**Summary**

Yield spreads on emerging market economies' (EMEs') sovereign bonds are important indicators of financial fragility for country surveillance purposes. They are typically used as a measure of the markets' perception of the risk that a country might default and to assess EME external financing conditions. But EME spreads are influenced by a large number of determinants – credit risks, liquidity risks, and market risks – and inferring their exact information content is not straightforward.

This paper develops an empirical model relating secondary market sovereign spreads to a set of country-specific fundamentals, controlling for external factors, market risk and liquidity in bond markets. The aim is to explain the long-run determinants of EME bond spreads, together with some short-run dynamic behaviour. The estimated equation is reduced form, and posits that the fair-value spread is a function of the probability of default and the recovery rate in the event of default. In turn, the probability of default is linked to a set of macro-prudential indicators affecting the country's solvency and liquidity position. To underpin the selection of credit spread determinants (fundamentals), the paper discusses a simplified model of sovereign borrowing that formalises the consumption choices of an indebted small open economy. This model points to a set of variables that are important components of the internal and external constraints on government debt obligations. The data set for the estimation is a ragged-edge panel of secondary market spreads and a number of country-specific macro-prudential indicators obtained from a variety of sources. Estimates are obtained using the pooled mean group technique, which assumes a dynamic error correction equation with heterogeneous cross-sectional coefficients in the short-run equations and homogeneous coefficients in the long-run relationship.

We use this model to address three main questions. First, we ask what proportion of the change in market spreads is explained by changes in the underlying fundamentals, controlling for external factors, liquidity and market risk. Second, we provide a benchmark measure of sovereign risk against which to compare actual market spreads. Finally, we use the model to explain patterns in spreads, from an *ex-post* perspective. As a case study we analyse the generalised fall in secondary market EME bond spreads experienced between 1995 and 1997.

Data limitations highlighted in the paper mean that the results have to be interpreted with caution. Nevertheless, the model is informative and allows us to reach interesting conclusions. Our main finding is that market spreads broadly reflect fundamentals, but that non-fundamental factors also play an important role. Comparing market-based spreads against their fundamental-based counterparts we find that credit risk is typically priced fairly closely to a theoretical equilibrium level, based on the selected set of macro-prudential indicators. In the cases of large absolute misalignments, we identify whether the divergence is due to unmeasured fundamentals or is likely to depend on market imperfections. Finally, the model suggests that the fall in spreads between 1995 and 1997 cannot be explained solely in terms of improved fundamentals. Assuming that our model provides a fair picture of fundamental-based sovereign credit risk, the divergence must be due to capital market imperfections, such as higher investor risk appetite resulting from lower global interest rates.

# 1 Introduction

With the rise in the value of bond financing by emerging market economies (EMEs) over the course of the 1990s, secondary market yield spreads have become important indicators of financial fragility for surveillance purposes. The Bank of England for example uses EME bond spreads as a measure of the market's perception of the risk that a country might default and to assess EME external financing conditions. But yield spreads are influenced by a variety of factors and inferring their exact information content may not always be straightforward.

Yield spreads measure the premium required by investors to hold securities issued by EME borrowers, which are perceived to be more likely to default on their obligations than a developed economy. This premium is measured as the difference between the yield on an EME bond and the yield on a bond of similar characteristics, but considered to be virtually free of default risk (typically a US Treasury security). Essentially, this premium serves to compensate bondholders for the risks to which they are exposed when holding EME debt securities: credit risk, market risk and liquidity risk (eg Cunningham, Dixon and Hayes (2001)).

Credit risk is the possibility that the debtor will not fulfil its obligations in full and on time. This risk of default depends on the fundamental characteristics of the issuer and on the ability of the lender to enforce the contract.(1) Market risk is the possibility that secondary market bond prices may move against the bondholder. Clearly, because changes in credit risk are one factor affecting secondary market prices, these two risks are related. But other factors may also give rise to market risk, such as changes in the willingness of investors to hold risky assets (risk appetite), and changes in other asset prices, which affect the opportunity cost of holding the security. Finally, liquidity risk is the risk that investors will not be able to liquidate their portfolios without depressing secondary market prices. Changes in market spreads thus reflect changes in the underlying macro fundamentals, leading investors to reassess their evaluation of a country's creditworthiness, and also the effect of external shocks (eg a change in US interest rates), changes in investors' risk appetite, and liquidity risk.(2) Disentangling the individual contribution of these factors may not always be easy.

(1) In other words, in the case of a sovereign borrower, willingness to pay may be as much a binding constraint as ability to pay. Eaton and Gersovitz (1981).

(2) The link between spreads and fundamentals is particularly emphasised by the proponents of the efficient market hypothesis. According to this view, investors are rational and have powerful incentives to exploit all the available information and to discriminate among borrowers. As a result, asset prices always reflect the information publicly available, as evidenced by the yield differential on bonds issued by sovereign borrowers with different credit ratings and macro characteristics (Edwards (1984)). However, other observers, more sceptical about market efficiency, emphasise that market failures and imperfect information may cause distortions in the way assets are priced. They point out that the information necessary to forecast returns on EME debt is costly to acquire and process, and that asset prices are often determined on the basis of incomplete knowledge of a country's economic and financial position. This practice may generate herding and market volatility. Calvo and Mendoza (1995) for example develop a model where the incentive to gather costly information is a declining function of opportunities for portfolio diversification (because gathering information on a country implies a fixed cost, which is independent of the investment size). Under this hypothesis, investors may fail to raise the risk premium to reflect deteriorating macro conditions. News about this trend can then disproportionately impact the prices of particular bonds and can affect the allocation of funds across countries, and new information about a particular country may lead investors to revise their expectations about the prospects for other countries with superficially similar characteristics. Chari and Kehoe (1997) argue that herding behaviour may result from informational frictions about countries on the margin, ie countries whose fundamentals are not obviously attractive or bleak.

The bond pricing literature suggests that EME credit spreads are a function of the market's perception of the risk of default and the expected recovery in the event of default. Models can normally be classified in two categories: structural and reduced form. Structural models of default risky assets posit a given stochastic process for assets and liabilities in the borrower's balance sheet and assume that default occurs if the asset value falls below a certain threshold, normally some proportion of liabilities. The default probability thus arises endogenously and depends on the average maturity of the debt, on the level of the risk-free interest rate, on the country's leverage ratio, and on the volatility of the underlying assets. These government-owned assets include official reserves and other fiscal assets, which in turn mainly consist of the net present value of the expected future fiscal primary surpluses.[3] The loss given default is normally also endogenous in this class of models and depends on how much the asset value after liquidation falls short of the face value of outstanding liabilities.[4] Reduced-form models in contrast obtain the value of a bond from a standard calculation of expected present value of the bond's contracted payment profile, where both the default probability and the recovery rate are exogenous. The default probabilities in turn are calibrated in a number of ways, for example using credit ratings or positing a relationship with a given set of macro-prudential indicators which are likely to affect the borrower's creditworthiness.

This paper develops a reduced-form model relating market spreads to a set of country-specific fundamental variables, controlling for investors' risk appetite and bonds' liquidity factors. The theoretical underpinning for the selection of the determinants of credit spreads is given by a simplified model of sovereign borrowing that formalises the consumption choices of an indebted small open economy. This model points to a set of variables that are important components of the internal and external constraints on government debt obligations. In our empirical estimation we also experiment with a number of additional factors that might be important determinants of credit spreads, though these are not discussed in the simplified theoretical model. The data set for the estimation is a ragged-edge panel of JP Morgan's EMBI and EMBI Global secondary market spreads and a number of country-specific macro-prudential indicators obtained from a variety of sources. Estimates are obtained using the pooled mean group technique due to Pesaran, Shin and Smith (1999). This is essentially a dynamic error correction model with heterogeneous cross-sectional coefficients in the short-run equations and homogeneous coefficients in the long-run relationship, which allows separating short-run dynamics and adjustment towards the equilibrium. The objective of the paper is to explain the long-run determinants of EME bond spreads, together with some short-run dynamic behaviours.

We use this model to address three main issues. First, we intend to assess what proportion of the change in market spreads is explained by changes in the underlying fundamentals, controlling for

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(3) See for example Draghi, Giavazzi and Merton (2003).

(4) This strand of literature follows the contingent claims approach developed by Merton (1974) for corporate debt. Applications to sovereign borrowers are still in an early stage and their value has been criticised on several grounds. In particular, some question the assumption that a simple stochastic process can capture the variation of a country's worth. Enforcement problems of sovereign debt contracts also mean that it is difficult to define a default trigger. Moreover, in a sovereign context insolvency does not normally result in the liquidation of the borrower's assets and partial repayment of the debt stock, but rather in a write-down of the stock of debt. And the process of sovereign debt restructuring is likely to be highly unclear until the crisis unfolds, so that investors may not have precise recovery scenarios to use when pricing a country's debt. For these reasons some questions that credit risk models designed for corporate debt – which have liquidation as the ultimate sanction – are also applicable to sovereign debt.

external factors, liquidity risk and market risk. Clearly, an important side benefit of this analysis is to improve our understanding of the empirical relationship between fundamentals and the determinants of EME financing costs.

Second, we aim to provide a benchmark measure of sovereign risk against which actual market spreads can be meaningfully compared. However, because the model is reduced form and is non-structural, it gives an econometrically fitted level of spreads based on the selected set of fundamental variables included in the estimating equation, rather than a theoretically justified measure that a structural model would imply. The benefits of this exercise are twofold. First, because the model relates credit risk to a set of common country-specific fundamentals and external shocks, it may be used to assess whether a certain level of market spreads is broadly consistent with the level implied by the selected fundamentals. Second, we may contrast from an *ex ante* perspective the model's assessment of the relative creditworthiness of two countries with that of market participants. In other words, we ask the question 'based on an assessment of fundamentals, is country X more creditworthy than country Y?' and if so, 'are markets pricing sovereign risk in the two countries accordingly?' In the paper we illustrate this application by looking at the relative pricing of Brazil and Colombia.

Third, we intend to use the model to explain patterns in spreads, from an *ex post* perspective. As a case study we analyse the generalised fall in secondary market EME bond spreads experienced between 1995 and 1997. The literature explains this fall in several ways, and ultimately the question of who is right has to be addressed empirically. For example, efficient market proponents point out that the trend was the consequence of the policies implemented in the early 1990s (economic and financial liberalisation, structural reforms), which led to a generalised improvement of macro and financial fundamentals in most developing countries. Others question whether fundamentals improved sufficiently to justify a decline of the magnitude experienced over the period. They suggest that the fall may simply reflect capital market imperfections, especially moral hazard following the bailout of Mexico by the IMF at the beginning of 1995, or higher risk appetite following the stimulative effect of more liberal credit conditions in the main financial centres (Eichengreen and Mody (1998a)).

Data limitations highlighted in the paper mean that the results have to be interpreted with caution. Nevertheless, the model is informative and allows us to reach interesting conclusions. Our main finding is that market spreads broadly reflect fundamentals, but that non-fundamental factors play perhaps a more important role. Comparing market-based spreads against their fundamental-based counterparts we find that recent market spreads mainly traded at a fair level, that is sufficiently close to a theoretical equilibrium level based on the selected set of macro-prudential indicators. In the few cases where we observe large absolute misalignments we identify whether the divergence is due to unmeasured fundamentals or whether it is likely to depend on markets' mispricing of risk. Alternatively, it is possible that the model breaks down during crisis periods. In addition, the model suggests that based on fundamentals, Brazil's *ex-ante* creditworthiness is lower than Colombia's, consistent with the evaluation provided by the markets. Finally, we find that the fall in spreads between 1995 and 1997 cannot be explained solely in terms of improved fundamentals.

The paper is organised as follows. Section 2 places the model in the context of the previous literature. Section 3 discusses a simple theoretical framework that we use as a guide to select the relevant macro-prudential indicators to include in the empirical estimation. Section 4 presents the data set and discusses some data limitations. Section 5 discusses the selected estimation framework – pooled mean group (PMG). Section 6 presents the results, and Section 7 discusses the main implications. The final section concludes.

## 2 Previous literature

A seminal work in the literature on lending behaviour in international markets is Edwards (1984), which provides a simple valuation framework for the determination of the sovereign risk premium conventionally used in most subsequent investigations. This framework is derived from a model that views EMEs as small borrowers in perfectly competitive financial markets. Under this assumption, a country's fair value spread is a function of the probability that it will default on its external obligations. In turn, this probability depends on a set of macroeconomic fundamentals and external shocks affecting the country's solvency and liquidity. Using this framework Edwards estimates the determinants of primary yields on bank lending to EMEs.

Edwards (1986) extends this analysis running separate estimates of default risk premia in the international bank loan and bond markets. From a theoretical point of view there are a number of economic, legal and institutional reasons why one would expect risk premia on the two instruments to be priced differently. These have been widely explored in the literature, which has concluded that bond lending involves greater risks than loan lending, an intuition that is supported by the empirical findings in Edwards (1986).(5) More recently, Min (1998) adopted the same framework to investigate the determinants of launch yield spreads on sovereign bonds issued in the early 1990s.

