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What drives credit risk in emerging markets? The roles of country fundamentals and market co-movements

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Abstract

This paper uses bond prices to investigate how the creditworthiness of Argentina, Brazil, Mexico and Venezuela is influenced by global, regional and country-specific factors. Each country's distance-to-default is estimated monthly for 1994–2001, by fitting the structural model of Cathcart and El-Jahel [Cathcart, L., El-Jahel, L., 2003. Semi-analytical pricing of defaultable bonds in a signalling jump-default model. The Journal of Computational Finance 6, 91–108] with a Kalman Filter to Brady bonds. A small set of variables is able to explain up to 80% of the variance of the estimated distance-to-default for each country. Surprisingly, country-specific variables account for only about 8% of the explained variance; the largest part of the variance (45%) is explained by regional factors, which relate to joint stock-market returns, volatility and market sentiment; global conditions, related mainly to US stock-market returns, explain another 25% of the variance. Of the 20% variance which remains unexplained, more than half is due to another common (but unidentified) factor. The conclusion is that the creditworthiness of these four emerging markets is driven mainly by a common set of factors, which are related closely to stock markets in the region and the United States.

JEL classification: G15; F34

Keywords: Credit risk; Emerging markets; Distance-to-default; Brady bond; Contagion; Structural model

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1. Introduction

Credit spreads are usually seen as a measure of the creditworthiness of bond issuers. Looking at their determinants, Collin-Dufresne et al. (2001) show that changes in credit spreads on corporate bonds cannot be explained by changes in the expected default risk of the firm; other identifiable variables, such as interest rates, also explain little of the variation. Most of the risk is systematic and cannot be diversified away.

Within the literature on sovereign debt, a number of relatively recent papers have explored the determinants of credit spreads. Macroeconomic variables, such as GDP growth, inflation and US Treasury yields, are found to be important. However, Kamin and von Kleist (1999), Eichengreen and Mody (1998) and Cantor and Packer (1996) have pointed out that it is not only country-specific fundamentals and external factors which drive fluctuations in sovereign spreads of emerging markets, but that "market sentiment" may also be important.

This paper uses a measure of creditworthiness which is implicit in the market prices of sovereign debt, namely the distance-to-default. We are interested in discovering whether variations in the distance-to-default can be attributed to changes in common factors across countries (possibly reflecting contagion effects) rather than to country-specific factors.

Trying to identify the content of the distance-to-default as a measure of creditworthiness of the country offers two main advantages over trying to explain credit spreads directly. Firstly, such a measure is like a Credit Rating Index in continuous time.[1] By extracting this measure from a credit-risk model, we are isolating default risk from other factors that usually affect credit spreads, such as time to maturity, coupons, and amortization schedules. Secondly, there is a potential application of such a measure within structural models (see, for example, Hull and White, 2001; Avellaneda and Zhou, 2001). Following the same idea from reduced-form models, where the correlation between issuers is imposed by correlating their hazard rates, in the case of structural models the relationship between issuers may be modelled by correlating their distances-to-default.

Understanding the variables that determine the dynamics of countries' creditworthiness is important for financial institutions. Furthermore, the analysis of the joint behaviour of sovereign credit risk and the mechanisms of contagion and default are vital for bond pricing, portfolio valuation, risk management and the regulation of financial institutions.

We use monthly prices for the Brady bonds of Argentina, Brazil, Mexico and Venezuela, during the period April 1994 to October 2001. The advantage of using Brady bonds is that they are highly liquid instruments. In addition, Brady bonds are partially collateralised and the collateral can be considered as a proxy for the recovery rate. We use an extended structural model suggested by Cathcart and El-Jahel (2003) and estimate it with a Kalman Filter to obtain the distance-to-default. The only other empirical test of this model is in a companion paper (Diaz Weigel and Gemmill, 2003) which focuses on methodological issues and uses the bonds of one nation (Mexico); here we are more interested in the economic factors which determine creditworthiness across four nations. An additional attractive feature of this study is that most

[1] This approach is discussed by Claessens and Pennacchi (1996), Cumby and Evans (1995), and Anderson and Renault (1999). They treat creditworthiness as an unobservable variable that follows a specific stochastic process. KMV Corporation (which is now part of Moody's) has also developed a creditworthiness variable ("the expected distance-to-default") based on a firm's equity-market prices.

of the literature on testing pricing models has been developed around investment-grade corporate bonds, rather than around sovereign bonds which have a lower rating.

The methodology of implementing the model and obtaining the distance-to-default consists of two steps. In the first stage, following Duffee (1999) and Keswani (2005), we estimate the parameters of the risk-free term structure. In the second stage we estimate the risky parameters, including those of the signalling (latent) variable, using a Kalman Filter. A transformation of this variable may be interpreted as the distance-to-default. Having extracted the distance-to-default implied by bond prices for each nation, we then investigate its economic determinants. Global factors, such as the US stock market and common shocks transmitted jointly via all four stock markets together, are the most important variables for all of the countries. Country-specific variables, such as reserves and stock-market returns, are also significant but much less important. We also test the significance of a sentiment variable towards emerging markets. According to the literature (see, for example, De Long et al., 1990), investors who trade on sentiment may have a systematic impact. We construct an index from the discounts of closed-end country funds that invest in Latin American markets, in order to proxy the sentiment of foreign investors. We find that this variable is significant and important for Argentina, Brazil and Mexico, but not for Venezuela.

Finally, we run a principal components analysis on the residuals of the above regressions and find that the first component captures approximately 60% of the residual variance. This indicates that, although important co-movements in the bond markets are the result of contagion via stock markets, there is still some co-movement which has to do with the bond market only.

The paper is organised as follows. Section 2 reviews the existing literature on the empirical determinants of credit risk. Section 3 introduces an extended structural model proposed by Cathcart and El-Jahel (2003) to price risky zero-coupon bonds, and a pricing model for Par Brady bonds. In Section 4 we present the data. The methodology and results of the estimated model are presented in Section 5. In Section 6 we analyse the variables that affect the distance-to-default. In Section 7 we present the results of estimating regression equations that explain the variations of the distance-to-default by using OLS. We also investigate the information contained in the residuals of these regressions. Section 8 gives the conclusions.

2. Literature review

There is a growing literature which investigates the determinants of credit spreads on both corporate bonds and sovereign bonds. In an empirical paper using a regression model, Collin-Dufresne et al. (2001) find that the variables predicted to be relevant by structural models, such as leverage ratio, interest rate, volatility and economic environment, explain less than 25% of the changes in credit spreads on corporate bonds. Most importantly, using principal components on the residuals of those regressions they find that there is an unobserved common factor that explains most of the residual variance. However, they are unable to find any economic meaning for such a common factor. Elton et al. (2001) also find that default risk explains only around 25% of corporate bond spreads. Other factors such as tax effects and a risk premium play an important role. They conclude that most of the risk in corporate bonds is systematic and cannot be diversified away.

Turning to sovereign bonds, Cantor and Packer (1996) conclude that per capita income, GDP growth, inflation and external debt are significant determinants of credit spreads for developed and developing countries. Kamin and von Kleist (1999), Eichengreen and Mody (1998) and Cantor and Packer (1996) argue that it is not only country-specific fundamentals which drive fluctuations in emerging-market sovereign spreads, but also changes in market sentiment. For example, Eichengreen and Mody (1998) find that changes in spreads are mainly due to shifts in market sentiment rather than in fundamentals.

In an extensive analysis, using spreads from 26 sovereign bonds, Westphalen (2001) finds that variables that are supposed to explain credit risk (according to structural models), explain no more than 20% of total variance. Some of the variables that he investigates are the spot interest rate, the slope of the term structure and the ratio of debt-service to exports. Using principal components, he concludes that there is a systematic factor explaining a significant part of the residual variance (67%). McGuire and Schrijvers (2003) start by finding that a common factor explains about one-third of daily changes in spreads for bonds from 15 emerging markets. This factor is related negatively to US interest rates and US stock-market volatility, but positively to the level of the US stock market. They suggest that "the common variation in emerging-market debt spreads is largely explained by changes in attitudes towards risk within the international investment community" (McGuire and Schrijvers, 2003, p. 77).

3. The model

We need a model in order to take bond prices and use them to reveal distance-to-default, our measure of creditworthiness. In the literature there are two approaches to modelling risky debt. The first is the structural approach, which has its origins in Merton (1974) (and has been extended in other directions by Black and Cox, 1976; Leland, 1994; Longstaff and Schwartz, 1995; Collin-Dufresne and Goldstein, 2001 among others). Within this framework default is defined as the first time a solvency variable (the firm's asset value) hits a particular barrier. This approach is conceptually appealing because it provides some insights into the default process of the firm in terms of firm-specific variables. However, an important drawback is that these models seem unable to produce the right size of credit spread close to maturity. One reason may be that the market value of the firm has been modelled as a diffusion process, and therefore as maturity approaches the probability of an unexpected default goes to zero and the spread also goes to zero (see Collin-Dufresne et al., 2003). Another potential reason may be that the liquidity of bonds declines near to maturity, thus imposing large transactions costs (see Ericsson and Renault, in press).

The second approach to valuing risky debt, the reduced-form approach, was introduced by Jarrow and Turnbull (1995). This assumes that default occurs by surprise, as the first jump of a Cox process (see also Duffee, 1999; Duffie and Singleton, 1999; Duffie et al., 2003). This approach is less intuitive than structural models, since default is driven by an exogenous variable; however, reduced-form models are mathematically more tractable and can be calibrated to credit spreads quite easily.

