International Financial Transmission: Emerging and Mature Markets*

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Abstract

With an increasingly integrated global financial system, we frequently observe that shocks to individual asset markets affect financial markets worldwide. The aim of this paper is to quantify the comovements between bond markets in the US and emerging market economies. Following Rigobon (2003) we exploit the changing volatility of the data to fully identify a structural VAR, without imposing ad-hoc restrictions. Our results indicate that shocks that widen emerging market sovereign debt (EMBIG) spreads tend to have a negative effect on US interest rates (consistent with "flight quality" episodes), while the effect of US interest rates on EMBIG spreads is mixed. We also find that shocks that raise EMBIG spreads tend to raise US high yield spreads and vice versa, constituting an important channel through which crises in EMEs can affect mature markets. Forecast error variance decompositions show that the variance of both EMBIG and US high yields spreads is mainly explained by shocks to US long rates.

JEL classification: C32, F30, G15

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1 Introduction

Financial markets worldwide have become increasingly integrated. One consequence of this is that we observe a large degree of comovement across financial markets, as shocks to individual markets or countries are transmitted internationally. Such spill-over effects were most notable during several financial crises episodes in emerging market economies (EMEs) over the past decade. From a central banking perspective, understanding the mechanisms through which shocks are transmitted across financial markets is important for gauging the extent to which financial crises and volatility in emerging market economies can affect the financial systems in developed countries, and *vice versa*.

The aim of this paper is to quantify the linkages between bond markets in the U.S. and EMEs. In particular, we want to analyse through which channels shocks are transmitted across markets. We are particularly interested in two questions. First, what is the causal relationship between US interest rates and emerging market bond spreads? On the one hand, US interest rates might influence EMEs in different ways. An intuitive argument suggests that rising US interest rates should increase the financing costs of EMEs, thus raising their default risk and increasing the spreads that EME borrowers have to pay over risk-free rates. Furthermore, decreases in riskless rates are often thought to be associated with a "search for yield", as investors shift into more risky assets such EME debt and drive their spreads down. But EMBIG spreads and US interest rates could also move in the opposite direction if the latter are the result of strong output growth in the US which is generally supportive of lower EMBIG spreads. On the other hand, episodes of emerging market turmoil often seem to be associated with a "flight to quality" and thus a negative effect of EMBIG spreads and risk-less rates, as investors shift out of risky assets and into "safe-haven" assets such as US government debt. However, previous studies have failed to find clear evidence of a positive effect of US interest rates on EME bond spreads[1], and only few studies have sought to quantify the reverse influence of EMEs on financial markets in mature economies.[2]

A second question concerns the relationship between spreads on risky debt in emerging and mature markets. It is well known that EMBIG and US high yield spreads tend to move together. But are US high yield spreads influencing EMBIG spreads, or does the influence run the other way round? This relationship is particularly important because it represents one possible channel through which EME crises might negatively affect mature markets.

[1] See e.g. Eichengreen and Mody (1998) and Kamin and von Kleist (1999).
[2] See for example Sáez, Fratzscher and Thiemann (2007).

Studies of financial market comovement are often complicated by endogeneity bias. When two variables, such as US government bond yields and EMBIG spreads, are both endogenous, estimation results in structural models will be biased. To circumvent this bias researchers have typically resorted to restrictions, effectively imposing that influences run only one-way. We do not want to impose such restrictions because it is precisely the direction of influence that we are trying to uncover. Using a relatively new methodology we are able to estimate a structural VAR model without imposing the ad hoc restrictions that are commonly used for identification in the VAR literature. Following Rigobon (2003), we exploit the changing volatility of the data to identify our model. The crucial assumption underlying this methodology is that the coefficients describing the comovement of our endogenous variables are constant over the whole sample period: our results should therefore be thought of as capturing average, long-run effects.

Our results shed light on how structural shocks to individual variables are transmitted through the system. We can distinguish between *direct* and *overall* spillover effects. An initial structural shock that increases EMBIG spreads has direct effects on the other variables: for example, it reduces US long-term government bond yields and increases US high yield spreads. However, following this first round of spillover effects, lower US government bond yields may feed back on the US high yield market, which could in turn affect EMBIG spreads and so forth. The overall effects of the initial structural shocks tend to have the same sign as the direct effects, although the magnitude typically differs.