Kamin and Kleist (1999) relate sovereign primary yields in bond and loan markets to borrowers' creditworthiness as summarised by the credit ratings issued by the major rating agencies, controlling for instrument characteristics. The main feature of this study is that macroeconomic, liquidity and solvency indicators are not included in the estimating equation. This reflects the well-established result (eg Cantor and Packer (1996)) that ratings are highly correlated to a small set of macroeconomic fundamentals and so adding both sets of variables would lead to multicollinearity.(6) In line with previous research, this study shows that EME spreads have strong and well-defined relationships with credit ratings and thus with borrower creditworthiness. It also finds that borrowers in Latin America and Eastern Europe are systematically charged higher spreads than borrowers in Asia and the Middle East. However, contradicting earlier findings, it shows that while spreads on bonds are systematically higher than spreads on bank loans, the elasticities to changes in the underlying determinants (ratings, maturity etc) are very similar for both instruments. Moreover, the model explores the relationship between EME

(5) Edwards (1986) surveys the theoretical literature on the differences between the bond and loan markets.
(6) Eichengreen and Mody (1998a, 1998b) and Dell'Ariccia, Goedde and Zettelmeyer (2000) consider both macro fundamentals and rating information, on the grounds that ratings often incorporate a broader assessment of sovereign risk than that based on mere macro fundamentals. However, to address the potential multicollinearity problem, these studies do not include the rating themselves, but rather a residual from the regression of the ratings on all included fundamentals.

launch bond spreads and industrial country interest rates. Though in principle there are a number of reasons why one would expect the two to be linked, the model cannot identify any robust, statistically significant relationship between the two variables.(7)

A common characteristic of all these studies is that they use primary yields as a measure of credit risk, a feature that may lead to sample selection biases. As observed in Eichengreen and Mody (1998a, 1998b) in poor market conditions, when secondary spreads rise, primary spreads do not rise proportionately, and in some cases they fall. Factors that increase the perceived risk of EME debt, while raising secondary market spreads, may have the opposite effect on launch spreads in so far as riskier borrowers are rationed out of the market, leaving only low-risk borrowers to launch new issues. As a consequence, a sample of primary yields may not be entirely random and estimates based on it may be biased.

One way to correct for this bias is to model primary yields simultaneously with a binary decision to issue or not to issue (Eichengreen and Mody (1998a, 1998b)). In practice, this method involves defining a Heckman correction model that accounts for the joint determination of the issue and pricing decisions, controlling for selectivity. This amounts to jointly estimating a two-equation model, including a 'traditional' linear relationship between launch spreads and a set of fundamentals, and a probit equation to account for the fact that spreads will only be observed when positive decisions to borrow and lend are made. The cost of this modelling strategy is that the database has to be supplemented with information on non-issuing countries, to allow estimation of the probit equation. The model provides clear evidence that bond issuance is not a random event and that selectivity biases can be significant when estimating a model of primary issues. For example, once these factors are taken into account, Eichengreen and Mody find that interest rates in developed countries become an important determinant of capital flows to EMEs – contradicting the findings in Kamin and Kleist (1999).

Another way to correct for sample selectivity is to use secondary market spreads, which do not suffer from this type of bias. A few recent papers have done this. Goldman Sachs (2000) estimate a long-run equilibrium model of EME sovereign spreads using monthly data from quotes of benchmark, long-maturity, sovereign bonds, which increase the length of the time series but raise issues about which bond to choose and how representative it is. To estimate their model, Goldman Sachs (2000) adopt the pooled mean group technique developed by Pesaran, Shin and Smith (1999), which involves defining a dynamic, error correction panel where short-run parameters are allowed to vary by cross-sections, while long-run elasticities are restricted to be identical across groups. Dell'Ariccia, Goedde and Zettelmeyer (2000) use EMBI Global spreads to assess the presence of moral hazard in international lending following the Russian crisis in 1998. The benefit of using EMBI Global spreads is that these are a balanced panel of readily available secondary market spreads, and that they are more broad-based than benchmark bonds. But there is a disadvantage in that time series are shorter (the EMBIG series starts in 1997). Estimates are obtained using a conventional, static, fixed-effect model. But for a robustness check, the model is also run on a database of launch spreads which has broader country coverage

(7) See Kamin and Kleist (1999) and Eichengreen and Mody (1998b) for a discussion of the links between industrial country interest rates and EME spreads.

than the EMBIG, correcting for the selectivity bias using a Heckman correction algorithm, as in Eichengreen and Mody (1998a, 1998b).

Both Goldman Sachs (2000) and Dell'Ariccia *et al* (2000) need to interpolate their macro fundamental databases to obtain a sufficiently high number of observations, raising the issue of the appropriateness of doing so. Clearly, interpolation increases the sample size at the cost of imposing a given (in most cases, linear) model on the data generating process of the missing observations.

This paper uses the same database as Dell'Ariccia *et al* (2000), thus getting around the sample selection problems encountered in earlier literature, and the pooled mean group estimation technique used in Goldman Sachs (2000). However, we are careful in considering the implications of merging the EMBI and EMBI Global data sets, which raises quite separate selectivity issues than the previous literature on primary yields. We also attempt to minimise the need to interpolate macroeconomic series by using information from individual central banks and Ministries of Finance – thus building as high a frequency data set of macro fundamentals as possible.

## 3 Theoretical framework and variable selection

A conventional approach to modelling equilibrium sovereign yields is to assume that the spread over a risk-free interest rate is a function of the probability of default of a country and of the loss given default. In reduced-form models, this probability of default is exogenously determined and is tied to the sustainability of a given level of external debt through liquidity or solvency indicators, and hence to a set of macroeconomic fundamentals. For example, assuming risk neutral lenders and competitive financial markets, and following the standard model of risk premia, Edwards (1984) obtains a simple log-linear relationship of spread determinants:

$$\log s_{it} = \alpha + \sum_{j=1}^{J} \beta_{jit} x_{jit} + \varepsilon_{it} \qquad \textbf{(1)}$$

where $s_{it}$ is the yield spread of country $i$ at time $t$, $\alpha$ is an intercept coefficient, the $\beta_j$s are slope coefficients, the $x_j$s are a set of $J$ macro fundamentals, and $\varepsilon$ are i.i.d. error terms. In the context of more complex theoretical frameworks, Feder and Just (1977), Eaton and Gersovitz (1980) and Sachs (1981) derive similar relationships.

The theoretical underpinning for the selection of the set of variables $x_j$s in equation **(1)** is provided by a model of sovereign borrowing that formalises the consumption choices of an indebted small open economy (SOE). The SOE typically tries to smooth its consumption path over time by borrowing from abroad when domestic resources are scarce and paying back its debts when resources are abundant. In this setting, foreign lenders focus on two issues. The first is the ability of the SOE to generate enough foreign exchange resources to service its external obligations. The second is the SOE government's ability to generate enough domestic resources to purchase the foreign exchange required for servicing its external obligations.

This discussion can be formalised by introducing a simple dynamic programming problem:

$$\begin{aligned}
Max \quad & U_0 = \sum_{t=0}^{\infty} \beta^t u(C_t), \\
s.t. \quad & G_t + rD_t \leq T_t + D_{t+1} - D_t, \\
& Y_t = C_t + G_t, \\
& T_t = f(Y_t), \\
& Y_t = (1+g)Y_{t-1}
\end{aligned} \qquad \textbf{(2)}$$

where $U_0$ is an intertemporal welfare function depending on consumption ($C_t$), and $\beta$ is the discount factor. This function is maximised subject to two constraints. The first is the government budget constraint, where primary public spending ($G_t$) and interest payments on the existing stock of external debt ($rD_t$) are financed through taxation ($T_t$) and debt issuance ($D_{t+1} - D_t$). For simplicity we assume that all external debt is public. The second constraint is the usual accounting identity, equating total domestic output ($Y_t$) to the sum of private and government consumption. Rearranging this identity using the government budget constraint we get:

$$D_{t+1} - D_t \geq Y_t - C_t - T_t + rD_t \qquad \textbf{(3)}$$

In our simple setting, equation **(3)** represents the country's current account and hence the external constraint. This is defined as the change in total external debt between $t$ and $t + 1$ and has to be greater than or equal to the sum of private saving ($Y_t - C_t - T_t$) plus interest payments on the stock of external debt. The last two equations in problem **(2)** are required to close the model and define respectively tax revenues as a function of output and the evolution of output over time (which for simplicity is assumed to be exogenous).

In flow terms, the government budget constraint and the external constraint (given by equation **(3)**) motivate the importance of liquidity indicators, as borrowers need not only to be solvent in the long run, but also to fulfil their obligations at each point in time. These indicators are the fiscal budget balance, external debt amortisation, interest payments on external debt, and the amount of short-term debts (which define the country's gross external financing needs). As financing sources the model highlights the role of the current account balance. Official reserves (which are not discussed in our simple setting) are also important as they provide a buffer of foreign liquidity to insure against a temporary inability to roll over debts on the market.

It is easy to show that the two constraints can be rearranged in NPV terms in the following form:

$$(1+r)D_t \leq \sum_{i=0}^{\infty} \frac{PS_{t+i}}{(1+r)^i} \qquad \textbf{(4)}$$

$$(1+r)D_t \leq \sum_{i=0}^{\infty} \frac{(C_{t+i} + T_{t+i} - Y_{t+i})}{(1+r)^i} \qquad \textbf{(5)}$$

where $PS_t = T_t - G_t$, is the government primary fiscal surplus. Equation **(4)** gives the condition for the long-term sustainability of fiscal policy, and shows that for a borrower to be solvent the stock of external debt must be no greater than the net present value of future fiscal primary surpluses discounted by the cost of capital. Equation **(5)** provides the condition for the sustainability of external debt – ie that the stock of external debt must be no greater than the present value of future private saving.

In stock terms, these constraints motivate the selection of a number of solvency indicators. For example, the sustainability of fiscal policy suggests the relevance of a low stock of public debt, low cost of capital, and high output growth rate, as tax collection varies proportionally with the level of economy activity. On the other hand, external solvency suggests the importance of low external indebtedness and, though not highlighted in this simple setting, high trade openness. Trade openness is key to external solvency. A low degree of openness may indicate that the required expected trade surpluses to meet future foreign debt repayments may not materialise. Additionally, incentives to repay debts are lower if the economy is relatively closed, because the losses from sanctions following debt repudiation are a smaller fraction of output. High rates of output growth and low interest rates are also important for external solvency as, *ceteris paribus*, they imply that lower trade surpluses would be compatible with sustainable external debts.

More complex models would highlight the role of external competitiveness indicators, such as the nominal or real exchange rate overvaluation, and the terms of trade, because these variables affect the allocation of resources between the tradable (which generates foreign exchange reserves) and the non-tradable sector. Additionally, a less competitive exchange rate can affect a sovereign's creditworthiness because it may lead to capital flight on the expectation of future realignment. Alternatively, currency devaluation may exacerbate fiscal problems when the economy has an open capital account but a relatively small tradable sector. This is because when exports are low and public debts are mainly foreign-currency denominated, currency devaluation provides a limited boost to economic activity and government revenues, while the domestic currency value of external debt service rises in tandem with the devaluation.

Oil prices are another important indicator that may affect the creditworthiness of an indebted SOE through several channels. The first and most obvious is through the consequences on world growth. For example, Hamilton (1983) finds that all but one post-war US recession was preceded by oil price increases. Slow world growth may tighten international capital availability and may lead to lower export growth in EMEs. Additionally, high oil prices may lower a country's external competitiveness and cause a deterioration of the trade balance. This may lead to an increased demand for foreign capital in oil importing countries, and possibly cause a balance of payment crisis. Clearly, the story is different for oil exporter countries, whose creditworthiness may be worsened by low oil prices, if for example government revenues are dependent on oil. However, with a few notable exceptions (eg Venezuela and Russia) oil exporter countries tend to have low levels of external debts, and in most cases are net exporters of capital.

More generally, many indebted EMEs are commodity exporters – and hence the relevance of an index of commodity prices. Domestic inflation is also an important factor. Min (1998) argues that sovereign risk depends on macroeconomic policy discipline, and that inflation can be broadly regarded as a proxy for the quality of economic and monetary management (eg, because high inflation may reflect accommodation of fiscal imbalances). McDonald (1982) estimates that high inflation is typically associated with a larger probability of a balance of payment crisis, and consequently with a higher probability of default. A history of debt crises can also be reflected in the cost of capital for EMEs, because sovereign borrowers face costs when they default in terms of rationed access to capital.

## 4 The data set

There are two issues related to the construction of a panel for our empirical investigation: the selection of an appropriate source for sovereign spreads and the choice of a set of explanatory variables.

For the choice of the dependent variable we look at secondary market spreads, to limit the selectivity biases associated with launch yields (as discussed earlier). To avoid the disadvantages of using specific instruments (as in Goldman Sachs (2000)), we draw the data from JP Morgan's indices of EME sovereign spreads (as in Dell'Ariccia *et al* (2000)). These include US$-denominated sovereign and quasi-sovereign (ie guaranteed by a sovereign) instruments that satisfy certain criteria, to ensure sufficient liquidity of the bonds. The spread of a bond is calculated as the premium paid by the EME over a US government bond with comparable features. A country's spread is then calculated as the average of the spreads of all the bonds that satisfy the inclusion criteria, weighted by the market capitalisation of the instruments. This measure of spreads brings a number of potential benefits, such as that it is readily available, that spreads are calculated as averages over portfolios of bonds and thus time series are continuous, without breaks as bonds mature, and that it only includes liquid instruments.