We are going to use a structural model, but which also incorporates a potential jump-to-default (hazard-rate variable) as found in reduced-form models. The result of this estimation is a distance-to-default, expressed as the implied size of a creditworthiness variable relative to a barrier. Our distance-to-default is conceptually equivalent to that used by the KMV subsidiary of Moody's Corporation. The KMV methodology is proprietary and therefore not fully documented, but the general principles are described in Crosbie and Bohn (2003) and Lando (2004) and reviewed critically by Bharath and Shumway (2004).[2] To the best of our knowledge,

[2] Efforts to test the performance of the model in predicting the expected default frequency for companies include Bohn (2005) and Aguais et al. (2004).

there has been no previous study which has estimated the distance-to-default with a structural model for sovereign borrowers, with the exception of Keswani (2005) who focuses on the forecasting performance of structural and reduced-form models for Brady bond prices. Claessens and Pennacchi (1996) and Cumby and Evans (1995) also have some structural features. In the KMV approach the distance-to-default is transformed into an expected default frequency, but we prefer to report the distance-to-default because the character of that transformation is not obvious and we know that distance-to-default and expected default frequency are monotonically related.

3.1. An extended structural model of a risky zero-coupon bond

We implement the structural model proposed by Cathcart and El-Jahel (2003), which is an extension of Longstaff and Schwartz (1995). Apart from structural features, Cathcart and El-Jahel (CEJ) introduce a reduced-form feature: a stochastic hazard rate of default, which is a linear function of the spot interest rate. Thus default can occur smoothly (expectedly) when a signalling variable falls below a specific threshold, or suddenly (unexpectedly) when a jump in the risk-free interest rate occurs. The assumptions of the model are the following:

Assumption 1: Markets are frictionless and trading is carried out in continuous time. There are no taxes, transaction costs or informational asymmetries.

Assumption 2: The risk-adjusted dynamics of the short-term interest rate follow a Cox et al. (1985) process:

$$\mathrm{d}r_t = \kappa_r(\mu_r - r_t)\mathrm{d}t + \sigma_r\sqrt{r_t}\mathrm{d}Z_r \tag{1}$$

where μ_r is the long-term mean of the interest rate, κ_r is the speed of adjustment of r_t towards the mean, σ_r is the volatility and Z_r is a standard Wiener process.

Assumption 3: Following the structural approach, there is a "signalling variable", x_t, which summarises the set of factors that determine the creditworthiness of the country. Under the risk-neutral measure this variable follows a Geometric Brownian Motion:

$$\mathrm{d}x_t = \alpha_x x_t \mathrm{d}t + \sigma_x x_t \mathrm{d}Z_x \tag{2}$$

where α_x and σ_x are constants and Z_x is a standard Wiener process. Thus default occurs at the first time the signalling variable x_t hits a constant barrier x_ℓ.

Assumption 4: In line with reduced-form models, default can also occur unexpectedly as a jump event. The hazard rate is a linear function of the short-term interest rate: $h_t = a_r + b_r r_t$, where a_r and b_r are positive constants.

Assumption 5: If, during the life of the security, either the signalling variable hits the barrier x_ℓ, or a default jump occurs, then the bondholder receives a proportion δ of the bond face value, where δ is the recovery rate.

In addition, the correlation between the signalling process and the interest rate is assumed to be zero.[3] In other words, the instantaneous correlation between Z_x and Z_r is zero.

Under the above assumptions, CEJ proves that the price of a risky discount bond may be expressed as:

$$H(x_t, r_t, \tau) = P_t(r_t, \tau) - P_t(r_t, \tau)(1 - f(x_t, \tau)g(r_t, \tau))(1 - \delta) \tag{3}$$

where

$$f(x_t, \tau) = \Phi\left(\frac{y + \left(\alpha_x - \frac{1}{2}\sigma_x^2\right)\tau}{\sigma_x\sqrt{\tau}}\right) - \exp\left(\frac{-2\left(\alpha_x - \frac{1}{2}\sigma_x^2\right)y}{\sigma_x^2}\right)\Phi\left(\frac{-y + \left(\alpha_x - \frac{1}{2}\sigma_x^2\right)\tau}{\sigma_x\sqrt{\tau}}\right) \tag{4}$$

$$y = \ln(x_t / x_\ell) \tag{5}$$

$$g(r_t, \tau) = \exp(C(\tau) + D(\tau)r_t) \tag{6}$$

and $C(\tau)$ and $D(\tau)$ are solutions to the following system of ordinary differential equations:

$$\frac{1}{2}\sigma_r^2 D(\tau)^2 + \left(\sigma_r^2 \widetilde{B}(\tau) - \kappa_r\right)D(\tau) - D_\tau(\tau) - b_r = 0 \tag{7}$$

$$\kappa_r \mu_r D(\tau) - C_\tau(\tau) - a_r = 0$$

subject to the initial conditions $C(0) = 0$ and $D(0) = 0$.[4]

The function $1 - f(x_t, \tau)g(r_t, \tau)$ can be interpreted as the probability of default due either to the signalling process x_t hitting the default barrier x_ℓ, or to an unexpected jump in the interest rate r_t. Hence the survival probability, i.e. the probability at t that no default has occurred prior to $\tau(\tau > t)$, can be expressed as follows:

$$1 - \gamma_t(\tau) = f(x_t, \tau)g(r_t, \tau) \tag{8}$$

The key feature of the model is that a simple transformation of the signalling variable x_t can be defined as the distance-to-default and can be interpreted as a measure of creditworthiness of the country. Let $y(t) = \ln(x_t / x_\ell)$ denote the risk-neutral distance-to-default process. Using Itô's lemma and Eq. (2), the risk-neutral distance-to-default satisfies the following diffusion equation:

$$\mathrm{d}y_t = \alpha_Y \mathrm{d}t + \sigma_Y \mathrm{d}Z_Y \tag{9}$$

where

$$\alpha_Y = \left(\alpha_X - \frac{\sigma_X^2}{2}\right) \text{ and } \sigma_Y = \sigma_X \tag{10}$$

We can think of this variable as a function of the asset value in the case of a firm (see Avellaneda and Zhou, 2001; Hull and White, 2001), or in the case of a country as any combination of economic fundamentals that determines the probability of default. Another perspective is

[3] This assumption facilitates the numerical solution of the model.

[4] $\widetilde{B}(\tau) = 2(\exp(\phi_1\tau) - 1)/\phi_4$ as defined in the CIR model for the risk-free term structure (see Appendix A).

that this measure can be seen as a credit rating in continuous time (consistent with the KMV methodology).

3.2. The pricing of a Par Brady bond

In this section we discuss how the CEJ model for a risky zero-coupon bond can be applied to Brady bonds. Brady bonds are dollar-denominated coupon bonds which are partially collateralised by highly-rated instruments and were issued by several emerging countries at the beginning of the 1990s under the Brady Plan.[5] There are two features of these bonds that facilitate the empirical implementation of a pricing model: firstly, Brady bonds are highly liquid instruments; secondly, the collateral of Brady bonds can be used as a proxy for the recovery rate. The price of a Brady bond B_t can be seen as the sum of three components, according to the following equation:

$$B_t = FP_t(r_t,\tau) + CF\sum_{i=1}^{q} P_t(r_t,\tau_i) + CF\sum_{i=q+1}^{N}(1-\gamma_t(\tau_i-n))P_t(r_t,\tau_i) \qquad (11)$$

where F is the face value of the bond, C is the coupon rate, $P_t(r_t,\tau_i)$ is the price of a default free zero-coupon bond at time t that matures at time τ_i, q is the number of guaranteed coupons, and $1-\gamma_t(\tau)$ is the survival probability.

The first term of the above equation corresponds to the present value of the face value F with maturity τ. The principal is fully guaranteed; therefore it is discounted at the risk-free rate. The second component accounts for the present value of q guaranteed coupons, each with maturity τ_i. The third term corresponds to the value of the risky coupons, so it takes account of the probability of default $\gamma_t(\tau)$. If n is the length of the rolling interest guarantee, then each coupon with maturity τ_i is paid if and only if default has not occurred before $\tau_i - n$. Note that we assume that the recovery rate is zero for any other cash flows not included in the rollover guarantee. Finally, in order to incorporate the CEJ model within the Brady pricing formula, we only need to substitute the survival probability $1-\gamma_t(\tau)$ of Eq. (11) by $f(x_t,\tau)g(r_t,\tau)$ from the model's Eq. (8).

4. Data

We use end-of-month market prices of Par Brady bonds from Argentina, Brazil, Mexico, and Venezuela reported by Bloomberg and Datastream, during the period April 1994 to October 2001. The characteristics of the four countries' bonds are displayed in Table 1. All the bonds were issued with an initial maturity of 20 years and with semi-annual payments. In the case of Argentina and Brazil, the bonds were issued with initial coupon of 4%, but this rose in steps over time to reach 6% in the seventh year. For Mexico and Venezuela, the rate of the coupon is 6.25% and 6.75%, respectively, for the whole life of the instruments. The principal of all the bonds is guaranteed by a Treasury zero-coupon bond, and rolling coupons up to 18 months are also guaranteed.