We find strong evidence for "flight to quality": EME structural shocks tend to lower US government bond yields, especially on long-term debt. Conversely, the impact of movements in US long interest rates on EMEs appears to be more mixed. We find that the *overall* effect of shocks to US long-term rates on EMBIG spreads is negative. This is in line with the previous empirical literature and could suggest that GDP growth in EMEs comoves with US long rates to the extent that the latter reflect robust US output growth. We do find a positive *direct* effect of US long-term government bond yields on EMBIG spreads, although the coefficient is close to zero and not statistically significant. This suggests that although the direct effect of a rise in US interest rates may be to raise the financing costs of EMEs, it could be partially offset by procyclical interest rates or even by second round effects through other variables.

We also find strong spillover effects both from EMBIG to US high yield spreads and *vice versa*. One explanation for this comovement is that an increase in risk aversion causes investors to shift out of risky assets, including both US corporate and EME bonds, in response to disruptive shocks. This suggests that the high yield market is an important channel through which financial crises can spread. For example, mature markets may be adversely affected by crises in EMEs when US high yield spreads rise (as in the Russian/LTCM crisis 1998) as firms find it more expensive to access the debt markets.

While we allow structural shocks to be heteroskedastic (indeed this is crucial to identify the model), we assume that the coefficients are stable. Is this assumption justified? Especially in the context of EMEs the size of spillover-effects seems to change in times of market turmoil. However, even with stable coefficients the importance of different transmission channels can change in high volatility periods. Intuitively, the effect of an EME shock on US high yield spreads (to take an example) is given by the estimated coefficient multiplied by the size of the shock. Thus, as the size of the shock to EME spreads varies (between tranquil and crisis periods in EMEs), so will the spillover effect between EMEs and mature markets. With our methodology it is impossible to test for whether parameters are stable across volatility regimes. Instead, we check for parameter stability by estimating the model separately for the first and second half of the sample. Although parameters do change quantitatively, almost all parameters have the same sign across both periods. This is remarkable, especially given the fact that the volatility of EMEs has declined substantially over the later part of the sample. Also, for the reduced form model the null hypothesis of parameter stability is not rejected in a standard multivariate Chow test.

A crucial step in our estimation procedure is the identification of volatility regimes. The idea in choosing regimes is to identify periods in which the volatility of the underlying unobserved structural shocks differs. We employ two different methods of regime choice to check whether our results are robust to the exact regimes chosen. We also discuss how our choice of volatility regimes corresponds to actual events, such as for example financial crises in EMEs.

The theoretical literature on financial markets and contagion has identified several channels through which shocks may be transmitted across financial markets[3], and there is a large number of empirical studies on the comovement of international financial markets. The empirical literature can be roughly classified into two broad strands: studies on the (long-run) comovement of financial markets, and studies analysing "contagion", typically defined as an increase in the correlation between markets in times of crises.[4] Research

[3]Examples include the correlated information channel (King and Wadhwani, 1990), links between financial institutions (Allen and Gale, 2000), portfolio rebalancing (Kodres and Pritsker, 2002), herd behavior (Calvo and Mendoza, 2000; Chari and Kehoe, 2003), wealth effects (Kyle and Xiong, 2001), and the role of information markets (Veldkamp, 2006).

[4]See Gagnon and Karolyi (2006) for an extensive review of the empirical literature on comovement of international financial markets, and Dornbusch, Claessens and Park (2000) and Dungey et.al. (2003) for surveys of the empirical literature on contagion.

in the first strand has generally focused exclusively on the comovement of markets for just one asset class (typically stock markets). Furthermore, most studies either do not identify the contemporaneous feedback effects between the endogenous variables, or use standard, but *ad-hoc* restrictions for identification. An exception to both of these limitations is the paper by Ehrmann, Fratzscher and Rigobon (2005), who analyse the interlinkages between US and European financial markets (including bonds, stocks, and exchange rates), employing the method developed in Rigobon (2003) to identify a structural VAR.

Empirical research in the second strand has attempted to establish whether or not contagion occurred, based on two different methodologies: tests for increases in correlations in crises times[5], and tests for whether the probability of a crisis in some market A, given that there is a crisis in market B, is higher than the unconditional probability.[6] However, the literature on contagion faces the same identification challenges mentioned above, which have to be circumvented by making restrictive assumptions. For example, Favero and Giavazzi (2002) test for nonlinearities in the transmission of shocks in European money markets; to identify their model they have to assume that several reduced-form coefficients are equal to zero.