JP Morgan publish two variants of their EME sovereign spread indices (Cunningham (1999)). The broadest measure, the EMBI Global, comprises mainly Eurobonds and Brady bonds with minimum face value of US$500 million and maturity of at least 2½ years, and covers a wide cross-section of 27 countries, from 1998 onwards. A narrower measure including only Brady bonds and other restructured sovereign instruments, the EMBI, is available from 1991 but covers only 5 EMEs from 1992, and 11 from 1995. A choice between the two indices poses a trade-off between a longer time series (EMBI) and a wider cross-section (EMBIG). To by-pass this problem, we construct a ragged-edge, unbalanced panel of spreads using the broadest cross-section available at each point in time. This data set has a break at the point in time when we switch from one index to the other, a feature that may potentially affect estimation results in two ways. First, it may lead to sample selectivity bias, though of a different type from that highlighted in the literature on launch yields. Here the bias arises because observations may not be random as good debtors would be systematically excluded from the ragged-edge panel during the period covered by the EMBI, since this index only tracks returns on Brady and restructured bonds. Second, the measures of credit risk embedded in the EMBI and EMBIG may differ systematically because of the composition of the underlying portfolios in the two indices. Typically, we may expect EMBI country spreads to be higher than their EMBIG counterpart because they refer to restructured bonds.

The former problem can be corrected using a Heckman correction model (as in the early literature on primary yields) – an issue that we leave for further extensions of this research. In order to assess how important the latter issue is we have tried a number of experiments. Chart 1 compares the EMBI and EMBI Global spreads at different points in time, for the countries that are included in both indices. It shows that observations tend to cluster around the 45-degree line, but EMBI spreads tend to be slightly higher than the corresponding EMBIG spreads.

A more formal test is to measure the correlation coefficients between the individual EMBI and EMBIG country series and perform a t-test for the equality of sample means and variances. The basic idea of this test is that if the two series have the same first and second moments, they would differ by a random component (ignoring differences in higher moments). The results are reported in Table 1 and indicate that the hypothesis of equality of the sample means in the two country series is rejected in seven out of eleven countries, while equality of sample variances is rejected in six cases. However, the correlation coefficients are high, ranging between 92% and 99%. The Jarque-Bera statistics suggest that spread series have non-normal distributions.

Table 2 summarises the estimation output of the following simple model:

$$EMBIG_{it} = a_i + b_i EMBI_{it} + u_{it} ,$$

which we use to run a Wald test of the joint hypothesis: $H_0$: $a_i = 0$; $b_i = 1$. The rationale for this test is that under $H_0$ the EMBI and EMBIG would differ only by a random component. As shown in the table, at conventional significance level this hypothesis can be accepted only in the case of Bulgaria, and in 10 out of 11 countries there appear to be systematic differences between the two indices. However, in most cases the slope coefficients are close to unity (despite the statistical hypothesis of $b_i = 1$ not being accepted) and the R-squared of the regressions are always very high, ranging between 87% and 99%, which implies a high correlation between the two indices.

Overall this suggests that the two indices differ somewhat, but that they are sufficiently strongly correlated not to rule out the use of a ragged-edge panel of sovereign spreads. The analysis does however suggest some caution when interpreting the results. Moreover, the costs of using a ragged-edge panel should be weighted against the benefits. Clearly an important benefit is to increase dramatically the sample size, from 1,472 monthly observations using the EMBIG alone to 2,005 merging the two databases. Obviously, a wider sample size increases the degrees of freedom and puts fewer constraints on model selection and estimation technique.

The right-hand side variables of the model are a set of country-specific macro-fundamentals and external indicators chosen using the results from the section on the variable selection, but also keeping in mind the limited degrees of freedom due to the low sample size and high number of estimation parameters. This explains why for example we do not collect data on commodity and oil prices, and a number of other factors that are likely to affect the creditworthiness of some but not all the countries in our panel. Also, in assembling the database we face a number of data issues, such as that EME data are not always published and/or are not timely, that sources are not entirely consistent, and data are frequently revised.

To compile our database we use a number of different sources. Data on external debt are drawn mainly from the World Bank's Global Development Finance. Other macro-prudential indicators are drawn from the IMF's *International Financial Statistics*, the IIF, and from local economy ministry and central bank web sites. Using these sources, we assemble an unbalanced panel of 2,005 monthly observations, covering 5 countries from 1992 to 1995, 11 countries from 1996 to 1997, and 23 countries from 1998 onwards. For each cross-section, the complete database consists of 24 variables (the dependent variable, 16 country-specific macro fundamentals, five common external indicators, and two debt-specific dummies).

In most cases macro data are only available on a yearly or quarterly basis. Coupled with the short time series of spreads this implies a low size of our estimation sample, a feature that would limit the selection of appropriate estimation technique (pooled mean group for example cannot be employed on short samples). To increase the sample size we opt for a panel of monthly observations and generate missing observations by linear interpolation. Interpolation has been extensively used in previous studies (Goldman Sachs (2000); Dell'Ariccia *et al* (2000)). Clearly, it comes at the cost of imposing a (linear) model on the data generating process of the relevant indicators. However, it is possible to argue that this cost is not high in some cases, for example for stock variables (such as external debt and official reserves) which presumably do not change suddenly over time. Moreover, the cost of any alternative might be potentially higher. For example, we could drop all low frequency (eg yearly) indicators, but this might lead to omitted-variable bias and heteroscedasticity. Alternatively, we could drop single observations and work with a database of low-frequency (eg yearly or quarterly) data, but this would imply the loss of potentially relevant information and lower degrees of freedom, and thus would restrict model selection and estimation techniques.(8)

Table 3 summarises some simple descriptive statistics of the data. Panel A contains the statistics for the whole sample; panels B and C refer to the two sub-samples of Latin American and non-Latin American countries. Confirming earlier findings (eg Min (1998)) the table shows that on average Latin American countries pay higher spreads than non-Latin countries (932 basis points versus 692 basis points). The external debt-to-GDP ratio of Latin American countries is lower than in non-Latin countries, but in the former trade openness as measured by the sum of imports and exports over GDP is lower (35% against 68%), inflation is higher (97.8% against 68.2% per annum) and the current account deficit is higher (2.3% of GDP versus 0.8%). Moreover, reserves are lower in Latin America (10% of GDP compared with 17% in non-Latin countries) and the ratio of external debt amortisation to reserves (a liquidity indicator) is higher (60% against 42%).

## 5 Estimation issues

We run the empirical estimations using the pooled mean group estimator (PMG) due to Pesaran, Shin and Smith (1999). This is essentially a dynamic error correction model that allows the short-run parameters to vary across individual groups, while restricting long-run elasticities to be identical across groups. Thus PMG is applicable to panels with cross-sectional variation in the short-run dynamics but long-run commonality in the equilibrium relationship.

Since Edwards (1984), it has been conventional to test models which use log-spreads (rather than their level). We follow this convention here, but unlike Edwards we allow for a cross-sectional specific intercept term, $\alpha_i$. Under these hypotheses, a general long-run model of (log)-spread determinants for country $i$ at time $t$ is given by the following equation:

$$\log s_{it} = \alpha_i + \sum_{j=1}^{J} \beta_{ji} x_{jit} + \varepsilon_{it}, \quad i = 1,2,...N, \; t = 1,2,...T \qquad \textbf{(6)}$$

(8) Generally in the literature a longer span of data is considered better than more high-frequency observations. However, Hansen and Hodrick (1980) show that there is information in higher-frequency data at a given span.

If we assume that all the variables are $I(1)$ and cointegrated, then the error term $\varepsilon_{it}$ is $I(0)$ for all $i$. Assuming a fixed lag of one for the dependent and the independent variables, the resulting ARDL specification is:[(9)]

$$\log s_{it} = \mu_i + \lambda_i \log s_{it-1} + \sum_{j=1}^{J} \gamma_{1ji} x_{jit} + \sum_{j=1}^{J} \gamma_{2ji} x_{jit-1} + u_{it} \qquad \textbf{(7)}$$

This can be rearranged to give the error correction equation:

$$\Delta \log s_{it} = \phi_i \left[ \log s_{it-1} - \alpha_i - \sum_{j=1}^{J} \beta_{ji} x_{jit} \right] - \sum_{j=1}^{J} \gamma_{2ji} \Delta x_{jit} + u_{it} \qquad \textbf{(8)}$$

where:

$$\phi_i = -(1-\lambda_i)\,, \; \alpha_i = \frac{\mu_i}{(1-\lambda_i)}\,, \; \beta_{ji} = \frac{\gamma_{1ji} + \gamma_{2ji}}{(1-\lambda_i)}$$

The term in square brackets in equation **(8)** is the long-run relationship and the $\beta_{ji}$ are the long-run elasticities. The assumption of long-run commonalities in the equilibrium relationship (pooled model) requires the following restriction in equation **(8)**: $\beta_{ji} = \beta_j$ for all cross-sections $i$, that is constant long-run slope coefficients for all cross-sections. The error correction coefficient $\phi_i$ and the short-term elasticities ($\gamma_{2ji}$) are unrestricted and are allowed to vary in each cross-section. Thus the estimating model becomes:

$$\Delta \log s_{it} = \phi_i \left[ \log s_{it-1} - \alpha_i - \sum_{j=1}^{J} \beta_{j} x_{jit} \right] - \sum_{j=1}^{J} \gamma_{2ji} \Delta x_{jit} + u_{it} \qquad \textbf{(9)}$$

Three main reasons underpin our choice of PMG rather than alternative procedures commonly used for panel data (such as pooled OLS, static fixed effects, mean group estimates). First, PMG assumes a dynamic model, which is more likely to capture the nature of the data. Second, PMG imposes homogeneity of long-run coefficients, which leads to more stable and economically plausible estimates. Baltagi and Griffin (1997) and Boyd and Smith (2000) show that pooled estimators have desirable properties and typically outperform their heterogeneous counterparts. For example, they find that pooled models tend to produce more plausible estimates even for panels with relatively long time series and that they offer overall superior forecast performance.[(10)] By contrast, heterogeneous estimators are normally unstable (individual country estimates vary within wide ranges) and unreliable, though they have the desirable property of allowing for differences among countries. PMG, which assumes long-run commonalities but permits short-term elasticities to vary across groups, combine the benefits of both classes of estimators. Third, PMG allows separating short-term dynamics and the adjustment towards the long-run equilibrium. This is important because, as shown by Haque, Pesaran and Sharma (2000), neglecting cross-country heterogeneity in short-run responses can lead to misleading inferences about the key determinants of the dependent variable in the regression. If differences across countries are ignored, one can overestimate the relative importance of specific explanatory

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(9) The presence of lagged variables in the estimating equation is not necessarily inconsistent with the efficient market hypothesis. Significant lags may be due to publication lags and data problems, and do not necessarily imply that markets are only slowly incorporating public information.

(10) Boyd and Smith's (2000) explanation of why pooled models outperform their heterogeneous counterparts centres on the relative variability of the data between the individual time series and panels. They find that in most cases the efficiency gains from pooling appear to more than offset the biases due to cross-sectional heterogeneity.

variables and at the same time obtain significant, but spurious, non-linear effects for some of the potential determinants.

## 6 Results

We estimate equation **(9)** using maximum likelihood, as in Pesaran, Shin and Smith (1999). The estimates are computed with the Newton-Raphson algorithm, which uses both the first and the second derivatives of the likelihood function. These maximum likelihood estimators are referred to as PMG, to highlight both the pooling implied by the homogeneity restriction on the long-run coefficients, and the averaging across countries used to obtain means of the estimated error-correction coefficients and other short-run parameters. For a long-run relationship to exist the error correction coefficient has to be different from zero ($\phi_i \neq 0$, for all $i$ in equation **(9)**).

The model allows alternative lag specifications. In general, we obtain most estimates from restricted ARDL models, imposing a common fixed lag of one for all cross-sections. But we also test more complex lag structures adopting a selection criterion through a two-step approach, as suggested by Pesaran, Shin and Smith (1999). This method involves stacking equation **(8)** by cross-section and running unrestricted ARDL with common lag structures for each country separately (we have tried maximum common lags of one and two). These estimates are then used to choose the appropriate lag order for each variable, using the Schwartz Bayesian Criterion (SBC) subject to a pre-specified maximum lag. Then, using these SBC determined lag orders we impose homogeneity and compute the maximum likelihood estimators of the long-run coefficients.

To choose a preferred model, we try a number of alternative specifications and select the model that best fits the data using a general-to-specific approach. But because we have to take into account the limited degrees of freedom and the high number of estimation parameters implied by the PMG technique, we are only able to test parsimonious models. Imposing homogeneity of long-run parameters, Table 4 reports PMG estimates for three alternative model specifications. Because the dependent variable is the log of sovereign spreads, all the parameters in the table represent semi-elasticities. The results are quite satisfactory, both from the viewpoint of the explanatory power of the regressions, and from the viewpoint of the sign and level of significance of the coefficients. In particular, all regression coefficients are statistically significant at conventional significance levels, with the exception of the coefficient on the current account balance-to-GDP ratio in one of the specifications and the coefficients on the fiscal budget-to-GDP ratio. Additionally, coefficients are broadly signed according to expectations, with few exceptions: the coefficients on the current account-to-GDP ratio and on US corporate yield spreads in Model (A) (where however the former is not significant); the coefficients on the fiscal budget-to-GDP in Models (B) and (C) (also insignificant), and that on the ratio of short-term external debt to total external debt in Model (C).[11] Moreover, estimates look generally robust across all models in the table (and indeed across most other models that we have tried).