Fig. 1 shows the Brady prices of the four countries over the sample period. The effects of several crises can easily be observed. The end of 1994 and the first quarter of 1995 show a price

[5] The purpose of this plan was to reduce the sovereign debt in emerging countries.

Table 1
Characteristics of Par Brady bonds

Country	Issue date	Principal amount (US Bln)	Semi-annual coupon	Final maturity	Collateral/interest guarantees[b]
Argentina	Apr 1993	14.9	Step-up[a]	Apr 2023	Z-C/12 months
Brazil	Apr 1994	8.4	Step-up[a]	Apr 2024	Z-C/12 months
Mexico	Mar 1990	22.6	6.25%	Dec 2019	Z-C/18 months
Venezuela	Dec 1990	6.7	6.75%	Mar 2020	Z-C/14 months

[a] In the case of Argentina and Brazil the first coupon is 4% but this increases periodically up to 6% in year seven.
[b] Z-C means that the principal is collateralised by zero-coupon US Treasury bonds.

fall which was due to the Mexican peso devaluation. Another dramatic fall occurs around August 1998, when Russia fell into default. Although for most of the time prices for the four countries remain very close to each other, the gap between them widens at the end of the period.

Table 2 gives descriptive statistics of the monthly bond prices and returns over the sample period. Panel A indicates that the first-order autocorrelation parameter is quite high for all of the bonds, showing that prices may be non-stationary. An augmented Dickey–Fuller test indicates that we cannot reject the presence of a unit root in any of the cases. Therefore, it makes more sense to analyse returns rather than prices. Panel B shows that the means and standard deviations of returns are similar for all of the countries. Returns are slightly negatively skewed and leptokurtic (kurtosis exceeds 3) in all of the cases. The matrix of cross-correlations in Panel C shows how closely returns move together: the correlation coefficients vary between 0.66 and 0.76. Looking at Fig. 1, this common behaviour is more noticeable before the Russian crisis of August 1998 than after it. Such differences are more dramatic at the end of the sample, where the Argentinean default is approaching and the Mexican bond shows particular strength.

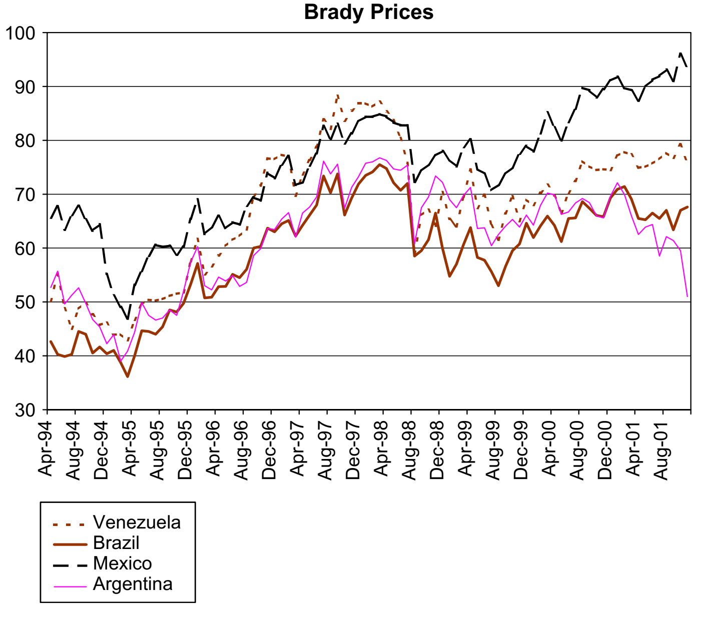

Fig. 1. Market prices of Brady bonds.

Table 2
Summary statistics of monthly Brady prices and their returns

	Mean	Std dev	Minimum	Maximum	Skewness	Kurtosis	Autocorrelation
Panel A: Prices							
Argentina	62.067	9.684	39.000	76.750	−0.522	2.313	0.931
Brazil	59.284	10.396	36.125	75.500	−0.575	2.281	0.938
Mexico	74.954	11.315	46.906	96.370	−0.340	2.421	0.942
Venezuela	67.390	12.368	42.875	88.250	−0.360	2.123	0.940
Panel B: Returns							
Argentina	0.001	0.057	−0.216	0.117	−0.832	4.532	−0.128
Brazil	0.005	0.054	−0.208	0.109	−0.910	4.738	−0.062
Mexico	0.004	0.043	−0.155	0.125	−0.901	5.337	0.020
Venezuela	0.005	0.057	−0.253	0.116	−1.102	6.384	−0.128

	Argentina	Brazil	Mexico	Venezuela
Panel C: Correlation of the returns				
Argentina	1			
Brazil	0.755	1		
Mexico	0.716	0.717	1	
Venezuela	0.701	0.662	0.673	1

Data are obtained from Bloomberg and Datastream. The sample corresponds to monthly observations of prices during the period April 1994 to October 2001. Returns are calculated as the difference of natural logs of prices. The autocorrelation coefficient corresponds to the first order serially correlated coefficient.

In order to estimate the parameters of the risk-free process implicit in the model, we use monthly Treasury and Bonds rates with maturities: 3 months, 6 months, 1, 2, 3, 5, 10, and 30 years, from Bloomberg.

5. Implementation of the model

We use a Kalman Filter to estimate the distance-to-default, which is an unobserved, latent variable, and simultaneously estimate the parameters of the model for each country. (More detail on technical procedures is given in the companion paper by Diaz Weigel and Gemmill, 2003.)

We assume that market bond prices $\boldsymbol{B}_t$ are observed with error ε_t. Thus, the relationship between the signalling variable and observed prices is

$$\boldsymbol{B}_t = B(t, r_t, y_t; \Psi, \Gamma) + \varepsilon_t \tag{12}$$

where y_t is the distance-to-default that determines the creditworthiness of the country and satisfies the dynamics of Eq. (9); Γ is the set of parameters that determines the movements of the risk-free-term structure in the CEJ model[6] and is determined by a CIR process; Ψ is the set of parameters that determines the risky parameters, i.e. those of the signalling process and of the hazard rate.[7]

[6] $\Gamma = \{\kappa_r, \mu_r, \sigma_r\}$ which is the set of parameters of a CIR process (see Appendix A).

[7] $\Psi = \{\alpha_x, \sigma_x, a_r, b_r\}$.

Table 3
Estimation results for the parameters of the CEJ model

Country	Hazard rate		Latent signalling variable	Standardised long-term drift of distance-to-default	Log likelihood function
	$a_r(\times 10^3)$	$b_r(\times 10^3)$	α_x	α_y	QML
Argentina	0.00000	0.00114	0.18709* (4.136)	−0.31291	176.42
Brazil	0.00010	0.00172	0.23020** (8.815)	−0.26980	182.73
Mexico	0.00087	0.00413	0.35632** (20.900)	−0.14368	186.88
Venezuela	0.00000	0.00003	0.27274** (14.135)	−0.22726	169.18

The figures in brackets correspond to the likelihood ratio statistics (LR) that test the significance of the parameter.
* and **mean that parameters are significant at 95% and 99% confidence levels, respectively.
a_r and b_r are the parameters of the hazard rate defined as $\lambda = a_r + b_r r_t$.
α_x is the drift of the latent variable x_t and has been estimated using the specification of the following transition equation in the Kalman Filter:

$$y_{t|t-1} = y_{t-1} + \left(\alpha_x - \frac{\sigma_x^2}{2}\right)\frac{1}{12} + \sigma_x\sqrt{1/12}\eta_t, \quad \text{where } y_t = \ln(x_t/x_\ell),$$

The critical value for the significance of α_x at 95% is $\chi^2_{95\%}(1) = 3.84$.
Variables are standardised by setting $\sigma_x \equiv 1$.
α_y is the drift of the distance-to-default, where $\alpha_y = \alpha_x - \left(\sigma_x^2/2\right)$.

The error ε_t in Eq. (12) is assumed Gaussian distributed, with mean zero and variance σ_ε. This term is also an indicator of the adequacy of the model. If the true underlying process is not that of Eq. (9), then Eq. (12) will be mis-specified and estimated prices will deviate systematically from observed prices.

Following Duffee (1999) and Keswani (2005) we implement the model using a two-stage procedure. In the first stage we estimate the parameters of the risk-free, one-factor CIR process. The estimation is done using an Extended Kalman Filter and Quasi-Maximum Likelihood. The advantage of using a Kalman Filter is that we can exploit all the information available in the term structure, across maturities and across time.[8] More detail on the estimation of the risk-free process is presented in Appendix A.

In the second stage of estimation, we use the parameters of the CIR process and estimate the risky parameters, i.e. the parameters of the signalling process and those of the hazard rate, again using an Extended Kalman Filter.[9] In addition, to calculate Brady prices according to Eq. (11), we also need the risk-free discount factors $P_t(r_t, \tau_i)$. We calculate them by fitting a cubic spline to the observed monthly yield curve.[10]

5.1. Estimation results and the distance-to-default

Estimates of the parameters of the model are given in Table 3. Variables are standardised by making $\sigma_x^2 \equiv 1$. Fig. 2 shows the observed prices against the one-step-ahead estimated values

[8] In addition a Filter allows us to obtain the implicit factor that drives the dynamics of the term structure; such a variable is usually interpreted as the short-term interest rate and determines the dynamics of the hazard rate under the CEJ model.