To sum up, the empirical literature on the comovement of international financial markets has the following limitations: (i) identification challenges have usually forced researchers to impose *ad-hoc* restrictions on the contemporaneous feedback effects among the endogenous variables; (ii) research has typically focused on comovement of markets for one specific asset, rather than linkages across asset classes as well as across countries. Addressing these limitations, our contribution is to analyse the relationships between bond markets in the US and EMEs, and to identify how shocks are transmitted across markets without imposing unrealistic restrictions. To our knowledge, this study is the first to analyse comovement between financial markets in EMEs and developed countries using the Rigobon (2003) methodology.

Our paper is structured as follows. The next section reviews some stylised facts about the correlations of our endogenous variables for tranquil and crisis periods. These findings are important for interpreting our final results concerning the comovements of financial markets, and they are also useful for deciding on starting values for the estimation of our model. The third section gives a brief introduction to the empirical methodology that we use, "Identification through heteroskedasticity", and outlines our empirical model and the choice of volatility regimes. The fourth section then presents

[5] For example, Forbes and Rigobon (2002).

[6] See e.g. Pesaran and Pick (2007).

the results. Section 5 presents some robustness checks. In particular, we estimate our model separately for the first and second part of the sample to check whether parameters can indeed be considered to be stable over time, as assumed. Furthermore, we employ an alternative method of regime choice to test the sensitivity of our results to the choice of volatility regimes. Finally, section 6 concludes and discusses avenues for future research.

2 Comovement of international financial markets: some stylised facts

Before we begin with the formal empirical analysis it is useful to look at some simple statistics of the raw data to get an idea of the relevant stylised facts. Our dataset includes daily data on US short- (3 month) and long-term (10 year) government bond yields, US high yield spreads, and EMBIG spreads (EMBI before 1998), from January 1997 to December 2006. In our empirical analysis below we will work with data in first differences in order to ensure stationarity.

Table 1 presents correlations of the differenced raw data, computed over the whole sample period.[7] Note first that US short- and long-term government bond yields are positively correlated, but negatively correlated with US high yield spreads. This second finding seems to contradict the conventional wisdom that higher risk-free interest rates should increase the financing costs of risky borrowers and hence their default risk, which should be reflected in spreads. Furthermore, since spreads are computed as the difference between the yields of risky and risk-less assets with corresponding maturity, spreads should be increasing in risk-less rates for simple "mathematical" reasons.[8] One possible explanation for this puzzle could be that US high yields spreads tend to be low when the US economy is booming and profits in the corporate sector are high. During such economic upturns, inflationary pressures may build up that induce monetary policymakers to raise interest rates, which then translates into higher long term rates,

[7] We present correlations of differenced data for consistency with the empirical results below.

[8] To see this, consider the following simple example taken from Kamin and von Kleist (1999). Let i denote the yield of a risky asset which is repaid with probability p, and r denote the yield of a corresponding risk-less asset. Then we have

$$1 + r = p \cdot (1 + i) + (1 - p) \cdot 0$$

From this, the spread is computed as

$$i - r = \frac{(1 + r)(1 - p)}{p}$$

which is increasing in r.

Table 1: Correlations, 1997-2006

	US 3m	**US 10y**	**US HY**	**EMBIG**
US 3m	1.00			
US 10y	0.29	1.00		
US HY	-0.12	-0.32	1.00	
EMBIG	-0.06	-0.12	0.17	1.00

Data in first differences.

leading to a negative correlation between spreads on risky debt and risk-less rates.

The correlation between EMBIG and US high yield spreads is positive, suggesting a high degree of comovement across markets. Finally, the correlations between EMBIG spreads and US government bond yields are negative. This is surprising as we would again expect correlations between EMBIG spreads and risk-less US government bond yields to be positive: higher risk-less rates should increase financing costs and hence the default risk of risky borrowers; furthermore, following a decrease in risk-less rates, investors tend to "search for yield" and shift into more risky assets in order to earn higher returns, thus driving the prices of these assets up and their yield spreads over risk-less debt down.[9] However, this finding could again be explained by US interest rates being pro-cyclical.