[11] It is possible that the odd sign of these coefficients stems from neglected non-linearities in model parameters, a hypothesis that we could not test owing to the parsimony constraint imposed by the selected modelling strategy.

Interestingly, the models point towards strong relationships between EME spreads and external factors. These are always highly significant, and have a strong economic impact on EME spreads in all the models under consideration. In particular, higher short-term US interest rates raise borrowing costs for EMEs, as indicated by the positive elasticity on 30-day US T-bill yields. This is consistent with the main theoretical literature and earlier empirical findings. For example, Kamin and Kleist (1999) discuss reasons why industrial country interest rates are expected to be positively correlated with EME credit spreads. And Eichengreen and Mody (1998b) provide supporting empirical evidence (but *contra*, see Min (1998), and Kamin and Kleist (1999)). By contrast, higher long-term US interest rates – measured by the yield of a benchmark 10-year US government bond – have a strong negative impact on EME spreads. Taken together, short and long-term US interest rates suggest that the slope of the US yield curve is probably more important than the two independent levels, and that when the US yield curve becomes steeper EME spreads fall. One possible explanation for this effect is the behaviour of leveraged investors who may increase the demand for EME assets (pushing prices up and spreads down) when global credit conditions allow cheap borrowing.

One feature of our modelling strategy is that it controls for changes in liquidity and market premia. The need to control for liquidity risk arises because the bonds in the EME indices, while probably the most liquid available, may still likely be affected by some illiquidity problems. For US corporate bonds, for example, the current view is that the liquidity premium accounts for a larger proportion of the credit spread than do credit premia.(12) To control for this, and for lack of better data, we include the yield spreads between low and high-rating US corporate bonds as an explanatory variable of Model (A). The sign of the coefficient suggests that when this yield spreads rises EME spreads fall. Additionally, the models include the S&P 500 equity index to control for market risk. The sign of the coefficient suggests some complementarities between EME bonds and developed economies equity assets in investors' portfolios.

One advantage of PMG over traditional fixed effect panel models is that it allows the short-run dynamic specifications to be different in each cross-section. Table 4 reports two of these short-term elasticities, calculated as averages of the cross-section specific coefficients. One of them is the error correction coefficient, which is statistically significant in all regressions, suggesting that we can accept the hypothesis of a long-run relationship. The coefficient is also negative, implying that spreads tend to return back to equilibrium following a shock, and takes values between –0.15 and –0.39 across the three models. These values mean that between 15% and 39% of the gap between the equilibrium and the observed level of spreads is closed in each period, or that the half-life of the gap – the time required for the gap to halve – is between 3.8 and 1.5 months.

PMG imposes homogeneity of the long-run slope coefficients, but this is a hypothesis that can be tested using a likelihood ratio test, since PMG is a restricted version of the set of individual group estimates. Though it is common practice to use pooled estimators without testing the implied restrictions, in cross-country studies the likelihood ratio tests normally reject equality of error variances and slope coefficients at conventional significance levels. This is clearly the case in our models (bottom of Table 4). We will return on this point later, but one possible explanation

(12) I owe this point to an anonymous referee.

is that the group-specific estimates may be biased because of omitted variables or measurement errors that are correlated with the regressors. If the bias is non-systematic and averages to zero over groups, pooled estimation would still be appropriate despite the homogeneity assumption being rejected. Unfortunately there is no obvious way to determine from the data whether this is the case (Pesaran, Shin and Smith (1999)).

Comparing the diagnostic tests for the three models (Table 4) we see that on balance Model (A) shows a relatively better performance. While Model (C) minimises issues of error term heteroscedasticity and serial correlation in the country-specific regressions, and Model (B) is the least affected by functional form misspecification, Model (A) maximises the sum of the corrected R-squared. Moreover, this model has low standard deviation of error terms and minimises issues of error term non-normality. For this preferred model (A), Table 5 reports some cross-section specific diagnostic statistics. The adjusted R-squared is negative in two cases (Côte d'Ivoire and Croatia), and the weighted average of this statistic is 0.22. Individual country statistics are generally not high, but as observed in Goldman Sachs (2000) the model is intended to provide a predicted value of equilibrium spreads in the long term and thus a certain degree of misalignment in the short run must be expected. The standard deviation of the restricted model error terms varies between 5% in Panama and South Africa and 11% in Cote d'Ivoire and Morocco. At the 5% significance level, the restricted model error terms show problems of serial correlation in 8 out of 23 cross-sections, non-normality in 16, functional form misspecification in 17, and heteroscedasticity in 20.[(13)]

Reassuringly, the lagged dependent variable bias (which causes the estimates of $\phi_i$ to underestimate the true values for small $T$) is not a problem here, for two reasons. First, $T$ is relatively large in our sample, ranging between 60 and 135 months. Second, even if estimates suffer a downward lagged dependent variable bias this may be offset by the upward heterogeneity bias discussed in Pesaran and Smith (1995).[(14)]

As we have discussed earlier, the lag structure that best fits the data is first chosen testing a number of unrestricted ARDL models, that is models where the long-run coefficients are not required to be the same across countries. To shed more light on the quality of the estimation output, Table 6 reports the output for these group-specific, unrestricted models. The cross-sectional averages of these coefficients (and the associated *t*-statistics) are also included at the bottom of the table. These are the mean group estimates (MGE). The picture is broadly

[(13)] PMG corrects for cross-sectional heteroscedasticity as it allows the variances of the error terms to differ across groups. However, despite this correction embedded in the model, heteroscedasticity may still affect the results because of the nature of the time series. In particular three potential sources of heteroscedasticity may affect pooled models: *i*) aggregation over cross-sections of different size (unbalanced panel); *ii*) cross-sectional variances may differ across countries; *iii*) cross-sectional variances may differ across time. While PMG corrects for the first two types of heteroscedasticity, it does not correct for the third. The tests are described in Pesaran and Pesaran (1997).

[(14)] Two further caveats relate with the use of a ragged-edge, unbalanced panel of spreads. First, because spreads for a given country may be systematically different under the EMBI and EMBIG there may be a structural break in the panel when switching from one index to the other. In theory, this is a hypothesis that may be tested formally. The test requires that we isolate two sub-samples based on the alleged breakpoint, and assumes that the error terms in the two sub-samples have the same variance. But because the latter hypothesis does not hold in this case (as we have discussed in the text) the test cannot be carried out. However, we look at this problem in Section 4 using alternative tools and conclude that our investigation supports a ragged-edge panel. Second, the spread panel may be affected by sample selection biases (as discussed in Section 4). On this problem future research might try to use a Heckman procedure, as per primary yields.

similar to that presented for the restricted models. It is comforting that the long-run relationship is statistically significant in the majority of the countries (the hypothesis of no long-run relationship ($H_0$: $\phi_i = 0$) is rejected in 21 of the 23 cross-sections in the panel). The error correction coefficient varies from –0.09 in Brazil (half-life of the gap of around 6 months) to –0.77 in China (half-life of a fraction of a month). The long-run individual slope coefficients are more dispersed than the restricted estimates reported in Table 4. For example, the individual estimates of the external debt-to-GDP ratio vary from –15.3 in Croatia (which however is not statistically significant at conventional significance levels) to 8.84 in South Africa, which compare oddly with a long-run estimate of 0.25 in the restricted model. Additionally, these individual estimates are mostly insignificant – only 66 of the 230 coefficients reported in the table are statistically different from zero.

Boyd and Smith (2000) consider a number of explanations for this wide dispersion of cross-country estimates. First, they suggest that the dispersion may be the product of poor data – and indeed this may be plausible in our analysis, given the data limitation highlighted in previous sections. Second, it may be the result of simultaneity bias. One example of simultaneity bias is endogenous capital flows, but these would have to be highly speculative to create such large effects. Moreover, the covariances would have to be economically implausible to give, for example, a negative effect of the external debt-to-GDP ratio on spreads. Third, it may be the result of spurious regressions. The variables are not cointegrated and the error term is I(1). Thus the coefficient estimates converge to non-degenerate random variables, accounting for the dispersion. But stationarity of the regressors is not strictly required in PMG, and we have tried modelling the first difference of spreads, with broadly similar dispersions.

Clearly, it is possible that countries are really different. While this may be true in the case under consideration, it cannot explain the size of the measured differences, which are so large as to be implausible. As we have mentioned before, a more plausible explanation may be that country-specific shocks and measurement errors associated with unobservable variables act like omitted variables correlated with the regressors. If these are structural factors, operating in all time periods and countries, they would cause a systematic bias in the average estimate of the long-run parameters. But if they are not structural, but just happen to be correlated in a particular sample, they would average to zero and would cancel out across countries or over time. Such correlated shocks would cause structural instability (because the biases are not constant overt time), heterogeneity (because the biases are not constant over countries) and forecasting failure. If we estimate an equation for each individual group we might experiment with different specifications until plausible estimates are obtained ('Tender, Loving Care' discussed in Boyd and Smith (2000)). But in models with large groups this in not possible and a statistical solution is robust estimators which reduce the effect of outliers. A simple version of this involves using pooled estimators.

For the unrestricted ARDL models discussed so far, Table 7 reports diagnostic tests and other tests of goodness of fit. These tests show that the overall explanatory power of the equations is satisfactory. In 15 of the 23 countries considered the model explains over 50% of the change in the log of spreads, and in all but 6 countries (Argentina, Croatia, Morocco, the Philippines, Thailand and Venezuela) the corrected R-squared is higher than 30%. The standard error of the regressions varies from 4% in Panama to 8% in Morocco. Unsurprisingly, the equality of error variances across countries does not seem to be an appropriate assumption, a result born out by formal statistical tests: at the 5% confidence level, there is evidence of heteroscedastic error terms in 21 of 23 equations. Serial correlation is a problem in 7 countries, functional form misspecification in 18, and non-normal errors in 15.

To summarise, the restricted model provides overall satisfactory results in terms of sign and level of significance of coefficients, and in terms of explanatory power of the regressions, though because some variables may be missing the goodness of fit measures presented are probably lower bounds. Additionally, the specification tests suggest that the choice of a pooled model is probably more appropriate than mean group or other common unrestricted estimators. But the diagnostic statistics also suggest that there is a systematic pattern of the cross-sectional error terms, which we take as evidence that the market assessment of a country's creditworthiness may be more broad-based than that provided by the model. In other words, if spreads react to common external shocks, creditor factors, risk appetite, moral hazard and so on and these factors are not explicitly modelled, they will affect the regression residuals, generating a certain degree of error persistence and non-normality.(15)

## 7 Implications

This section discusses the main implications of the model, comparing our estimation output with actual market spreads. Given the set of estimated coefficients for the preferred Model (A) in Table 4, we calculate for each country the fitted (predicted) spreads using the actual values of the explanatory variables (the macro fundamentals) at end-March 2003, and compare these with the corresponding market spreads. The results are reported in Table 8, together with the estimated misalignment expressed as the difference in basis points between the actual and predicted spreads. Similarly to Goldman Sachs (2000), the last column of Table 8 indicates whether bonds are trading at 'fair' value, are 'high' or 'low', using an evaluation criterion based on the 95% confidence interval around the (log of) fitted spreads. In particular, we define market spreads as 'fair' if they trade within the 95% confidence interval, 'high' if they rise above the upper bound of the confidence interval, and 'low' if they fall below the lower bound. Based on this criterion, Table 8 suggests that in March 2003 spreads were mainly trading at a fair level, that is sufficiently close to a theoretical equilibrium level based on fundamentals, and that spreads were too high or low in 5 of the 23 countries included in the sample. The table also shows that the largest absolute misalignments are for Argentina (which the model under-prices by more than 4500 basis points), and Côte d'Ivoire (under-priced by 1131 basis points). Large absolute misalignments are also reported for few countries where the evaluation is 'fair' (more than 600 basis points in Venezuela and Nigeria, and around 300 basis points in Brazil), but in these cases the volatility of the fitted values is also high.

The occurrence of large misalignments raises a general issue of interpretation: what do we make of spreads that are very different from those predicted by the model? Clearly, one possibility is

(15) To define the likelihood function, PMG requires that the disturbances are normally distributed but this assumption is not strictly required for the asymptotic results on consistency, relative rates of convergence, and asymptotic distribution of the maximum likelihood estimators.

that markets might be mispricing sovereign risk, but equally plausibly markets might be pricing risk correctly but have more information than the model. Unfortunately, there is no obvious way to address this problem, and the issue has to be resolved on a case by case basis. To this end, it is helpful to distinguish between measured fundamentals, which are included in the model, and unmeasured fundamentals. This should allow a more qualified assessment about whether the divergence is due to mispricing or unmeasured fundamentals.

On one hand, unmeasured fundamentals can probably help to explain the divergence in the pricing of sovereign debt in Nigeria, where markets likely supplement their country risk assessment with additional factors such as political risk, quality of institutions, and 'willingness to pay', which are not included in the model. Similarly, in Côte d'Ivoire the market price of sovereign risk may reflect political instability and the dependence of the macroeconomic outlook on a single commodity, cocoa. Oddly, the model also provides a poor prediction of Argentine spreads (1500 basis points, against market spreads four times as high), and again we believe that is due to unmeasured fundamentals, as the model does not explain the debt default announced by the government at the end of 2001.(16) Unmeasured fundamentals in this case may be a by-product of the regression format, which contains only contemporaneous or backward-looking variables, while the market may be forward-looking. A misalignment of around 270 basis points is also reported for Lebanon where the bias is likely to be caused by poor data quality.