[9] Observe that Eq. (12) is non-linear in y_t and we should therefore apply an Extended Kalman Filter that consists of a linearising function $B(\cdot)$, based on the first-order term of a Taylor series expansion. Since it is not possible to apply a simple Kalman Filter, our estimates will be Quasi-Maximum Likelihood.

[10] Data from Bloomberg and Datastream.

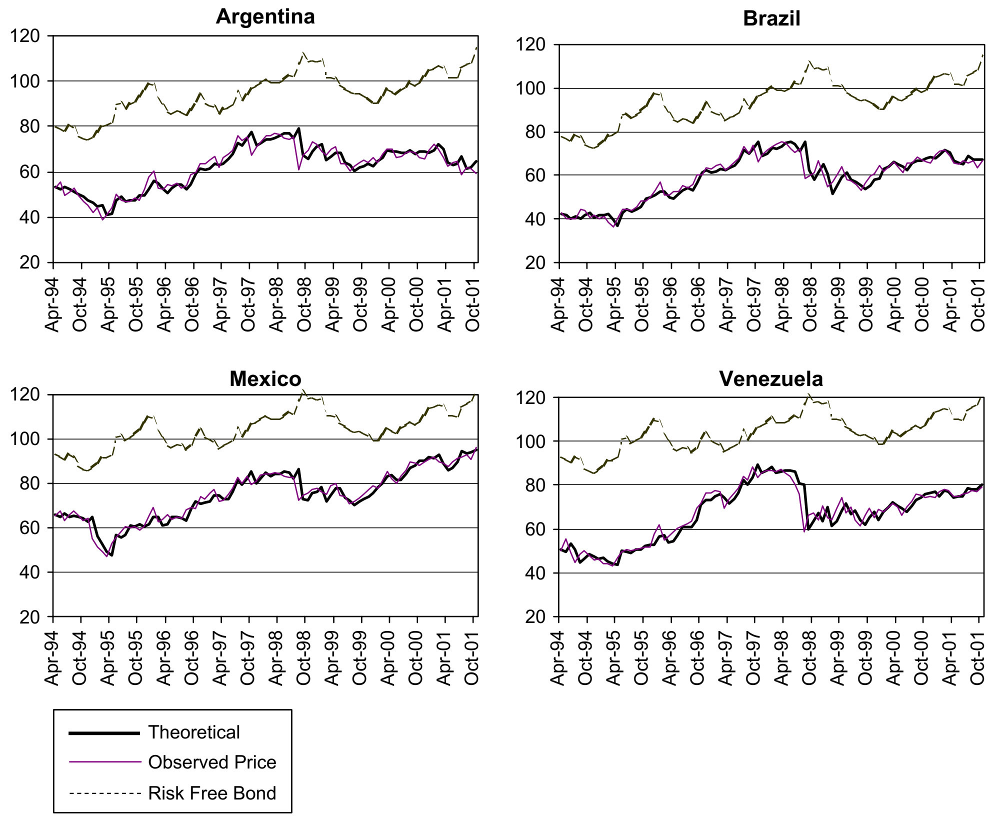

Fig. 2. Observed prices versus theoretical prices (one-step-ahead fitted values). The upper series in each plot corresponds to a theoretical risk-free bond with the same maturity and coupon as the risky bond. Prices are in dollars.

$B_{t|t-1}$, giving an idea of the performance of the model to replicate prices in-sample. The fit seems to be quite good. For comparison, the graphs also show how much higher the prices of the bonds would have been if they had been risk-free, illustrating that discounts for the extra risk on these bonds range from about 20% to 50% over this period.

There are several features to observe in Table 3. First, in all of the cases the coefficients of the hazard rate are close to zero and not significant. Therefore, in all of the cases, the reduced-form hazard-rate feature does not provide any additional information to the structural framework. Since the hazard rate is not significant, the credit-risk dynamics of the bond prices must depend only on the signalling variable and its barrier. The further the signalling variable is from the default barrier, the greater the distance-to-default and the higher the bond price. The drift parameter α_x of the signalling variable (x_t) (Table 3) is significantly positive for all four countries, with values in the range 0.18709–0.35632. This positive drift is not, however, sufficient to make the signalling variable drift upwards relative to the barrier and so increase the distance-to-default. From Eq. (10), the drift of the distance-to-default is given by $\alpha_y = \left(\alpha_x - \sigma_x^2/2\right)$ which, because σ_x^2 has been standardised to one, becomes equal to $(\alpha_x - 0.5)$: this is negative for all four countries. The negative drift of the distance-to-default means that lenders were increasingly pessimistic about the long-term future of these economies over the period of April 1994 to October 2001 and expected a slight worsening in their

Table 4
Diagnostic tests

	Normality test Jarque–Bera	Autocorrelation Q statistic ($k = 1$)	Heteroscedasticity
Argentina	391.6993 (0.000)	1.0016 (0.317)	26.9976 (0.559)
Brazil	431.5358 (0.000)	0.9265 (0.336)	30.7267 (0.385)
Mexico	204.1265 (0.000)	0.2993 (0.584)	13.2891 (0.996)
Venezuela	371.0545 (0.000)	0.2213 (0.638)	22.0513 (0.852)

p-Values are shown in brackets.
The standard residuals are defined as: $\tilde{v}_t = v_t/\sqrt{f_t}$, where $v_t = \boldsymbol{B}_t - B_{t|t-1}$.
For the description of the heteroscedasticity test see Harvey (p. 259).

creditworthiness. The most negative drift arises for Argentina (−0.31) and the least negative for Mexico (−0.14), as might be expected.

Table 4 shows the diagnostic tests for each country; these are carried out using the standardised one-step-ahead residuals defined as follows, according to Harvey (1989):

$$\tilde{v}_t = v_t/\sqrt{f_t}, \quad \text{where } v_t = \boldsymbol{B}_t - B_{t|t-1} \text{ and } f_t = \mathrm{var}(v_t) \tag{13}$$

Though there is a lack of normality for all of the countries' standardised residuals (according to the Jarque–Bera test), there is no evidence of autocorrelation or heteroscedasticity. Therefore, the models are not mis-specified.

Fig. 3 plots the one-step-ahead residuals from the model for each country. It shows no evident systematic behaviour, but does suggest that some important events are not captured fully:

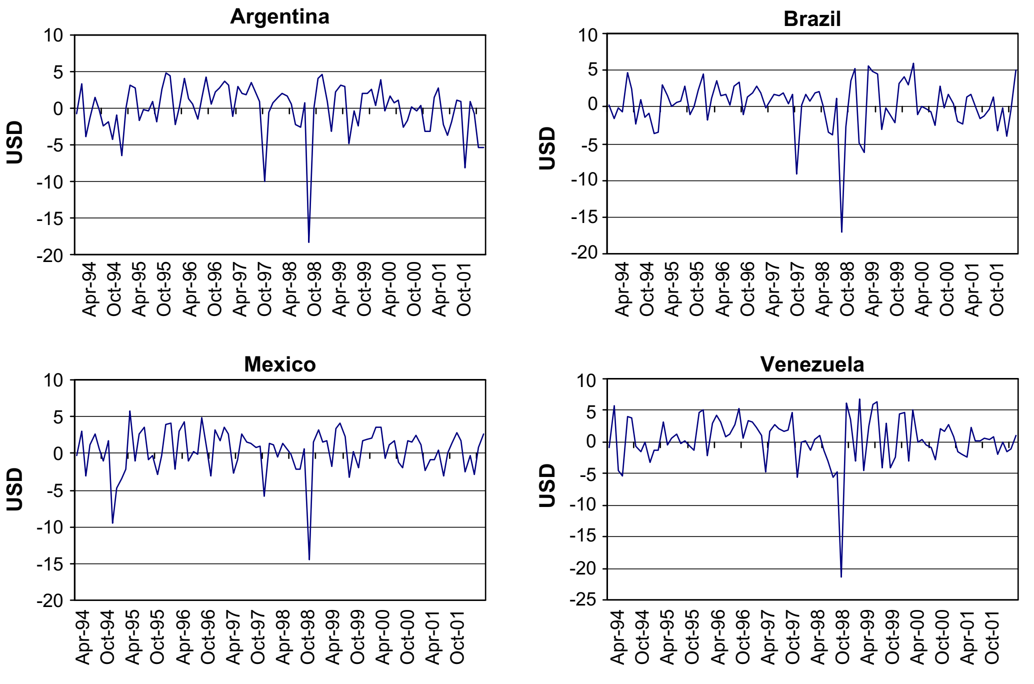

Fig. 3. One-step-ahead residuals, $v_t = \boldsymbol{B}_t - B_{t|t-1}$.