It is interesting to also look at how correlations change during periods of financial market turmoil. As an example, Table 2 summarises the correlations for the period of the Russian/LTCM crisis 1998. Note that the magnitude of all correlations increases, while the sign of the correlation coefficients stays the same. The strong correlation between EMBIG spreads and US high yield spreads in that period is an indication of the contagion that occurred following the Russian default, possibly through an increase in investors' risk aversion. The strong negative correlation between US government bond yields and EMBIG spreads may reflect the "flight to quality".

Figure 1 plots the correlation between US long-term government bond yields and EMBIG spreads versus EMBIG volatility (computed over moving windows of 21 days) to illustrate how correlations change in times of financial market volatility. The Asian (1997-8) and Russian (1998) financial crises are marked by spikes in EMBIG volatility, and by a corresponding fall of the correlation between EMBIG and US long-term yields. Again, this could be interpreted as a "flight to quality", or as the result of the provision

[9] Note however that correlations of US government bond yields and EMBIG spreads are positive when the variables are analysed in levels.

Table 2: Correlations during the Russian/LTCM crisis

	US 3m	US 10y	US HY	EMBIG
US 3m	1.00			
US 10y	0.49	1.00		
US HY	-0.26	-0.74	1.00	
EMBIG	-0.21	-0.45	0.55	1.00

Data in first differences.

of ample liquidity by the Federal Reserve in the face of the LTCM crisis.

There are two ways to interpret these findings. First, the changing correlations in time of financial market turmoil could imply that the relationship between our variables is non-linear, so that spillover effects change in times of high volatility. This is the approach taken by the empirical literature on financial contagion. In contrast, for our econometric model we will assume that the underlying parameters that govern the feedback effects between variables stay the same, and that different transmission channels will dominate in times of crises because the size and volatility of the underlying structural shocks that change.

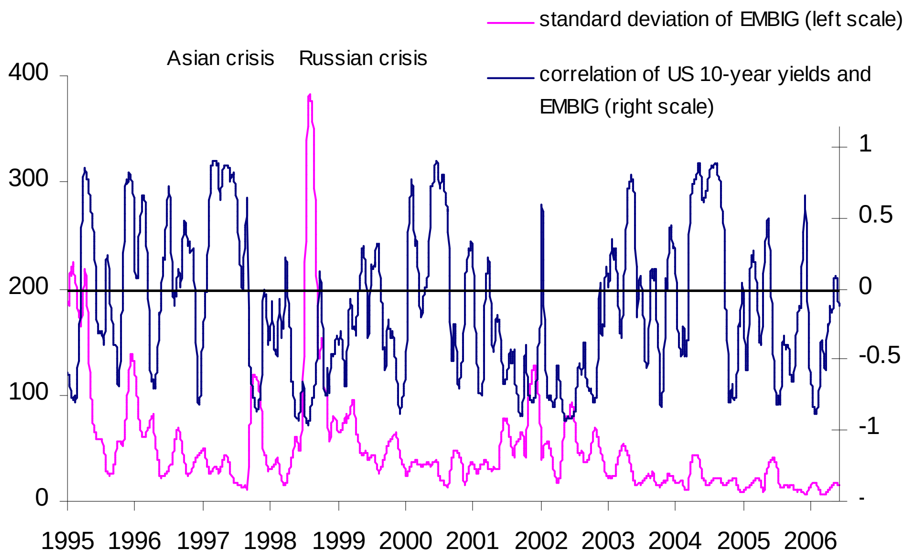
Correlations indicate how financial variables move together, but do not provide information about the source of that comovement. A high correlation between EMBIG spreads and US government bond yields could be caused by EMBIG spreads affecting US interest rates (e.g., flight to quality); by US interest rates affecting EMBIG spreads (e.g., financing costs); or causation could run through some third factor such as US high yield spreads (e.g., a financial crisis in some EME increases EMBIG spreads, and US high yield spreads increase as well because of higher risk aversion; to ease the burden on the economy, the Federal Reserve lowers interest rates). To analyse through which channels these feedback effects occur, we estimate a fully identified structural VAR below.