On the other hand, based on the selected set of fundamentals, the model predicts that sovereign risk in Bulgaria should be around 450 basis points, roughly the same level as in Peru (Table 8). By contrast, market spreads in the former are around 220 basis points lower than in the latter. But there is no clear-cut reason to view Bulgaria as more creditworthy than Peru. Both countries (which have roughly similar per capita income) have recorded similarly low inflation rates and a relatively stable exchange rate in recent years. They have sustained restrained fiscal policy under IMF led economic programmes, and the fiscal deficit has been steadily declining. On the plus side, Bulgaria is more open to foreign trade and has higher foreign reserves relative to GDP than Peru. But Peru's external indebtedness is lower than Bulgaria's and on average its external debt is of longer duration. Moreover, Peru's external financing needs and current account deficit are also lower. The same line of argument may be applied to Morocco and the Philippines. Interestingly, the model prices Colombia's sovereign spreads at around 500 basis points, and Brazil's at around 750 basis points, which on itself would suggest a significant difference in the creditworthiness of the two countries. This is consistent with the views prevailing in the market (though in both countries market spreads are somewhat higher than the level consistent with the selected set of fundamentals) and with a comparative assessment of creditworthiness based on broad vulnerabilities to shocks. In particular, Colombia's external financing needs are lower than Brazil's and public sector debt is smaller. But unlike in Brazil, Colombia's debt dynamics are unstable on the basis of the prevailing macro financial variables without further fiscal consolidation.

(16) However, the model picks up somewhat the deterioration in Argentine fundamentals that followed the announcement of the debt moratorium in December 2001. For example, Chart 2 shows that predicted spreads rose significantly following the eruption of the crisis, peaking at 2200 basis points in September 2002 from around 1000 basis points immediately prior to the announcement of the default.

Importantly, when interpreting these results we have to bear in mind that the largest misalignments are reported for countries that face or have recently faced a financial crisis. This raises two issues. First, the model may break down during crisis periods and it may not be able to pick up and price accordingly a sharp deterioration of macro conditions. Clearly, if the purpose of the investigation is to generate accurate predictions of sovereign spreads for each country we would probably need to focus on a country-specific model, and test a wide range of relevant macro fundamentals and non-fundamental variables, until we obtain plausible estimates. Second, the term structure of interest rates in crisis countries normally inverts before the actual default, reflecting market concerns over sovereign liquidity. So while market spreads may be driven up by these short-term concerns, spreads based on fundamentals (which measure mainly solvency – as opposed to liquidity – and are thus related primarily to the long end of the yield curve) may actually remain unchanged.

Table 8 compares fitted and actual spreads for all the countries in the panel at a specific point in time. To add some perspective, Chart 2 provides the same statistics over the whole length of the sample, allowing us to make the following points. First, the model tracks actual spreads fairly well in most countries. This is reassuring given the relatively short time series for some of the countries under consideration, the parsimony constraint, and the focus on macro fundamentals and external factors as explanatory variables. Second, market spreads normally exhibit higher volatility than fitted spreads. This pattern might have been easily anticipated and can be explained essentially in terms of sluggish macro-prudential indicators, unmeasured fundamentals, and/or noisy market spreads. Third, for some countries (Argentina, Brazil, Ecuador, Nigeria, the Philippines and Venezuela) the misalignments rose significantly in the months between mid-1995 and 1998, as market spreads fell suddenly, while fundamental-based spreads remained largely unchanged. This may be due to market mispricing of sovereign risk, a point on which we will return later. Fourth, the chart reports large and persistent misalignments between fitted and market spreads in the cases of Côte d'Ivoire and Lebanon, which we think are mainly explained by poor data quality.

To summarise the points made so far, Chart 3 reports a composite market index obtained as an average of the country-specific EMBI and EMBIG spreads, weighted using their relative weights in the EMBIG index, together with the average (calculated using the same weights) of the fitted country-specific spreads. The chart shows that the misalignment between the two indices was high and volatile between end-1991 and 1995. However during this period the panel covers only 5 countries and the overall pattern of the two indices seems to be driven by the behaviour of the individual country series in Brazil and especially Nigeria. Interestingly, the chart also confirms our earlier finding that markets on average underpriced sovereign risk between 1995 and 1997, when market spreads fell well below their fundamental-based levels. If we believe that the model gives a true picture of fundamental-based sovereign credit risk, we might conclude that the misalignment is mainly due to market imperfections. For example, the fall may be the result of investor moral hazard (eg following the IMF rescue package during the Mexican crisis at the beginnings of 1995) or higher investor risk appetite following the stimulative effect of more liberal credit conditions in the main financial centres. The possibility of some form of mispricing would be consistent with the finding of a more compressed dispersion of EMBI credit spreads during the same period (Chart 4). Chart 3 also shows that misalignments have persisted in more recent times and that despite the recent fall, on average market spreads have remained still somewhat higher than their fundamental-based level.

## 8 Conclusions

This study investigates the empirical relationship between EME sovereign spreads and a set of common macroeconomic fundamentals, using a ragged-edge panel of JP Morgan EMBI and EMBIG secondary market spreads and a set of macro-prudential indicators. To underpin our choice of macro fundamentals, we introduce a simple model of an indebted SOE. The estimation technique is PMG, which posits a dynamic error correction model that allows short-run parameters to vary across individual groups, while restricting long-run elasticities to be identical across groups. This seems a sensible choice in a model of sovereign spreads because restricted (pooled) models are shown to perform better than their heterogeneous counterparts on a number of grounds. A number of specification tests performed on the data corroborate this, suggesting that a pooled model is more appropriate than a mean group estimator or unrestricted estimator.

The model provides overall satisfactory results in terms of the sign and significance of coefficients and in terms of explanatory power of the regressions. The regression results suggest a strong empirical relationship between sovereign spreads and external factors such as global liquidity conditions and US equity prices. But the diagnostic statistics also suggest that error terms in some country equations follow a systematic (non-random) pattern, which we take as evidence that the market assessment of a country's creditworthiness may be more broad based than that provided by the model. We use the estimated model to generate a time series of fitted (fundamental-based) country spreads, and compare these with actual market spreads. The purpose is threefold. First, we want to assess what proportion of the change in spreads is explained by changes in the underlying fundamentals. Second, we compare from an *ex-ante* perspective our assessment of a country's creditworthiness with that of market participants. Third, we explain the pattern in spreads, from an *ex-post* perspective. As a case study, we analyse the generalised fall in secondary market EME bond spreads experienced between 1995 and 1997.

We conclude that markets do take into account macro fundamentals when pricing sovereign risk (market spreads broadly reflect macro fundamentals) but non-fundamental factors also play an important role. Comparing market-based spreads against their model-based counterparts we find that spreads mainly trade at a level that is close to a theoretical equilibrium level based on our choice of fundamentals. Spreads are too high or low compared with the model-based benchmark in only 5 of the 23 countries included in the sample. In particular, we report large absolute misalignments in the case of Argentina and Côte d'Ivoire, and for a few countries where the market price is within the confidence interval around the fitted spreads (Venezuela, Nigeria, and Brazil among others) but where the volatility of the fitted values is also high. We suggest that unmeasured fundamentals can help to explain the divergence in the pricing of sovereign debt in some cases. And we quote the example of those countries where markets are likely to supplement their country risk assessment with additional information on political risk, quality of institutions, commodity dependence and 'willingness to pay', which are all excluded from the model. But we also suggest that mispricing may be at play in other cases. It is also possible that the model may break down during periods of crisis, possibly reflecting the occurrence of a structural break in estimation parameters, or yield curve effects.

The model suggests that markets on average underpriced sovereign risk between 1995 and 1997, when market spreads fell well below their fundamental-based levels. Assuming that the model provides a fair picture of fundamental-based sovereign credit risk, the misalignment must be due to capital market imperfections, such as investor exuberance due to moral hazard following the IMF bail-out of Mexico or higher investor risk appetite following the stimulative effect of more liberal credit conditions in the main financial centres. Moreover, these results corroborate the argument that the fall in market spreads cannot be explained entirely in terms of improved fundamentals. Finally, misalignments have persisted in more recent times. Despite the generalised fall in market prices, spreads have remained on average still somewhat higher than their fundamental-based level.

## Appendix – Tables and charts

### Table 1 –
### EMBI and EMBIG country series: tests for equality of means and variances[(a)]

| | | *t*-test for equality of sample means | | F-test for equality of sample variances | | Jarque-Bera statistic | | |
|---|---|---|---|---|---|---|---|---|
| | Obs | Statistic | Prob | Statistic | Prob | Statistic | Prob | Correl |
| Argentina | 1115 | 6.57 | 0.00 | 3.41 | 0.00 | 1750.5 | 0.00 | 0.98 |
| Bulgaria | 1115 | 0.00 | 0.99 | 1.00 | 0.99 | 103.1 | 0.00 | 1.00 |
| Brazil | 1115 | 3.01 | 0.00 | 1.11 | 0.07 | 817.0 | 0.00 | 0.99 |
| Ecuador | 1115 | 0.02 | 0.98 | 1.00 | 0.95 | 189.0 | 0.00 | 1.00 |
| Mexico | 1115 | 11.84 | 0.00 | 1.99 | 0.00 | 1312.9 | 0.00 | 0.98 |
| Nigeria | 824 | 15.67 | 0.00 | 1.19 | 0.01 | 114.8 | 0.00 | 0.92 |
| Panama | 1115 | 5.34 | 0.00 | 1.29 | 0.00 | 809.5 | 0.00 | 0.97 |
| Peru | 1115 | 0.16 | 0.87 | 1.01 | 0.85 | 188.8 | 0.00 | 0.99 |
| Poland | 1115 | 0.04 | 0.96 | 1.11 | 0.08 | 468.0 | 0.00 | 0.99 |
| Russia | 865 | 7.99 | 0.00 | 2.31 | 0.00 | 130.3 | 0.00 | 0.99 |
| Venezuela | 1115 | 6.55 | 0.00 | 1.75 | 0.00 | 116.5 | 0.00 | 0.99 |

Notes: (a) Observations are daily. Sample includes the subset of EMEs for which the EMBI and EMBIG spreads are simultaneously available and covers the period when the two indices overlap. The sample period is 31 December 1997 to 16 June 2002. For Nigeria the sample excludes the period from 31 March 1998 to 27 May 1999, when EMBI spreads are not available. For Russia the sample starts in December 1998.

### Table 2 –
### Test for equivalence of EMBIG and EMBI spreads[(a)]

| | | | | | | Test of $H_0$: $\alpha$=0, $\beta$=1 | |
|---|---|---|---|---|---|---|---|
| | $\alpha$ | $\beta$ | R-sq | DW | Obs | F-stat | Prob |
| Argentina | 297.86 | 0.53 | 0.97 | 0.17 | 1115 | 16504.6 | 0.00 |
| Bulgaria | 0.09 | 0.99 | 0.99 | 1.84 | 1115 | 0.03 | 0.97 |
| Brazil | 17.76 | 0.95 | 0.99 | 0.13 | 1115 | 2204.97 | 0.00 |
| Ecuador | 2.95 | 0.99 | 0.99 | 1.57 | 1115 | 4.40 | 0.01 |
| Mexico | 63.01 | 0.70 | 0.98 | 0.08 | 1115 | 15125.10 | 0.00 |
| Nigeria | -58.66 | 0.88 | 0.87 | 0.10 | 824 | 1095.36 | 0.00 |
| Panama | 45.36 | 0.86 | 0.95 | 0.10 | 1115 | 914.35 | 0.00 |
| Peru | -3.70 | 1.00 | 0.99 | 0.92 | 1115 | 30.41 | 0.00 |
| Poland | -9.31 | 1.04 | 0.97 | 0.13 | 1115 | 30.28 | 0.00 |
| Russia | 381.20 | 0.54 | 0.89 | 0.03 | 865 | 3887.97 | 0.00 |
| Venezuela | 161.96 | 0.75 | 0.99 | 0.15 | 1115 | 15950.01 | 0.00 |

Notes: (a) Observations are daily. Sample includes the subset of EMEs for which the EMBI and EMBIG spreads are simultaneously available and covers the period when the two indices overlap. The sample period is 31 December 1997 to 16 June 2002. For Nigeria the sample excludes the period from 31 March 1998 to 27 May 1999 (EMBI spreads not available). For Russia the sample starts in December 1998 (EMBI spreads not available earlier).