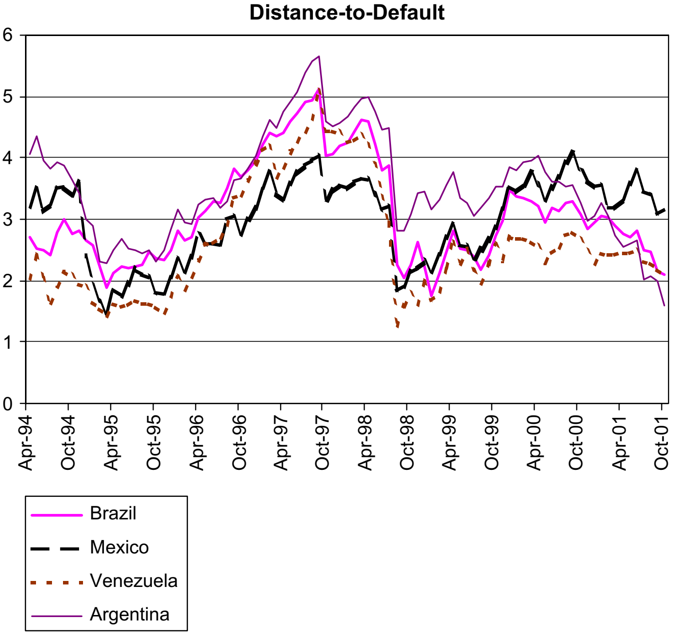

Fig. 4. The distance-to-default implied by the CEJ model.

the Mexican crisis at the end of 1994 is visible as a downward spike for Mexico and slightly for Argentina, but has little impact on Brazil and Venezuela; across all four nations, there is a small spike at the time of the Asian crisis in October 1997 and a much larger one at the time of the Russian devaluation in August 1998.

Because the distance-to-default has been estimated as the logarithm of the ratio of the signalling variable x_t to its barrier x_ℓ, it is a standardised variable and can be compared across countries. This is done in Fig. 4. The estimated distance-to-default of the Argentinean bond is consistently greater than those of the other countries until the year 2000, when it starts to plunge and finishes in October 2001 below the other three countries. This high credit rating of Argentina may be attributable to the peg of its currency with the dollar, giving the image of a very strong economy. In contrast, the Venezuelan distance-to-default is systematically smaller than those of the other countries, apart from the period between the third quarter of 1996 and the Russian crisis of 1998. The distances-to-default of the four nations show a large degree of common movement, rising after the Mexican crisis and plunging after the Russian crisis. We will explore the reasons for these movements later in this paper.

In order to have an idea of the performance of the distance-to-default as a measure of creditworthiness, we compare it with a Credit Rating Index based on the ratings issued by Standard and Poor's and Moody's. The ratings produced by those two agencies[11] have been converted into numerical indices that go from 1 to 22, where 1 represents the worst credit rating and 22 the best one. The Credit Rating Index is calculated as a simple average of those two numerical indices: the larger the index, the higher the credit rating of the country.

[11] We use the credit ratings assigned to the long-term debt issued by each country.

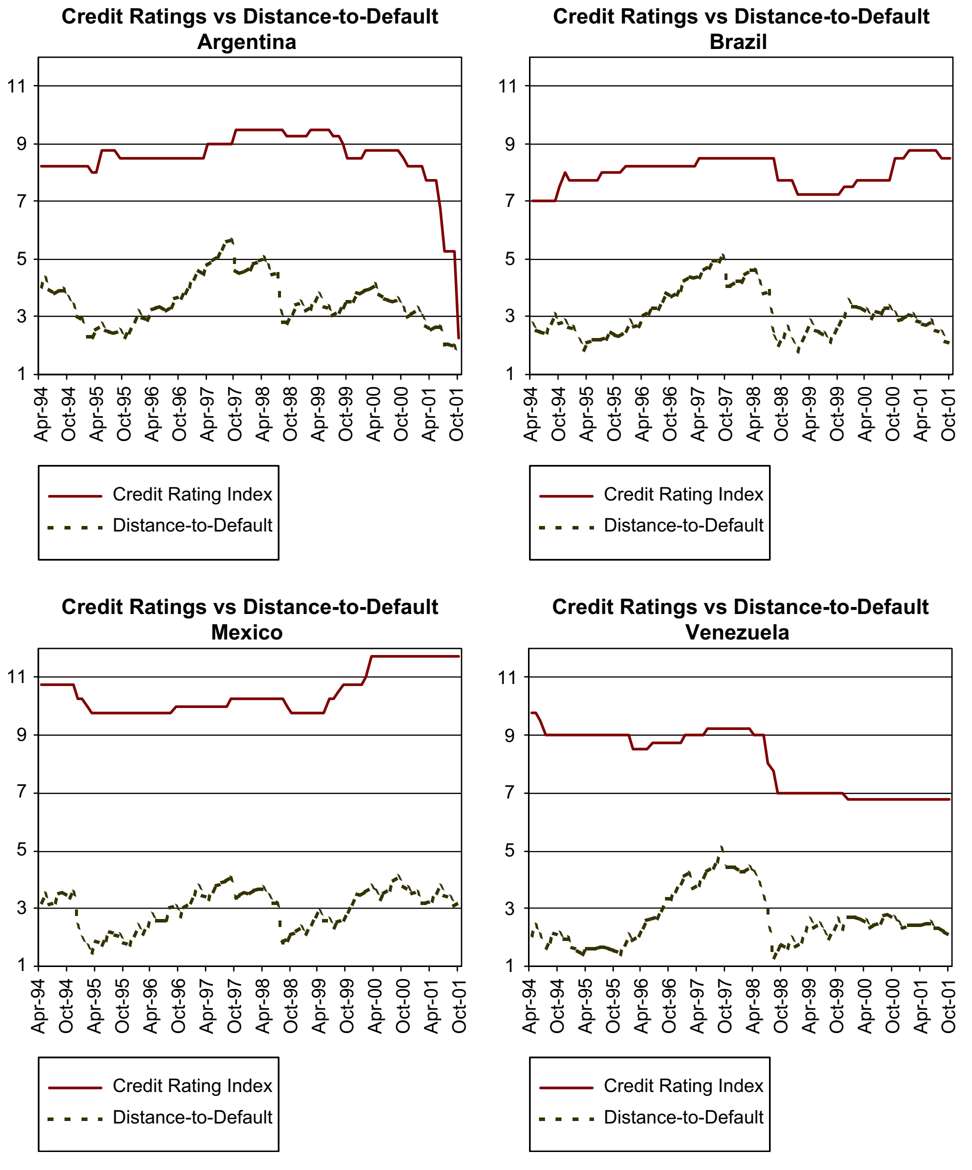

Fig. 5. Credit Rating Index versus the distance-to-default. The original categorical credit ratings from Standard and Poor's and Moody's have been transformed into a numerical scale and averaged in order to produce a Credit Rating Index. The larger the index the higher the credit quality of the country.

Fig. 5 compares the Credit Rating Index and the distance-to-default for each country. We can observe a fairly similar trend between the credit rating indices and the distances-to-default. After the Mexican crisis and before the Russian crisis, credit ratings predict a modest and joint recovery for the four economies. The recovery in this period is more marked when measured by the distance-to-default. After the Russian crisis all of the countries suffer a downgrading, according to both measures.[12] The country most affected by a downgrading from rating agencies is Venezuela, which is consistent with the dramatic fall in its distance-to-default.

Observe that whereas the distance-to-default for all of the countries registers a slight fall in October 1997 due to the Asian crisis, credit ratings remain stable. This suggests that the distance-to-default leads the credit ratings. On the other hand, the deterioration of Argentina is anticipated very much in advance by the rating agencies: the rating index starts falling early in 1999, whereas such deterioration is actually perceived by the market, according to the distance-to-default, only in 2000. Other inconsistencies between the two variables can be seen from the plots, but a fully comprehensive analysis of ratings versus distance-to-default is beyond the scope of this paper and left for further research.

5.2. Descriptive statistics and co-movements of the distance-to-default

Table 5 gives the descriptive statistics of the distance-to-default for all four countries over the sample period. The series in levels have been modelled as non-stationary processes, which is confirmed by their autocorrelation coefficients in Panel A (being close to unity). Looking at the first differences of the distance-to-default in Panel B, the statistics look very similar across all four countries. All four series exhibit means close to zero, small standard deviations, negative skewness and high kurtosis. Panel C displays the correlation coefficients of changes in the distance-to-default across countries: the coefficients range from 0.704 to 0.845, indicating a very high level of co-movement.

A more accurate description of the co-movements of the distance-to-default can be found by using principal component analysis (PCA), which decomposes them into orthogonal factors. Panel D in Table 5 shows that the eigenvalue of the first component is 3.289, meaning that one common factor is able to capture 82% of the total variance.[13] The coefficients of the first normalised eigenvector in Panel E indicate that this first component is a systematic factor, which affects the four indices of creditworthiness similarly (in terms of impact and direction). These results suggest that it should be possible to attribute most of the dynamics of the distance-to-default to common factors rather than to country-specific factors. We explore this subject further in the following section.

6. The theoretical determinants of the distance-to-default

In this section we discuss the economic variables that may be relevant to explaining movements in the distance-to-default.[14] They are introduced in three subsections, in which we justify their importance. The first set corresponds to global macroeconomic variables, such as the shape of the US Treasury curve and returns on the US stock market. The second set consists of factors which are common to all four nations, such as investor sentiment and the joint components of stock-market returns and volatility. The third set consists of country-specific factors, such as the domestic inflation rate and the level of reserves.[15]

[12] The fact that countries suffered a downgrading after Russia defaulted shows that credit rating failed to anticipate the Russian crisis. Some studies find evidence that credit ratings are backward-looking measures instead of forward-looking (see Kaminsky and Schmukler, 2002).

[13] The variables are standardised, so the sum of the eigenvalues should add to four.

[14] A table with descriptive statistics for the variables is available on request.

[15] All data are on a monthly basis from April 1994 to October 2001. The data were taken from several sources including Datastream, Bloomberg, the Central Bank of each country, the US Federal Reserve System and the US Treasury Department.