3 Empirical methodology

3.1 Some intuition: identification through heteroskedasticity

The variables in our sample are highly heteroskedastic. For example, Figure 1 shows that episodes of EME crises are clearly marked by higher EMBIG volatility. Rather than presenting a problem for estimation, this heteroskedasticity can actually be used to identify the model. We employ a method developed in Rigobon (2003), labelled

Figure 1: Correlation of 10-year US government bond yields and EMBIG spreads



EMBI before 1998. Volatility and correlations computed over 61-day windows.

"identification through heteroskedasticity".[10]

To illustrate the identification method consider a model with only two variables - say, EMBIG spreads and US government bond yields. Both variables should be treated as endogenous: following our intuition from the previous section a rise in US interest rates may increase EMBIG spreads, while a rise in EMBIG spreads could reduce US interest rates (e.g., if flight to quality occurs). Thus the relationship between EMBIG spreads and US 10-year interest rates might be captured by the equations below:

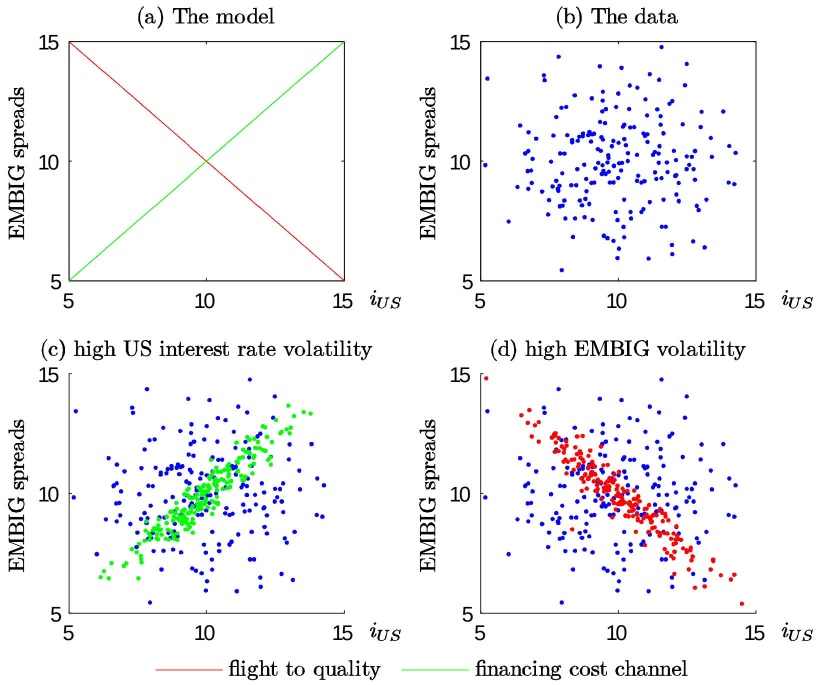
$$EMBIG_t = \alpha \cdot US10_t + \epsilon_t \tag{1}$$

$$US10_t = \beta \cdot EMBIG_t + \eta_t \tag{2}$$

where ε_t and η_t are structural shocks. We expect $\alpha > 0$ and $\beta < 0$. This situation is captured in panel (a) of Figure 2. A dataset of observations on EMBIG and US interest rates might look like the scatterplot on the right panel (b) of Figure 2. Clearly, it is impossible to separately identify the two relationships in (1) and (2). More formally, equations (1) and (2) can not be estimated directly because of endogeneity bias.

[10] See also Sentana and Fiorentini (2001).

Figure 2: Illustration of identification procedure



Now, suppose that we could distinguish periods in which the volatility of EMBIG spreads increases, while the volatility of US interest rates stays constant or increases only slightly. For example we could pick periods in which volatility, computed over a window of a certain number of days around the current period is above the upper 95% confidence bound. We could interpret the heteroskedasticity observed in the EMBIG and US interest rates as stemming from varying volatility in the structural shocks ε_t and η_t. Note that during periods when US interest rate shocks are very volatile the relationship in equation (1) is traced out, as shown in panel (c) of Figure 2. Similarly panel (d) shows how the relationship in equation (2) is traced out during periods when shocks to EMBIG are more volatile. This is intuitive: in times of high US interest rate volatility the effect of US interest rates on the financing costs of sovereign borrowers may dominate the data, and we are likely to find a positive correlation corresponding to equation (1). In times of EME crises however the relationship between US interest rates and EMBIG spreads may be dominated by flight to quality, allowing us to identify equation (2). Thus, estimating our model separately for periods of different volatility can help to identify the model.