## Table 3.a –
## Descriptive statistics: all sample[(a)]

| | Mean | Median | Max | Min | St dev | Skewness | Kurtosis | Jarque-Bera (p-value) |
|---|---|---|---|---|---|---|---|---|
| Spread | 792 | 581 | 7078 | 66 | 795.30 | 3.57 | 21.14 | 0.0 |
| Ext debt/ GDP | 56.80 | 51.75 | 451.62 | 13.38 | 30.87 | 3.57 | 32.57 | 0.0 |
| Budget/ GDP | -2.79 | -1.96 | 5.37 | -23.42 | 4.01 | -1.88 | 7.58 | 0.0 |
| Openness[(b)] | 54.46 | 47.93 | 409.41 | 12.06 | 36.94 | 2.85 | 16.01 | 0.0 |
| Trade bal/ GDP | -0.30 | 0.43 | 29.23 | -40.70 | 11.67 | -0.61 | 3.91 | 0.0 |
| Inflation | 56.43 | 7.07 | 4922.46 | -4.30 | 300.26 | 9.68 | 114.28 | 0.0 |
| Interest/ Ext debt | 6.10 | 5.91 | 13.04 | 1.85 | 1.79 | 0.85 | 4.50 | 0.0 |
| Amort/ Reserves | 49.38 | 38.46 | 394.61 | 4.92 | 39.15 | 2.20 | 11.61 | 0.0 |
| Curr account/ GDP | -1.40 | -1.97 | 26.70 | -38.67 | 8.06 | -1.49 | 9.35 | 0.0 |
| Arrears/ Ext debt | 1.07 | 0.00 | 15.82 | 0.00 | 2.52 | 3.44 | 15.83 | 0.0 |
| Reserves/ GDP | 13.68 | 11.84 | 57.66 | 1.60 | 8.70 | 1.23 | 4.56 | 0.0 |
| RER change[(c)] | 41.77 | 0.64 | 4821.97 | -80.12 | 289.09 | 9.97 | 120.85 | 0.0 |

Notes: (a) Spreads are in basis points, all other data are percentages. Spreads are annual. Flow data are 12-month moving averages. Percentage rate of changes are year-on-year changes. Panel covers 2,005 monthly observations over the period December 1991 to March 2003 and includes 23 unbalanced cross-sections: Argentina, Brazil, Bulgaria, China, Colombia, Côte d'Ivoire, Croatia, Ecuador, Korea, Lebanon, Malaysia, Mexico, Morocco, Nigeria, Panama, Peru, the Philippines, Poland, Russia, South Africa, Thailand, Turkey and Venezuela. (b) Defined as (Exports + Imports)/ GDP. (c) Plus sign is appreciation.

## Table 3.b –
## Descriptive statistics: Latin America[(a)]

| | Mean | Median | Max | Min | St dev | Skewness | Kurtosis | Jarque-Bera (p-value) |
|---|---|---|---|---|---|---|---|---|
| Spread | 932 | 698 | 7078 | 243 | 887.61 | 4.13 | 23.48 | 0.0 |
| Ext debt/ GDP | 52.18 | 48.00 | 182.72 | 22.55 | 23.81 | 1.77 | 8.31 | 0.0 |
| Budget/ GDP | -2.01 | -1.48 | 5.37 | -7.94 | 2.32 | -0.29 | 3.08 | 0.0 |
| Openness[(b)] | 35.02 | 32.40 | 66.43 | 12.06 | 15.53 | 0.16 | 1.75 | 0.0 |
| Trade bal/ GDP | 0.14 | -0.11 | 22.29 | -25.46 | 8.97 | -0.74 | 4.88 | 0.0 |
| Inflation | 97.83 | 9.64 | 4922.46 | -1.79 | 437.54 | 6.93 | 57.46 | 0.0 |
| Interest/ Ext debt | 6.63 | 6.66 | 9.81 | 2.92 | 1.39 | -0.33 | 2.54 | 0.0 |
| Amort/ Reserves | 60.51 | 48.55 | 202.21 | 15.52 | 37.82 | 1.24 | 3.81 | 0.0 |
| Curr account/ GDP | -2.28 | -3.02 | 14.43 | -14.40 | 4.79 | 0.84 | 4.48 | 0.0 |
| Arrears/ Ext debt | 0.61 | 0.00 | 11.14 | 0.00 | 1.43 | 3.56 | 17.94 | 0.0 |
| Reserves/ GDP | 9.60 | 8.32 | 21.61 | 1.98 | 4.32 | 0.83 | 2.76 | 0.0 |
| RER change[(c)] | 79.13 | 0.64 | 4821.97 | -59.64 | 423.15 | 7.10 | 60.05 | 0.0 |

Notes: (a) Spreads are in basis points, all other data are percentages. Spreads are annual. Flow data are 12-month moving averages. Percentage rate of changes are year-on-year changes. Panel covers 831 monthly observations over the period December 1991 to March 2003 and includes 8 unbalanced cross-sections: Argentina, Brazil, Colombia, Ecuador, Mexico, Panama, Peru, and Venezuela. (b) Defined as (Exports + Imports)/ GDP. (c) Plus sign is appreciation.

## Table 3.c –
## Descriptive statistics: all sample excluding Latin America[(a)]

| | Mean | Median | Max | Min | St dev | Skewness | Kurtosis | Jarque-Bera (p-value) |
|---|---|---|---|---|---|---|---|---|
| Spread | 692 | 464.5 | 5783 | 66 | 706.56 | 2.66 | 13.15 | 0.0 |
| Ext debt/ GDP | 60.08 | 56.80 | 451.62 | 13.38 | 34.65 | 3.76 | 32.44 | 0.0 |
| Budget/ GDP | -3.35 | -2.22 | 5.28 | -23.42 | 4.79 | -1.60 | 5.42 | 0.0 |
| Openness[(b)] | 68.23 | 57.84 | 409.41 | 14.07 | 41.26 | 2.66 | 13.16 | 0.0 |
| Trade bal/ GDP | -0.61 | 2.20 | 29.23 | -40.70 | 13.25 | -0.51 | 3.26 | 0.0 |
| Inflation | 27.12 | 5.59 | 1722.36 | -4.30 | 128.40 | 10.14 | 113.54 | 0.0 |
| Interest/ Ext debt | 5.72 | 5.25 | 13.04 | 1.85 | 1.94 | 1.50 | 5.97 | 0.0 |
| Amort/ Reserves | 41.51 | 33.06 | 394.61 | 4.92 | 38.17 | 3.22 | 20.41 | 0.0 |
| Curr account/ GDP | -0.78 | -0.59 | 26.70 | -38.67 | 9.68 | -1.68 | 7.90 | 0.0 |
| Arrears/ Ext debt | 1.39 | 0.00 | 15.82 | 0.00 | 3.03 | 2.88 | 11.23 | 0.0 |
| Reserves/ GDP | 16.57 | 15.00 | 57.66 | 1.60 | 9.80 | 0.74 | 3.29 | 0.0 |
| RER change[(c)] | 15.32 | 0.63 | 1629.11 | -80.12 | 119.95 | 10.37 | 118.23 | 0.0 |

Notes: (a) Spreads are in basis points, all other data are percentages. Spreads are annual. Flow data are 12-month moving averages. Percentage rate of changes are year-on-year changes. Panel covers 1,174 monthly observations over the period December 1991 to March 2003 and includes 15 unbalanced cross-sections: Bulgaria, China, Côte d'Ivoire, Croatia, Korea, Lebanon, Malaysia, Morocco, Nigeria, the Philippines, Poland, Russia, South Africa, Thailand, and Turkey. (b) Defined as (Exports + Imports)/ GDP. (c) Plus sign is appreciation.

**Table 4 –**
**PMG estimates of long-run coefficients**[a]

| | Model (A)[b] | Model (B)[b] | Model (C)[c] |
|---|---|---|---|
| External debt/ GDP | 0.25 | 0.70 | 0.73 |
| | (0.12)** | (0.13)* | (0.12)* |
| Fiscal budget/ GDP | -0.72 | 0.27 | 0.47 |
| | (0.58) | (0.47) | (0.37) |
| Openness | -0.37 | -0.35 | -0.24 |
| | (0.11)* | (0.13)* | (0.11)** |
| Amortisation/ Reserves | 0.19 | 0.23 | -0.10 |
| | (0.06)* | (0.04)* | (0.05)** |
| Interest payments/ External debt | - | 5.69 | - |
| | | (1.32)* | |
| Current account/ GDP | 0.14 | -1.25 | -1.34 |
| | (0.35) | (0.29)* | (0.29)* |
| Short-term external debt/ External debt | - | - | -2.32 |
| | | | (0.33)* |
| Yield of 30-day US T-bill | 8.88 | 6.68 | 7.21 |
| | (1.39)* | (0.85)* | (0.71)* |
| Yield of 10-year US government bond | -8.00 | -8.55 | -4.67 |
| | (2.13)* | (1.40)* | (1.33)* |
| Log of yield spread between low and high-rating US corporate bonds | -0.44 | - | - |
| | (0.18)* | | |
| Log of US S&P 500 equity index | -0.60 | -0.38 | -0.24 |
| | (0.12)* | (0.12)* | (0.06)* |
| Constant[d] | 0.78 | 0.65 | 1.04 |
| | (0.12)* | (0.12)* | (0.26)* |
| Error correction coefficient[d] | -0.15 | -0.19 | -0.39 |
| | (0.02)* | (0.04)* | (0.09)* |
| Observations | 1982 | 1982 | 1838 |
| Cross sections | 23 | 23 | 21 |
| R-Squared[e] | 0.40 | 0.40 | 0.27 |
| RBAR-Squared[e] | 0.21 | 0.21 | 0.10 |
| Standard deviation of regressions[e] | 0.065 | 0.065 | 0.069 |
| Maximised Log likelihood | 2891.51 | 2895.51 | 2623.26 |
| No. of model parameters | 262 | 262 | 146 |
| Chi-sq test for:[f] | | | |
| Serial correlation | 8 | 7 | 4 |
| Functional form misspecification | 17 | 16 | 17 |
| Normality | 16 | 18 | 18 |
| Heteroscedasticity | 20 | 22 | 15 |
| LR test for equal long-run parameters: | | | |
| Chi-square stat | 427.41 | 497.89 | 812.07 |
| Degrees of freedom | 198 | 198 | 180 |
| p-value | 0.00 | 0.00 | 0.00 |

Notes: (a) Dependent variable is log of spreads. Figures in parenthesis are standard errors. Sample period is December 1991 to March 2003. Observations are monthly. (b) A fixed lag of one has been selected for all groups. All 23 cross-sections have been included. (c) The Schwarz-Bayesian criterion has been used to select the appropriate lag orders for each group, conditional on a maximum lag of two. Two groups (Côte d'Ivoire and Croatia) have been excluded from estimations. (d) Average of group-specific coefficients. (e) Average of group-specific statistics. (f) Tests of estimation residuals from cross-section equations based on 5% significance level. Statistics shown indicate number of cross-sections where the null hypothesis cannot be rejected. * Significant at 1% s.l.. ** Significant at 5% s.l..

**Table 5 –**
**Model (A): diagnostic statistics**

| | Obs | RBAR-Sq[(a)] | Sigma[(b)] | Ch-SC[(c)] | Ch-FF[(d)] | Ch-NO[(e)] | Ch-HET[(f)] | LL[(g)] |
|---|---|---|---|---|---|---|---|---|
| Argentina | 119 | 0.15 | 0.08 | 0.22 | 14.39 | 56.85 | 28.45 | 147.77 |
| Brazil | 135 | 0.24 | 0.07 | 0.71 | 11.92 | 69.97 | 11.84 | 185.67 |
| Bulgaria | 100 | 0.26 | 0.06 | 2.08 | 17.89 | 71.70 | 43.71 | 149.97 |
| China | 63 | 0.19 | 0.06 | 6.96 | 7.09 | 35.46 | 34.33 | 97.00 |
| Colombia | 63 | 0.28 | 0.06 | 0.02 | 4.03 | 1.76 | 7.27 | 99.91 |
| Côte d'Ivoire | 60 | -0.10 | 0.09 | 24.80 | 21.18 | 140.28 | 31.31 | 71.17 |
| Croatia | 63 | -0.25 | 0.08 | 1.00 | 9.11 | 2.16 | 7.48 | 83.19 |
| Ecuador | 93 | 0.27 | 0.07 | 0.72 | 2.29 | 2.71 | 43.52 | 124.49 |
| Korea | 63 | 0.27 | 0.07 | 11.72 | 1.76 | 5.72 | 1.68 | 92.66 |
| Lebanon | 60 | 0.04 | 0.06 | 4.10 | 0.11 | 0.02 | 2.11 | 98.31 |
| Malaysia | 63 | 0.29 | 0.06 | 0.01 | 1.41 | 2.35 | 5.99 | 103.37 |
| Mexico | 135 | 0.35 | 0.06 | 1.13 | 14.89 | 7.76 | 43.44 | 211.55 |
| Morocco | 63 | 0.12 | 0.09 | 11.85 | 17.21 | 123.60 | 36.50 | 74.52 |
| Nigeria | 135 | 0.21 | 0.07 | 2.29 | 18.84 | 19.63 | 22.61 | 185.60 |
| Panama | 73 | 0.36 | 0.05 | 4.46 | 8.58 | 2.39 | 18.01 | 134.25 |
| Peru | 70 | 0.13 | 0.06 | 1.07 | 7.22 | 4.06 | 5.89 | 104.87 |
| Philippines | 135 | 0.18 | 0.06 | 0.62 | 3.24 | 51.64 | 17.96 | 197.51 |
| Poland | 100 | 0.23 | 0.06 | 5.87 | 3.90 | 38.38 | 23.18 | 153.85 |
| Russia | 63 | 0.56 | 0.06 | 2.27 | 35.03 | 60.78 | 50.96 | 96.38 |
| South Africa | 63 | 0.30 | 0.05 | 2.64 | 5.35 | 2.62 | 5.01 | 112.63 |
| Thailand | 65 | 0.08 | 0.08 | 1.64 | 1.60 | 111.61 | 0.77 | 81.50 |
| Turkey | 63 | 0.31 | 0.06 | 20.26 | 11.27 | 8.84 | 5.97 | 102.64 |
| Venezuela | 135 | 0.25 | 0.07 | 1.43 | 26.78 | 78.97 | 67.98 | 182.72 |

Notes: (a) Corrected R-squared. (b) Standard deviation of regressions. (c) Chi-square test of residual serial correlation. (d) Chi-square test of functional form misspecification. (e) Chi-square test of normality of residuals. (f) Chi-square test of heteroscedasticity. (g) Maximised Log-likelihood.