Table 5
Summary statistics of the distance-to-default

	Mean	Std dev	Minimum	Maximum	Skewness	Kurtosis	Autocorrelation
Panel A: Levels							
Argentina	3.518	0.871	1.596	5.644	0.335	2.648	0.910
Brazil	3.094	0.826	1.743	5.116	0.698	2.485	0.927
Mexico	2.989	0.678	1.462	4.067	−0.483	2.008	0.903
Venezuela	2.632	0.944	1.246	5.087	0.833	2.611	0.945
Panel B: Differences							
Argentina	−0.028	0.301	−1.675	0.341	−2.354	12.450	0.106
Brazil	−0.007	0.296	−1.625	0.525	−2.285	12.694	0.100
Mexico	0.000	0.297	−1.378	0.429	−1.949	9.125	0.060
Venezuela	0.001	0.300	−1.695	0.480	−2.089	12.644	0.054

	Argentina	Brazil	Mexico	Venezuela
Panel C: Correlations of the differences of the distance-to-default				
Argentina	1			
Brazil	0.845	1		
Mexico	0.766	0.747	1	
Venezuela	0.768	0.744	0.704	1

	Comp 1	Comp 2	Comp 3	Comp 4
Panel D: Loadings of the PCA of the variations of the distance-to-default				
Eigenvalue	3.289	0.296	0.263	0.152
Variance prop.	0.822	0.074	0.066	0.038
Cumulative prop.	0.822	0.896	0.962	1.000

Variable	Vector 1	Vector 2	Vector 3	Vector 4
Panel E: Eigenvectors				
Argentina	0.515	0.007	−0.382	0.768
Brazil	0.508	−0.027	−0.585	−0.632
Mexico	0.488	−0.696	0.523	−0.061
Venezuela	0.488	0.717	0.489	−0.091

The distance-to-default had been estimated by fitting the CEJ model in the period April 1994 to October 2001.

6.1. Global factors

The importance of global factors in the development of Latin American countries, in particular the role of US interest rates and US stock returns, has been widely discussed in the literature on capital flows (see, for example, Chuhan et al., 1998; Calvo et al., 1993). Here we will consider the following variables:

1) *Interest rates*. Regarding the effect of interest rates on default, the literature on sovereign bonds is rather different from that on corporate bonds. For sovereign bonds the main argument has been that higher interest rates increase debt-service burdens, decreasing the ability to pay and therefore increasing the possibility of default. Cline and Barnes (1997), in a study of 11 emerging markets, find a positive though insignificant effect of treasury rates on credit spreads during the mid-1990s. Kamin and von Kleist (1999) find no statistically significant

relationship between those variables, but Westphalen (2001) finds a negative and mostly significant effect for a sample of 215 sovereign bonds across four continents. Eichengreen and Mody (1998) find that when the US treasury rates increase, only countries with good credit ratings are able to make new issues and this reduces the average spread.

For corporate bonds the evidence is rather clear that credit spreads fall when interest rates rise (Longstaff and Schwartz, 1995; Duffee, 1998, 1999; Collin-Dufresne et al., 2001). The reason for a negative relationship is that an increase in the level of the risk-free rate implies a higher drift on the value of the firm's assets, so the incidence of default is reduced and consequently the size of credit spreads falls. This argument could also hold for sovereign bonds, if an increase in rates signals a recovery in the world economy (Gibson and Sundaresan, 2001). In theory the slope of the yield curve should also have an impact, if greater slope predicts an increase in rates. Duffee (1998) confirms this, but Collin-Dufresne et al. (2001) do not.

In our study, we extract the first two principal components of the yield curve and use them as independent variables to represent the level and slope of the yield curve, respectively.[16] We hypothesise that, on balance, both the level and the slope will have a positive impact on the distance-to-default.

2) *S&P500 returns*. Several papers have argued that globalisation has increased the dependence of emerging markets on industrial countries. In particular, world economic conditions are likely to affect the creditworthiness of countries. The importance of stock returns on credit spreads at the aggregate level has been discussed extensively in the literature (see, for example, Campbell and Ammer, 1993; Fama and French, 1993). We consider the US stock index (S&P500) as a proxy for global economic performance and hypothesise that it will have a positive impact on the distance-to-default.
3) *Oil prices*. Oil products constitute an important part of the exports of Venezuela and Mexico. Hence oil prices significantly affect the budget deficits of those countries: the higher the price, the higher the revenues and consequently the greater the distance-to-default. The price considered here is that of Brent Crude.

6.2. Common (Regional) factors

1) *Regional stock-market returns*. We find that (dollar-value) returns on the stock markets of the four nations move together quite closely: the first principal component explains 64% of the total variance. We use this first component, purged of US influences,[17] as our measure of regional returns.
2) *Regional stock-market volatility*. We use the same approach for volatility as just explained for stock-market returns. We find that, for the four nations together, the first principal

[16] Recall that in the Cathcart and El-Jahel model the yield curve is a one-factor CIR process. Its estimation using a Kalman Filter generates a latent variable that drives the term structure and is identified as the short-term spot rate. We find that variations of this latent variable are highly correlated with the first principal component of the term structure (the correlation coefficient is equal to 0.975).

[17] A regression shows that nearly half (48%) of the regional returns (first principal component) can be explained by US stock-market returns and changes in the level and slope of the US yield curve. We therefore take the residuals from that regression as our "orthogonalised" measure of regional stock-market returns.

component of volatility can explain 52% of its variance. We use this component as our measure of regional volatility.

3) *Regional investor sentiment*. Several authors have pointed out that, in addition to country-specific fundamentals, changes in market sentiment can be important in driving fluctuations of credit spreads on emerging-market debt (see, for example, Cantor and Packer, 1996; Eichengreen and Mody, 1998; Kamin and von Kleist, 1999). Eichengreen and Mody (1998) argue that some participants in the bond market do not discriminate in an informed way amongst borrowers. Since information is costly, investors value bonds using incomplete information about fundamentals, leading to herding behaviour under some circumstances. The discount on closed-end funds[18] has often been cited in the literature as a measure of investor sentiment. We construct an index of sentiment towards these countries, using data from three UK closed-end country funds that invest in Latin American shares.[19] We hypothesise that an increase in the regional discount is a signal of deterioration in perceived creditworthiness and will reduce the distance-to-default for each nation.

6.3. Country-specific factors

1) *Country-specific stock-market returns*. For each nation, stock-market returns are regressed on the four-nation regional returns (as estimated with principal components above) and the unexplained residual is then used as a measure of country-specific stock-market returns.
2) *Country-specific stock-market volatility*. The same procedure as used for returns is used for volatility: changes in each nation's volatility are regressed on changes in the regional volatility and the residuals are changes in country-specific stock-market volatility. It is worth noting that Campbell and Taksler (2003) find that company-specific volatility is an important determinant of corporate-bond yields and our analysis is similar but directed to sovereign-bond yields.
3) *International reserves*. Reserves are a measure of liquidity and indicate the short-run ability of a country to pay its foreign debt. Thus, we hypothesise that the higher the level of reserves, the smaller will be the probability of default and the greater the distance-to-default.
4) *Inflation rate*. This is often used as an indicator of how well a country manages its monetary policy. High inflation rates may indicate imprudent policies, such as excessive borrowing, and so a higher probability of default. It is therefore hypothesised that inflation is negatively related to the distance-to-default.

7. The empirical results on factors affecting the distance-to-default

The regression of the distance-to-default on the global, regional and country-specific factors is estimated with the following specification:

[18] Discount is defined as the negative value of the premium, which is calculated as (share price – NAV)/NAV, where NAV is the Net Asset Value.

[19] The closed-end country founds considered are: Abeerden Latin America, Deutsche Latin America and F&C Latin America. Historical share prices and NAVs were obtained from Datastream.

$$\begin{aligned}\Delta\text{distance}_{it} = \alpha &+ \{\beta_1\ \Delta\text{US-rate-level}_t + \beta_2\ \Delta\text{US-rate-slope}_t \\ &+ \beta_3\ \text{US-stock-returns}_t + \beta_4\ \Delta\text{oil-prices}_t\} \\ &+ \{\beta_5\ \text{regional-stock-returns}_t + \beta_6\ \Delta\text{regional-stock-volatility}_t \\ &+ \beta_7\ \Delta\text{regional-sentiment}_t\} + \{\beta_8\ \text{country-specific-stock-returns}_{it} \\ &+ \beta_9\ \Delta\text{country-specific-stock-volatility}_{it} + \beta_{10}\ \Delta\text{reserves}_{it} \\ &+ \beta_{11}\ \Delta\text{inflation}_{it}\} + \varepsilon_{it} \qquad (14)\end{aligned}$$

where the variables have been defined in the section above and the brackets { } group them into global, regional and country-specific categories; subscript i denotes nation; subscript t denotes month; α is an intercept term; and ϵ_{it} is a disturbance term. The choice of whether to use levels or changes for individual variables was based upon tests of stationarity.[20]

Table 6 presents the results based upon OLS estimation. Whenever necessary, standard errors have been corrected for heteroscedasticity using the White method. We should point out that the original database consists of a wider set of variables than that discussed above, including several lags for each variable.[21] The final model for each country has been selected by applying the General-to-Specific Approach (see Hendry and Doornik, 2001).