Note that the choice of regimes is very important to properly identify the model: identification works best if the change in relative volatilities is large across regimes, as shown in Figure 2. The next section introduces our empirical model and explains identification through heteroskedasticity more formally.

3.2 The empirical model

We use a vector autoregressive model to account for the fact that no variable is truly exogenous. Following Ehrmann, Fratzscher and Rigobon (2005) our structural model is given by

$$Ay_t = \vartheta(t) + \Pi(L)y_{t-1} + \Gamma z_t + \mu_t \tag{3}$$

where y_t is the vector of endogenous variables, z_t is a common shock, and μ_t is a vector of structural shocks. A, $\Pi(L)$ and Γ are parameter matrices, with $\vartheta(t)$ including both constants and a time trend. Of particular interest to us is the matrix A, which determines the contemporaneous feedback effects among the endogenous variables. We make the following standard assumptions:

$$E(\mu_t) = E(z_t) = 0$$

$$E(\mu_t \mu'_{t-i}) = E(z_t z_{t-j}) = E(\mu_t z_{t-k}) = 0$$

$\forall i, j, k \neq 0$. While we assume that the covariances of the structural shocks are equal to zero, the inclusion of the common shocks z_t serves to introduce some correlation among the underlying shocks that drive the system.

To capture the changing volatility of our endogenous variables that we observe in the data, we allow the variances of both structural and common shocks to change across the sample. In particular, we assume that there are $s = 1, ..., S$ volatility periods or regimes, and that the shock variances are constant within each regime, but different across regimes. For each regime s, we have

$$\begin{aligned} E\left(\mu_t \mu'_t\right) &= \Omega_{\mu,s} \\ E\left(z_t^2\right) &= \Omega_{z,s} \end{aligned}$$

We cannot estimate equation (3) directly because of endogeneity bias. Therefore, we need to work with the reduced form model, which is computed by multiplying both sides of (3) with A^{-1}. This yields

$$y_t = B_0 + B_1 y_{t-1} + u_t \quad (4)$$

where $B_0 = A^{-1}\vartheta(t)$, $B_1 = A^{-1}\Pi(L)$ and $u_t = A^{-1}\Gamma z_t + A^{-1}\mu_t$. Since the same variables appear on the right hand side of every equation in (4), OLS can be used to estimate the reduced form parameters B_0 and B_1.[11] However, we want to go further and identify the structural parameters in the matrices A and Γ. To do this, we can use "Identification through Heteroskedasticity", implemented through GMM estimation. Clearly, the residuals from the regression in (4) will reflect the underlying structural shocks μ_t. Therefore it is natural to use these residuals to determine volatility regimes for the structural shocks. How this can be done is described in the next section.

To obtain moment conditions for GMM estimation, rearrange equation (4) to yield

$$y_t - B_0 - B_1 y_{t-1} = A^{-1}\Gamma z_t + A^{-1}\mu_t$$

The left-hand side in this expression can be proxied for with the VAR residuals. The volatility of z_t and μ_t changes across regimes $s = 1, ..., S$, and hence we can compute the variance-covariance matrix of the VAR residuals separately for each regime s. This leads to GMM moment conditions which are given by

$$A\Omega_{e,s}A' = \Gamma\Omega_{z,s}\Gamma' + \Omega_{\mu,s} \quad (5)$$

where $\Omega_{e,s}$ is the covariance matrix of the residuals (which can compute from the data), and $\Omega_{\mu,s}$ and $\Omega_{z,s}$ are the covariance matrices of the structural and common shocks (which we want to estimate), all in regime s. Note that $\Omega_{\mu,s}$ is diagonal (as we assume the structural shocks to be uncorrelated), and that one common shock implies $\Omega_{z,s} = Var(z_s)$, a scalar. If there are n endogenous variables, $\Omega_{e,s}$ will have $N = n \cdot (n+1)/2$ distinct elements, so that equation (5) delivers N moment conditions for each regime which we summarise in the column vector m_s. Therefore, with S regimes, we obtain $N \cdot S$ moment conditions which can be used for GMM estimation. Let θ denote a vector containing the structural parameters which we want to estimate, including the parameters in the matrices A and Γ, as well as the covariance matrices of the shocks, $\Omega_{z,s}$ and $\Omega_{\mu,s}$ for regimes $s = 1...., S$. We choose θ to minimise the objective function

$$\min_{\theta} m'm \quad (6)$$

[11] See e.g. Enders (2003), page 270.