## Table 6 –
## Model (A): group-specific estimates of error correction and long-run coefficients[(a), (b)]

| | Phi | DGDP | BDGT | OPN | AMRS | CABG | TBY | USLY | LUCS | LEQ |
|---|---|---|---|---|---|---|---|---|---|---|
| Argentina | -0.18 | 2.28 | 14.34 | -5.49 | 1.14 | -6.02 | 7.54 | -7.01 | -0.79 | -1.30 |
| | (0.08)† | (1.62) | (10.82) | (4.53) | (0.46)‡ | (7.14) | (10.50) | (12.48) | (1.16) | (0.96) |
| Brazil | -0.09 | 5.97 | 9.66 | -10.09 | -1.07 | -16.49 | 17.40 | -8.26 | 1.00 | 0.91 |
| | (0.06) | (4.62) | (10.55) | (9.69) | (0.96) | (16.80) | (19.97) | (16.66) | (1.35) | (2.30) |
| Bulgaria | -0.31 | 0.84 | -0.32 | -0.97 | 0.34 | -0.81 | 10.63 | -5.12 | -0.29 | -0.47 |
| | (0.07)‡ | (0.50)† | (1.50) | (0.46)† | (0.26) | (1.16) | (3.89)‡ | (5.85) | (0.46) | (0.56) |
| China | -0.77 | -2.58 | -10.71 | -3.67 | -10.73 | -15.83 | 16.42 | -10.84 | 0.30 | -0.28 |
| | (0.14)‡ | (8.87) | (17.11) | (1.45)‡ | (8.08) | (8.01) | (5.79)‡ | (4.66)† | (0.32) | (0.63) |
| Colombia | -0.30 | 6.61 | -5.71 | -8.60 | -0.15 | -6.93 | 23.11 | -3.47 | 0.81 | -0.86 |
| | (0.16)† | (4.62) | (7.35) | (6.80) | (2.47) | (6.42) | (11.56)† | (16.78) | (0.73) | (1.48) |
| Côte d'Ivoire | -0.67 | -1.98 | -5.47 | 0.24 | 0.03 | 4.35 | 6.35 | 6.81 | -0.72 | -0.94 |
| | (0.15)‡ | (0.84)† | (8.61) | (1.91) | (0.08) | (11.45) | (11.34) | (9.16) | (0.55) | (1.09) |
| Croatia | -0.13 | -15.30 | 3.78 | -16.34 | 5.33 | 24.87 | -7.42 | -92.69 | 2.28 | -5.20 |
| | (0.11) | (13.51) | (10.29) | (12.09) | (8.34) | (24.30) | (16.44) | (82.40) | (2.71) | (6.55) |
| Ecuador | -0.25 | 3.33 | 6.40 | -6.15 | -0.04 | -1.99 | 6.16 | -16.76 | 0.45 | -0.27 |
| | (0.09)‡ | (0.90)‡ | (5.35) | (2.98)† | (0.22) | (1.86) | (6.80) | (10.70) | (0.80) | (0.68) |
| Korea | -0.57 | 1.21 | 5.69 | -0.20 | 0.15 | 0.80 | 7.26 | -11.25 | -0.92 | -0.51 |
| | (0.20)† | (1.19) | (3.95) | (0.86) | (0.38) | (3.54) | (5.93) | (9.30) | (0.54)† | (1.49) |
| Lebanon | -0.57 | 4.56 | -2.48 | -0.31 | 2.54 | -1.16 | 4.29 | -1.59 | 1.31 | -1.50 |
| | (0.15)‡ | (3.12) | (1.42)† | (2.18) | (0.97)‡ | (1.97) | (4.75) | (5.94) | (0.44)‡ | (0.90)† |
| Malaysia | -0.37 | -3.58 | 0.61 | -2.19 | 1.22 | -0.32 | 10.99 | 9.16 | -0.43 | -1.46 |
| | (0.10)‡ | (1.57)† | (3.87) | (0.83)‡ | (2.12) | (1.90) | (5.08)† | (10.54) | (0.58) | (1.24) |
| Mexico | -0.27 | 2.01 | 7.00 | 0.24 | -0.02 | -5.51 | -2.71 | -7.41 | -0.26 | 0.54 |
| | (0.07)‡ | (0.62)‡ | (3.39)† | (0.74) | (0.15) | (1.47)‡ | (3.83) | (4.79) | (0.35) | (0.49) |
| Morocco | -0.57 | 1.08 | -0.09 | -0.95 | -0.47 | 3.39 | 10.40 | -16.27 | 0.05 | -0.63 |
| | (0.14)‡ | (1.78) | (1.72) | (1.08) | (1.01) | (3.34) | (7.96) | (11.89) | (0.65) | (1.08) |
| Nigeria | -0.29 | 1.25 | 2.40 | -0.61 | 0.25 | -2.59 | 7.66 | -8.93 | 0.21 | -0.06 |
| | (0.07)‡ | (0.65)† | (1.35)† | (0.67) | (0.11)† | (0.83)‡ | (4.82) | (5.45) | (0.44) | (0.39) |
| Panama | -0.48 | 0.32 | 0.10 | -0.29 | 0.23 | -1.97 | 2.38 | -5.75 | -0.02 | -0.30 |
| | (0.12)‡ | (2.28) | (0.93) | (2.44) | (0.17) | (1.43) | (4.03) | (6.35) | (0.27) | (0.49) |
| Peru | -0.61 | -0.74 | -7.23 | -1.74 | 3.87 | -2.26 | 8.39 | -9.45 | -0.02 | -1.92 |
| | (0.13)‡ | (1.45) | (5.22) | (5.54) | (1.85)† | (3.77) | (3.32)‡ | (6.25) | (0.30) | (0.68)‡ |
| Philippines | -0.30 | 1.30 | 10.05 | 0.06 | 0.02 | 4.72 | -4.36 | -0.25 | -0.40 | -1.57 |
| | (0.06)‡ | (0.79) | (4.65)† | (0.58) | (0.23) | (1.15)‡ | (4.67) | (4.38) | (0.39) | (0.37)‡ |
| Poland | -0.27 | 4.05 | 8.77 | 1.97 | -2.18 | 6.88 | 2.14 | 0.07 | 0.55 | -0.42 |
| | (0.07)‡ | (1.49)‡ | (4.31)† | (1.81) | (0.79)‡ | (5.33) | (5.48) | (5.77) | (0.56) | (0.90) |
| Russia | -0.41 | 1.71 | 6.18 | 2.57 | 0.51 | -5.89 | 13.96 | -4.56 | -0.35 | -3.01 |
| | (0.14)‡ | (1.53) | (3.92) | (1.95) | (0.53) | (1.64)‡ | (4.84)‡ | (10.34) | (0.60) | (1.57)† |
| South Africa | -0.36 | 8.84 | -3.51 | -2.93 | 0.85 | -4.75 | 9.65 | -11.60 | 0.59 | -0.51 |
| | (0.11)‡ | (2.82)‡ | (7.07) | (1.04)‡ | (0.77) | (10.08) | (4.62)† | (7.15) | (0.62) | (0.87) |
| Thailand | -0.56 | 0.73 | 3.75 | 0.22 | 0.88 | 2.71 | 4.07 | -3.97 | -0.67 | -1.40 |
| | (0.14)‡ | (0.43)† | (4.96) | (0.36) | (1.39) | (1.43)† | (5.37) | (7.74) | (0.45) | (1.01) |
| Turkey | -0.52 | 0.42 | 2.11 | -2.46 | 0.63 | -3.39 | 6.39 | -2.57 | -0.26 | -1.22 |
| | (0.17)‡ | (0.97) | (1.73) | (0.88)‡ | (0.35)† | (2.15) | (8.00) | (8.91) | (0.37) | (0.90) |
| Venezuela | -0.18 | 1.17 | -4.55 | -0.94 | 0.55 | 1.96 | 4.62 | -5.36 | -0.78 | 0.16 |
| | (0.06)‡ | (1.69) | (2.85) | (1.59) | (0.60) | (1.51) | (8.22) | (9.94) | (0.86) | (1.60) |
| Min | -0.77 | -15.3 | -10.71 | -16.34 | -10.73 | -16.49 | -7.42 | -92.69 | -0.92 | -5.2 |
| Max | -0.09 | 8.84 | 14.34 | 2.57 | 5.33 | 24.87 | 23.11 | 9.16 | 2.28 | 0.91 |
| Avg. (MGE) | -0.39 | 1.02 | 1.77 | -2.55 | 0.17 | -1.14 | 7.19 | -9.44 | 0.07 | -0.97 |
| Std Error | (0.04)‡ | (0.95) | (1.31) | (0.90)‡ | (0.59) | (1.68) | (1.44)‡ | (4.00)‡ | (0.16) | (0.26)‡ |
| t-ratio | 10.16 | 1.07 | 1.35 | 2.83 | 0.28 | 0.70 | 4.98 | 2.36 | 0.44 | 3.69 |

Notes: (a) Dependent variable is log of spreads. Figures in brackets are standard errors. Estimates based on ARDL specification with a fixed lag of one for all cross-sections. Sample period is December 1991 to March 2003. Observations are monthly. (b) Key to column headings: Phi: Error correction coefficient. DGDP: External Debt/ GDP. BDGT: Fiscal budget/ GDP. OPN: Trade openness, defined as (Exports + Imports)/ GDP. AMRS: Amortisation/ Reserves. CABG: Current account balance/ GDP. TBY: Yield of 30-day US T-bill. USLY: Yield of 10-year US government bond. LUCS: Log of yield spread between low and high-rating US corporate bonds. LEQ: Log of US S&P 500 equity index. † Significant at 5% s.l.. ‡ Significant at 1% s.l..

**Table 7 –**
**Model (A): diagnostic statistics of group-specific estimates**

| | Obs | RBAR-Sq[a] | Sigma[b] | Ch-SC[c] | Ch-FF[d] | Ch-NO[e] | Ch-HET[f] | LL[g] |
|---|---|---|---|---|---|---|---|---|
| Argentina | 119 | 0.21 | 0.074 | 0.02 | 5.78 | 65.36 | 39.02 | 152.11 |
| Brazil | 135 | 0.30 | 0.064 | 0.18 | 16.96 | 58.71 | 14.91 | 190.49 |
| Bulgaria | 100 | 0.38 | 0.055 | 7.57 | 20.73 | 63.63 | 45.75 | 158.96 |
| China | 63 | 0.49 | 0.050 | 1.97 | 5.02 | 67.12 | 17.82 | 111.56 |
| Colombia | 63 | 0.40 | 0.055 | 0.11 | 8.37 | 0.51 | 8.32 | 105.46 |
| Côte d'Ivoire | 60 | 0.33 | 0.071 | 9.93 | 23.87 | 281.55 | 20.66 | 85.97 |
| Croatia | 63 | 0.15 | 0.064 | 0.65 | 2.73 | 0.18 | 4.65 | 95.47 |
| Ecuador | 93 | 0.41 | 0.064 | 0.15 | 2.63 | 1.19 | 50.77 | 134.46 |
| Korea | 63 | 0.40 | 0.061 | 15.16 | 0.11 | 2.86 | 10.65 | 98.86 |
| Lebanon | 60 | 0.39 | 0.046 | 0.49 | 0.07 | 0.36 | 0.42 | 111.77 |
| Malaysia | 63 | 0.50 | 0.048 | 0.19 | 0.88 | 0.59 | 1.77 | 114.46 |
| Mexico | 135 | 0.47 | 0.049 | 0.36 | 7.48 | 5.81 | 22.22 | 225.54 |
| Morocco | 63 | 0.28 | 0.081 | 5.94 | 13.35 | 193.8 | 19.92 | 80.74 |
| Nigeria | 135 | 0.32 | 0.062 | 1.63 | 10.48 | 35.07 | 23.02 | 195.69 |
| Panama | 73 | 0.50 | 0.040 | 2.99 | 8.47 | 6.66 | 19.12 | 143.44 |
| Peru | 70 | 0.35 | 0.055 | 0.45 | 13.24 | 3.60 | 12.69 | 115.03 |
| Philippines | 135 | 0.29 | 0.056 | 2.23 | 6.11 | 22.22 | 23.17 | 207.20 |
| Poland | 100 | 0.42 | 0.051 | 13.52 | 4.66 | 19.28 | 37.59 | 167.76 |
| Russia | 63 | 0.69 | 0.053 | 7.71 | 29.65 | 37.17 | 46.91 | 107.21 |
| South Africa | 63 | 0.44 | 0.044 | 2.21 | 5.47 | 2.51 | 8.30 | 119.92 |
| Thailand | 65 | 0.27 | 0.074 | 3.44 | 5.05 | 31.29 | 15.88 | 89.21 |
| Turkey | 63 | 0.43 | 0.052 | 8.93 | 9.5 | 4.80 | 3.97 | 108.71 |
| Venezuela | 135 | 0.28 | 0.066 | 1.38 | 27.19 | 82.44 | 61.38 | 185.19 |

Notes: (a) Corrected R-squared. (b) Standard deviation of regressions. (c) Chi-square test of residual serial correlation. (d) Chi-square test of functional form misspecification. (e) Chi-square test of normality of residuals. (f) Chi-square test of heteroscedasticity. (g) Maximised Log-likelihood.