All the regressions show the expected signs for all of the coefficients. The R^2 ranges from 60.4% for Venezuela to 81.1% for Brazil. According to the diagnostic statistics, the hypothesis of normality of the residuals cannot be rejected. The Durbin–Watson statistics tell us that there is no evidence of autocorrelation in any of the cases. Also, using the CUSUM test and the CUSUM of squares test, we do not find evidence of instability in the parameters. Hence the models seem well specified.

The results in Table 6 indicate that the selected factors can explain about 80% of the variance of changes in the distance-to-default for Argentina, Brazil and Mexico, and 60% for Venezuela. This is a surprisingly large proportion, considering that studies of changes in credit spreads for emerging-market bonds usually have R^2 values in the 10–20% range (e.g. Westphalen, 2001). Both the distance-to-default and the credit spread are calculated from bond prices, but the distance-to-default is a more sophisticated measure of creditworthiness. The KMV Division of Moody's has long argued for this approach when considering corporate bonds, but we are not aware that anyone has examined the efficacy of this approach until now for emerging-market bonds.

The results in Table 6 will be considered by moving from the general to the particular, i.e. from global variables to regional variables and then to country-specific variables. At the global level, changes in *US interest rates* are not significant for any nation and omitted from the final equations. However, the changes in the *slope of the US yield curve* have a positive effect on distance-to-default for all four nations, but if one-period lags are taken into account the effect disappears for Brazil and Mexico.

The *US stock-market return* has a positive and highly significant effect for all four nations. A simple regression of changes in the distance-to-default with this variable shows that it alone accounts for between 21% and 26% of the total variance for each country. An increase in

[20] A table giving details on the variables is available from the authors.

[21] The variables considered include US industrial production, total external debt as a percent of GDP, exports/industrial production, and exchange rate.

Table 6
Determinants of changes in the distance-to-default

Variable	Argentina	Brazil	Mexico	Venezuela
Intercept	−0.061 (−3.427)	−0.016 (−1.042)	−0.022 (−1.286)	−0.040 (−1.737)
$Dummy_{Oct\ 1997}$	−0.465 (−4.321)	−0.512 (−3.341)	−0.250 (−2.775)	
Global factors (changes)				
US rate-slope$_t$	0.041 (2.902)	0.043 (3.228)	0.039 (2.212)	0.056 (3.417)
US rate-slope$_{t-1}$		−0.027 (−2.096)	−0.037 (−3.056)	
US stock returns$_t$	2.899 (7.364)	2.223 (6.359)	2.390 (6.777)	3.379 (5.807)
US stock returns$_{t-1}$	0.889 (2.380)			
Oil price$_t$			0.016 (2.204)	0.019 (2.327)
Regional factors (changes)				
Regional stock returns$_t$	0.117 (7.800)	0.132 (10.456)	0.116 (9.668)	0.102 (5.947)
Regional stock volatility$_t$	−0.040 (−2.682)	−0.058 (−4.960)	−0.053 (−4.107)	−0.048 (−2.900)
Regional sentiment$_t$	−0.017 (−3.082)	−0.019 (−4.754)	−0.010 (−2.226)	
Regional sentiment$_{t-1}$		−0.015 (−3.975)		
Regional sentiment$_{t-2}$	0.014 (3.372)			
Country-specific factors (changes)				
Country-specific stock returns$_t$	1.223 (4.266)	0.961 (4.464)	1.545 (4.849)	0.556 (2.589)
Country-specific stock returns$_{t-2}$				0.458 (2.119)
Reserves$_t$	0.742 (2.800)		0.323 (3.565)	
R^2	0.790	0.811	0.786	0.604
S.E. of regression	0.147	0.136	0.146	0.196
Durbin–Watson statistic	1.788	1.737	1.977	1.956
F-statistic	26.296	37.774	28.67	17.671

The set of data is composed of monthly observations from the period April 1994 to October 2001. Regressions are run by using Ordinary Least Squares, where the dependent variable is the first difference of the distance-to-default. Whenever necessary, standard errors are adjusted for heteroscedasticity. The numbers in parenthesis correspond to the t-statistics.

returns of 1% for the S&P500 produces an impact of about +2.5% for Argentina, Brazil and Mexico, and +3.8% for Venezuela.

The *oil price* has a significantly positive effect on the distance-to-default for the two oil-exporting nations, Mexico and Venezuela, as expected.

Turning to regional variables, *regional stock-market returns* have a positive and highly significant impact on the distance-to-default for each of the four nations. Based upon simple regressions of changes in the two variables, this variable alone can explain about 23% of the variance of changes in the distance-to-default for each nation. As expected, *regional stock-market volatility* has a negative and significant effect on the distance-to-default for each of the four nations. Coefficients vary within a very small range of −0.058 and −0.040, suggesting a similar impact across countries. Running univariate regressions, we find that this variable is highly explicative: it accounts for about 18% of the total variance of the distance-to-default for Argentina, Brazil and Mexico, and about 11% for Venezuela.[22]

[22] Stock market volatility has commonly been used in the literature as a variable that measures turbulence in the markets or market sentiment. A scatter plot between the systematic volatility term and our market sentiment variable reveals no linear relationship between these two variables, eliminating the possibility of multicollinearity in the regression.

Regional investor sentiment (measured as a negative discount) is always contemporaneously negative and is significant for three of the four nations, the exception being Venezuela. The effect of an improvement in sentiment is to increase the distance-to-default for Brazil and Mexico, but for Argentina the positive contemporaneous effect is offset by a negative effect with a lag of two months.

Turning to country-specific variables, the regression *intercepts* are all negative, but only significant for Argentina, suggesting a general decline in creditworthiness over the sample period of 1994–2001. The *dummy variable* for October 1997 (the Asian crisis) is significant for all of the nations except Venezuela.

Country-specific stock-market returns have a positive and significant impact on the distance-to-default for all of the nations. Once the lagged response in Venezuela is taken into account, the effect is of similar magnitude for all four countries, ranging from 0.961 to 1.545. Neither *country-specific volatility* nor local *inflation* is significant for any nation. *Reserves* are significant only for Argentina and Mexico, for which they have the expected positive sign.

Overall, the results show that global and regional factors are far more important than country-specific factors in determining changes in creditworthiness for these four emerging-market countries. The distance-to-default is hugely affected by stock-market returns in the US and the region, and by the volatility of such returns (measured here at the regional level, but overlapping with US volatility). Investor sentiment has a role, but it is not a simple one. Similarly, the effects of the level and slope of US interest rates are not at all straightforward. Local stock markets do have an impact, as do reserves for some countries, but local inflation, which might have been expected to be important, is not significant at all.

If regressions are run with global, regional and country-specific sets of variables separately, then they explain approximately 30%, 50% and 10% of the variance of the distance-to-default, respectively, for all nations except Venezuela (for which the proportions are lower). Re-scaling these proportions according to the R^2 of about 0.8 for the first three nations (see Table 6), we can allocate about 25% of the variance to global factors, 45% to regional factors and 8% to country-specific factors.

If we apply principal component analysis to the residuals of the regressions in Table 6, we find that there is still a systematic factor across the four nations which explains about 60% of the remaining variance, i.e. about 12% of the total variance for the three main nations. Having accounted for systematic factors which come from the stock market, this remaining factor must be purely related to the bond market. In other words, there remains a small tendency for the bond markets to move together which cannot be explained by the economic fundamentals which we have considered.[23]

8. Conclusions and implications

Using an extended structural model and prices of Brady bonds, we have extracted a measure of the creditworthiness for four emerging economies. This estimated *distance-to-default* provides a continuous indicator of the perception of credit risk across time. We have then related the distance-to-default to global, regional and country-specific variables. This allows us to

[23] The referee suggested that the residual might be related to capital flows, as discussed by FitzGerald and Krolzig (2005). Such flows were not significant in the initial regressions and neither were they related to the first principal component of the joint residuals.

explain about 80% of the total variance of the distance-to-default for Argentina, Brazil and Mexico. For Venezuela we explain about 60%.

The sources of credit risk for these emerging markets can be split into three elements. The first element, which is the least relevant, is the result of shocks through country-specific fundamentals. These shocks represent only about 8% of the total explained variance of (changes in) the distance-to-default of Argentina, Brazil and Venezuela, but more in the case of Mexico. The second element is the result of global variables, such as US stock market returns and the slope of the US Treasury bond curve. Such variables contribute about 25% of the total explained variance. The third, and most important, element is the contribution of regional factors, such as a systematic component of the four stock markets, a systematic volatility component, and investor sentiment. These variables represent around 45% of the total explained variability. The residuals from our regressions show that there is a tendency for the bond markets of these countries to move together which cannot be explained with economic fundamentals and which accounts for about 12% of the variance.

We have found that the distance-to-default is largely driven by systematic global and regional factors, so investors should treat the credit risk of these emerging markets as non-diversifiable. There is a high level of contagion across Latin American bonds and this has important implications for the pricing and risk management of bond portfolios. It follows that credit ratings for these emerging markets should be based more strongly on global and regional economic factors than on local factors; the condition of the world economy is more important than local inflation or currency reserves. Our findings are consistent with waves of sentiment which spread from the US stock market to emerging markets in Latin America.

Our results concur with the finding of Collin-Dufresne et al. (2001) for US corporate bonds, that changes in credit spreads are driven mainly by systematic factors. In contrast to Campbell and Taksler (2003), who find for companies that firm-specific volatility is important for bond yields, we find for sovereign bonds that country-specific returns and volatility are less important than global and regional returns and volatility.