with

$$m = \left(\begin{array}{cccc} m_1 \cdot \frac{T_1}{T} & m_2 \cdot \frac{T_2}{T} & \dots & m_S \cdot \frac{T_S}{T} \end{array} \right)'$$

where T_s is the number of observations in regime s and T is the total number of all observations. Note that we multiply the moment conditions of regime s with the relative weight of the regime. In this way we attach more importance to moment conditions that represent a larger number of observations and thus are associated with less uncertainty. This implicitly defines a weighting matrix for GMM estimation.

Our estimation strategy is as follows. First, we estimate the reduced-form model given in equation (4) using OLS. We use the residuals from this regression to pick the regimes: since the volatility of the structural and common shocks changes across regimes, so will the volatility of the VAR residuals. For each regime we compute the covariance-matrix of the residuals and derive moment conditions according to equation (5). Finally, GMM is used to identify the structural form parameters of the original VAR.

3.3 Choosing the regimes

Remember from Figure 2 that regimes should be chosen such that the relative volatilities of different structural shocks vary significantly across regimes. Thus, it would be ideal to identify periods where only one variable was volatile, while the others were relatively "tranquil". What precisely is interpreted as "volatile" and "tranquil" could be decided by defining a reasonable volatility threshold. We use two alternative methods to choose regime. The first method uses a simple threshold rule, as in Ehrmann, Fratzscher and Rigobon (2005). As a robustness check, we also estimate a mixture of distributions model on the residuals to choose regimes. This second approach is discussed in section five.

Here we describe how to use a threshold rule for regime choice, following Ehrmann, Fratzscher and Rigobon (2005). The basic idea is to determine in which periods the EMBIG-residuals, to take an example, are very volatile, while residuals of the other variables are not. To do this we compute standard deviations of residuals for each of the n endogenous variables over fixed windows of 21 days. Let $\sigma_{i,t}$ be the standard deviation of residuals corresponding to endogenous variable i, computed over the period $t-10, ..., t, ..., t+10$. We then define a threshold according to

$$mean(\sigma_{i,t}) + c \cdot st.dev(\sigma_{i,t})$$

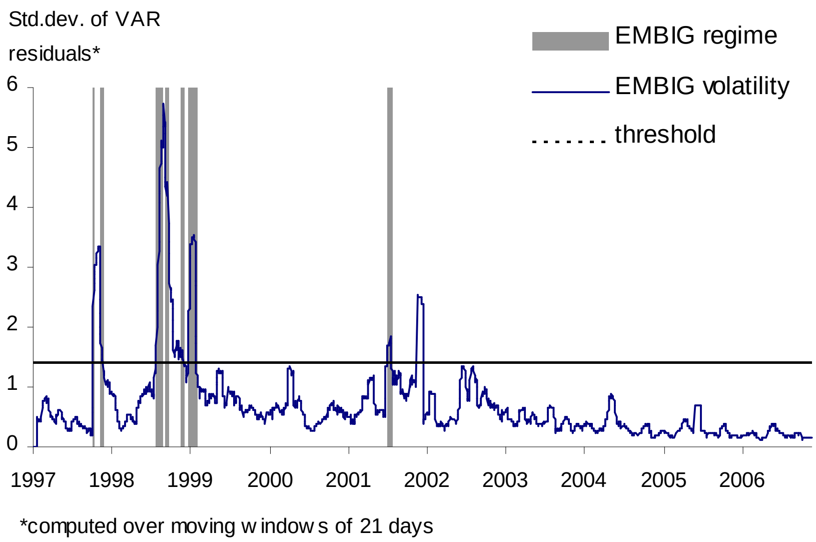
where we set $c = 1$.[12] Whenever $\sigma_{i,t}$ is above that threshold we consider residuals of variable i in period t to be volatile. We then define $n+1$ regimes, where n is the number of endogenous variables. In regime one we include periods where the residuals of all endogenous variables are tranquil. Furthermore, for each endogenous variable i, we identify a regime that includes periods where i's residuals are volatile, but the residuals of other endogenous variables are not.