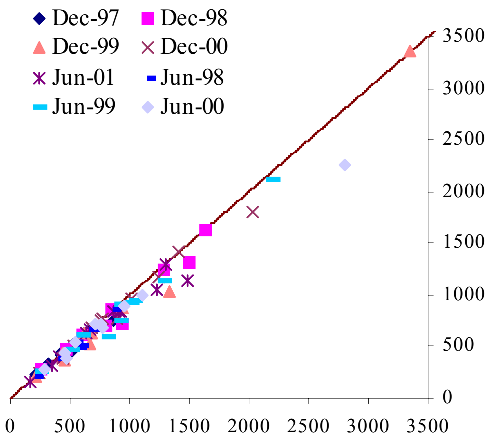
**Table 8 –**

**Actual and fitted spreads**[a]

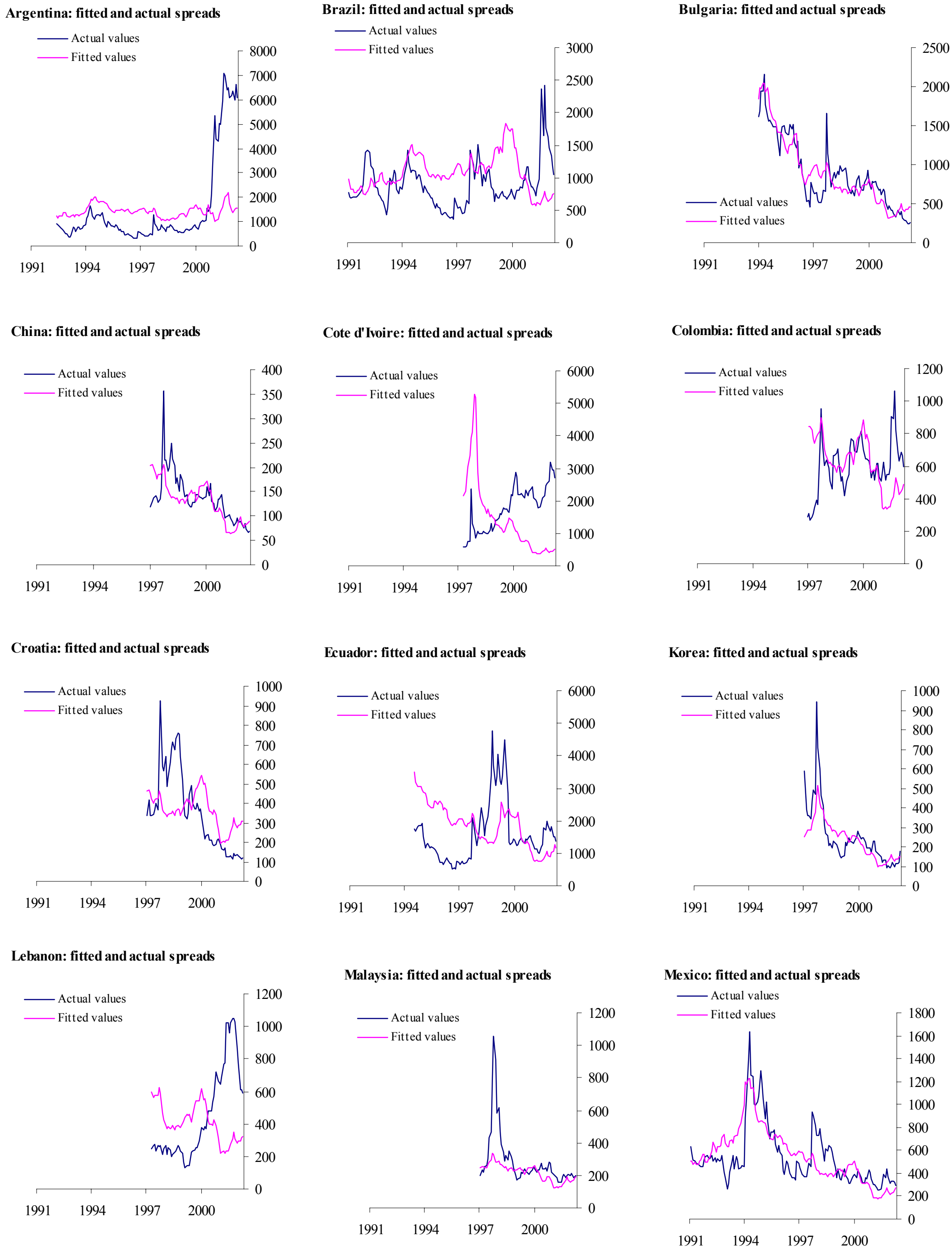
| Country | EMBIG spreads (1) | Fitted spreads (2) | Misalignment, (1)-(2) | St deviation of Fitted | Evaluation[b] |
|---|---|---|---|---|---|
| Argentina | 6096 | 1558 | 4538 | 247 | High |
| Brazil | 1050 | 748 | 302 | 279 | Fair |
| Bulgaria | 253 | 458 | -205 | 455 | Fair |
| China | 68 | 88 | -20 | 41 | Fair |
| Colombia | 595 | 509 | 86 | 156 | Fair |
| Cote d'Ivoire | 2703 | 517 | 2186 | 1131 | High |
| Croatia[c] | 118 | 306 | -188 | 87 | Low |
| Ecuador | 1372 | 1160 | 212 | 662 | Fair |
| Korea | 175 | 149 | 26 | 95 | Fair |
| Lebanon[c] | 592 | 321 | 271 | 114 | High |
| Malaysia | 200 | 192 | 8 | 51 | Fair |
| Mexico | 289 | 271 | 18 | 234 | Fair |
| Morocco | 372 | 454 | -82 | 193 | Fair |
| Nigeria | 1292 | 664 | 628 | 674 | Fair |
| Panama | 399 | 367 | 32 | 84 | Fair |
| Peru | 477 | 435 | 42 | 149 | Fair |
| Philippines | 536 | 364 | 172 | 198 | Fair |
| Poland | 176 | 199 | -23 | 93 | Fair |
| Russia | 365 | 559 | -194 | 347 | Fair |
| South Africa | 187 | 252 | -65 | 106 | Fair |
| Thailand | 120 | 116 | 4 | 78 | Fair |
| Turkey | 970 | 593 | 377 | 125 | High |
| Venezuela | 1406 | 781 | 625 | 412 | Fair |

Notes: (a) Data are for end-March 2003. (b) Based on the 95% confidence interval of (log) fitted spreads. By definition market spreads are 'fair' if $|EMBIG_i - Fitted_i| < 1.96*\sigma(Fitted_i)$. They are 'high' if $(EMBIG_i - Fitted_i) > 1.96*\sigma(Fitted_i)$. They are 'low' if $(EMBIG_i - Fitted_i) < -1.96*\sigma(Fitted_i)$. (c) For Croatia and Lebanon the country-specific error correction coefficients and intercept terms are statistically insignificant and, for the purpose of the forecasts, they have been replaced with the coefficients from the pooled model, which are unbiased estimators of the country-specific coefficients for large number of cross-sections.

**Chart 1 –**
**EMBI versus EMBIG spreads**

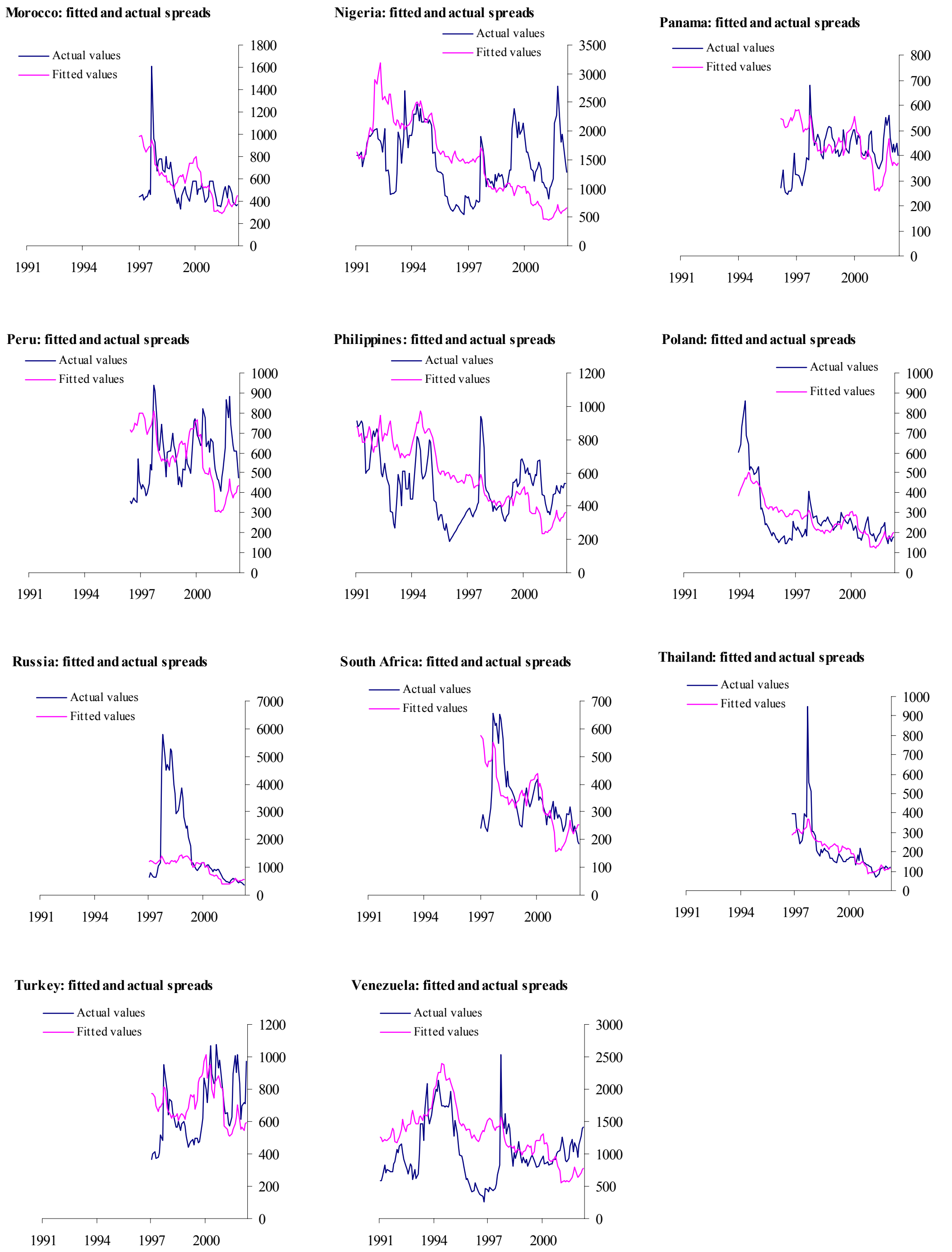


# Chart 2 –
# Individual countries' actual and fitted spreads[(a)]




(continued overleaf)

## Chart 2 (continued) –
## Individual countries' actual and fitted spreads[(a)]




Notes: (a) Fitted values obtained using the estimates of the common long-run parameters from Model (A) in Table 4 and country-specific intercept terms. For Croatia and Lebanon the country-specific error correction coefficients and the intercept terms are statistically insignificant and, for the purpose of these forecasts, they have been replaced by the coefficients from the pooled model, which are unbiased estimators of the country-specific coefficients for large number of cross-sections.

**Chart 3 –**
**Average market and fitted spreads[(a)]**

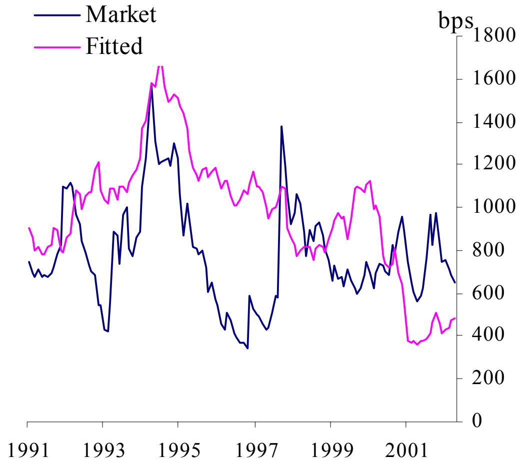
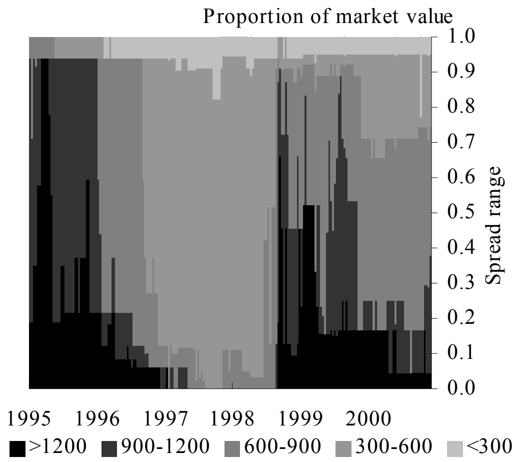



**Chart 4 –**
**Dispersion of EMBI spreads 1995-2001**




Notes: (a) Calculated as averages of country-specific fitted and EMBI/EMBIG market spreads, weighted using the rolling end-of-month country weights in the EMBIG index.

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