A shortcoming of our regression analysis is that we have fitted only one set of parameters for the whole sample. Though stability tests indicate reasonable robustness in our results, it is very likely that correlations between variables change over time or there could be regime-shifts. A larger sample period and different econometric technique may be needed to check this. It would also be useful to study countries from other regions, to see if our results generalise to more emerging-market bonds.

The search for the best proxies for global factors and country-specific fundamentals is a complicated task. Other model specifications or proxies for determining creditworthiness should also be able to be tested. Furthermore, other variables such as liquidity (left out of this study) are worth exploring in future research. It is possible that liquidity plays an important role in explaining the residual, systematic bond-market risk which we identify.

Finally, there is a large literature on the determinants of credit spreads for both corporate bonds and sovereign bonds. We have filtered the credit spread via a structural model in order to impute a distance-to-default. Intuitively, credit spreads and distance-to-default move in opposite directions, but there are some other factors such as maturity, collateral, or different coupons which affect the size of credit spreads but do not affect the distance-to-default. Further research is needed on whether the distance-to-default is indeed a better measure of creditworthiness. Our methodology is complicated and depends, for its estimation, on the past behaviour of bond prices. Nevertheless, identifying the distance-to-default could lead to the provision of market-based country ratings on a daily basis, analogous to those already provided by KMV for companies.

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Appendix A. The estimation of the risk-free term structure

In order to estimate the dynamics of the instantaneous nominal interest rate under the objective measure, we adopt the following formulation of the CIR model that considers the market price of risk:

$$\mathrm{d}r_t = (\kappa_r\mu_r - (\kappa_r + \lambda_r\sigma_r)r_r)\mathrm{d}t + \sigma_r\sqrt{r_r}\mathrm{d}Z_r, \quad r(0) = r_0$$

where Z_r is a Wiener process, μ_r is the long-term mean, κ_r is the mean reversion parameter, λ_r is the market price of risk and σ_r is the constant volatility parameter. In addition the condition $2\kappa_r\mu_r > \sigma_r^2$ must be satisfied in order to guarantee positive r_t.

According to Cox et al. (1985), the nominal price at time t of a pure discount bond with face value of one dollar and time to maturity τ is:

$$P_t(\tau) = \widetilde{A}(\tau)\exp(-\widetilde{B}(\tau)r_t)$$

where

$$\widetilde{A}(\tau) = \left(\frac{2\phi_1\exp(\phi_2\tau/2)}{\phi_4}\right)^{\phi_3}$$

$$\widetilde{B}(\tau) = \frac{2(\exp(\phi_1\tau) - 1)}{\phi_4}$$

$$\phi_1 = \sqrt{(\kappa_r + \lambda_r)^2 + 2\sigma_r^2},$$
$$\phi_2 = \kappa_r + \lambda_r + \phi_1, \;\; \phi_3 = 2\kappa_r\mu_r/\sigma_r \text{ and } \phi_4 = 2\phi_1 + \phi_2(\exp(\phi_1\tau) - 1)$$

The yield to maturity at time t of a discount bond that matures at time τ is an affine function of the instantaneous interest rate r_t:

$$R_t(\tau) = -\frac{\ln P_t(\tau)}{\tau} = -\frac{\log\widetilde{A}(\tau)}{\tau} + \frac{\widetilde{B}(\tau)}{\tau}r_t$$

We estimate the parameters of the model by implementing the approach used by Geyer and Pitchler (1998) and Duan and Simonato (1999). They argue that by using a Kalman Filter we can incorporate all the available information about the yield curve contained in time series and cross-sections. In their framework the system involves an observed variable which is the observed term structure, and an unobserved factor or variable that drives the dynamics of the term structure. The implementation of the Kalman Filter relies on the transition density of the unobservable variable $p(r_t|r_{t-1};\Gamma)$, which for the CIR model is a non-central χ^2. The estimation of the model can be carried out by substituting for this transition density with a normal distribution with mean and variance equal to those of the non-central χ^2, and consequently our parameter estimates will be Quasi-Maximum Likelihood.

The dynamics of the measurement equation for the observed yields $R_t(r_t,\Gamma,\tau_K)$ and the transition equation for the one-factor CIR model are defined as follows.

Measurement equation:

$$\begin{bmatrix} R_t(r_t,\Gamma,\tau_1) \\ R_t(r_t,\Gamma,\tau_2) \\ \vdots \\ R_t(r_t,\Gamma,\tau_M) \end{bmatrix} = \begin{bmatrix} -\ln\widetilde{A}(\Gamma,\tau_1)/\tau_1 \\ -\ln\widetilde{A}(\Gamma,\tau_2)/\tau_2 \\ \vdots \\ -\ln\widetilde{A}(\Gamma,\tau_M)/\tau_M \end{bmatrix} + \begin{bmatrix} \widetilde{B}(\Gamma,\tau_1)/\tau_1 \\ \widetilde{B}(\Gamma,\tau_2)/\tau_2 \\ \vdots \\ \widetilde{B}(\Gamma,\tau_M)/\tau_M \end{bmatrix} r_t + \begin{bmatrix} \varepsilon_{t,1} \\ \varepsilon_{t,2} \\ \vdots \\ \varepsilon_{t,M} \end{bmatrix}$$

where Γ is the set of parameters, τ_K is the time to maturity, $\varepsilon_t \sim \mathrm{NID}(0,Q)$ and Q is a diagonal $M\times M$ matrix that contains the variance of the errors for each maturity.

Transition equation:

$$r_{t|t-1} = \frac{\mu_r}{12}(1-\exp(-\kappa_r/12)) + \exp(-\kappa_r/12)r_{t-1} + \eta_t$$

where

$$\sigma_\eta = \sigma_r^2\frac{1-\exp(-\kappa_r/12)}{\kappa_r}\left(\frac{\mu_r}{2}[1-\exp(-\kappa_r/12)] + \exp(-\kappa/12)r_{t-1}\right).$$

The implementation of the filter generates all the necessary information to calculate the Quasi-Maximum Likelihood function (QML) (see Harvey, 1989, p. 126):

$$\ln L = -\frac{1}{2}N\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{N}\ln F_t - \frac{1}{2}\sum_{i=1}^{t} v_t' F_t^{-1} v_t$$

where N is the number of observations, v_t is an $N\times 1$ vector of errors $v_t = R_t - \widehat{R}_t\big(y_{t|t-1}\big)$,

$$F_t = \begin{bmatrix} \widetilde{B}(\Gamma,\tau_1)/\tau_1 \\ \widetilde{B}(\Gamma,\tau_2)/\tau_2 \\ \vdots \\ \widetilde{B}(\Gamma,\tau_M)/\tau_M \end{bmatrix} P_{t|t-1} \begin{bmatrix} \widetilde{B}(\Gamma,\tau_1)/\tau_1 \\ \widetilde{B}(\Gamma,\tau_2)/\tau_2 \\ \vdots \\ \widetilde{B}(\Gamma,\tau_M)/\tau_M \end{bmatrix}' + H;$$

and $P_{t|t-1}$ is the conditional variance of r_t and $\mathrm{var}(\eta_t) = H$.

A.1. Empirical results

We use US interest rates for eight maturities observed monthly during the period December 1993 to December 2000. The estimates of the parameters using Maximum Likelihood are shown in Table A1 below. Panel A shows the estimates of the parameters μ_r, κ_r, σ_r and λ_r, with their respective p-values in brackets. All the parameters except λ_r are highly significant (at 95% and 99%).

On analysing the one-step-ahead residuals, we find that they are mainly negatively-biased across short maturities, and highly autocorrelated (see Panel B, below). The autocorrelation is higher for the short end and long end of the curve than for intermediate maturities. Panel C also shows the square root of the mean square error in basis points (RMSE). Observe that the RMSE statistic is also higher for the short-term and long-term maturities than for other maturities. In summary, it seems that the one-factor CIR model cannot account for all the dynamics of the term structure.

Table A1
Estimation results for the CIR model

	μ_r	κ_r	σ_r	λ_r
Panel A: Parameter estimates				
Parameter value	0.0928** (0.0000)	0.0816** (0.0000)	0.1285** (0.0000)	−0.0280 (0.2444)
Log likelihood	3397.727			

Maturity	3M	6M	1Y	2Y	3Y	5Y	10Y	30Y
Panel B: Statistics of the one-step-ahead residuals								
Skewness	−0.379	−0.286	−0.757	−0.479	0.019	0.370	0.449	0.550
Autocorrelation	0.837	0.792	0.669	0.366	0.321	0.569	0.772	0.923
RMSE (basis points)	0.668	0.540	0.400	0.289	0.282	0.354	0.419	0.549

Maturity	3M	6M	1Y	2Y	3Y	5Y	10Y	30Y
Panel C: Correlation of the latent variable with the term structure								
Correlation	0.389	0.686	0.884	0.963	0.999	0.978	0.918	0.830

**Parameters are significant at 99% confidence level. p-Values are shown in brackets. Parameters are calculated using monthly observations of 3 and 6 months and 1, 2, 3, 5, 10 and 30-year US yields during the period December 1993 to December 2002.

$$\text{RMSE} = \sqrt{\text{mean(SSE)}}, \quad \text{SSE} = \sum (y_t - \hat{y}_{t-1})^2.$$

Correlations are measured using the first differences of the yields for each maturity.

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