If more than one variable is above the volatility threshold in some period t, we do not use that period for GMM estimation since such periods would not significantly help to identify the model. Therefore we may ignore information that is not contained in the data, but that can be obtained by identifying the economic events that volatility periods reflect. Some natural examples are financial crises in emerging markets, which could be interpreted as shocks to EMBIG; tightening cycles in US monetary policy, which would represent shocks to US short term government bond yields; and the US auto sector turmoil, which we could capture through shocks to US high yield spreads. Consider the case of the Russian/LTCM financial crisis. According to our definition of volatility, EMBIG spreads are volatile from August 10 until November 11, 1998. US high yield spreads are volatile from August 25, and US long term interest rates from September 1, 1998. Thus using our mechanical rule, only the period from August 10 to August 24 is included in the EMBIG volatility regime: the largest part of the data covering the Russian/LTCM crisis is not used for identification of the structural parameters! Clearly, we are loosing some valuable information. However, we know that the whole August-September 1998 period represents a shock to EMBIG spreads originating in the Russian default on August 17. It would therefore seem natural to include the days after August 25 in our EMBIG volatility regime.

Some previous studies have used straightforward economic intuition to identify volatility regimes. Rigobon and Sack (2004) analyse the effect of US monetary policy on asset prices. They use two regimes, one including periods of FOMC meetings and Fed chairman's testimonies to congress, and another including all other periods. The idea is that, clearly, monetary policy is more volatile on days when interest rate decisions are taken or when news about interest rate policies emerge. Similarly, Gonçalves and Guimaraes (2006) analyse the relationship between monetary policy and exchange rates in Brazil, identifying periods of Brazilian Central Bank policy meetings as regimes of higher interest rate volatility.

[12] Increasing c will decrease the number of periods in the volatility regimes, making identification harder; decreasing c will increase the number of volatility regime periods; however, it is then also more likely that more than one variable above the threshold so that the number of periods not used for GMM

Figure 3: EMBIG high volatility regime periods with threshold rule



In our case using economic reasoning for identifying the regimes is not always straightforward, as many events may correspond to shocks to several variables at once. Nevertheless we also combined the results from using the threshold rule with our economic intuition to define regimes. For example, we allowed for a longer period of the Asian crisis (according to our residual covariances, the Asian crisis lasts only from mid-November to December 1997), attributed all of the Russian crisis period to the EME shock regime, and extended the period of US high yield volatility in spring 2005 to cover the whole period of the US auto sector turmoil. Therefore, there are more observations in the regimes corresponding to EMBIG and US high yield volatility, and less observations in the regime corresponding to tranquility.[13] The resulting covariances from threshold rule and the combination of threshold rule and economic intuition were not very different, and the resulting GMM estimates for the structural coefficients were also very similar. Therefore, we just report the results from the regime choice using the threshold rule.[14]

Figure 3 shows the volatility of EMBIG residuals and the threshold which is used to

estimation rises.

[13] With the threshold rule, regime 1 (tranquility) includes 1836 observations, while regime 2 (US 3m volatility) has 166, regime 3 (US 10y volatility) 174, regime 4 (US HY volatility) has 72 and finally regime 5 (EMBIG volatility) 91 observations.

[14] Note also that Rigobon (2003, proposition 3) has shown that estimation by "Identification through Heteroskestacity" remains consistent even if the volatility windows are misspecified.

determine whether EMBIG residuals are considered to be volatile. Note the spikes in volatility corresponding to the Asian crisis 1997/98, the Russian/LTCM crisis (autumn 1998), and the Brazilian (beginning of 1999) and Argentinean (2001/2002) crises. However, as indicated in the graph, these episodes are only partly included in the EMBIG regime. The reason is that the volatility of other variables - notably US high yields spreads, but also US interest rates - tends to increase as well in times of EME crises, and that therefore such periods are excluded from GMM estimation because they would not help with the identification of the structural model.

4 Results

This section presents our empirical results. Using "Identification through Heteroskedasticity", we are able to estimate all parameters in the structural model of equation (3). This makes it possible to analyse not only the overall effects of structural shocks on the endogenous variables through the reduced form, but also to assess the importance of various transmission channels. We use data on bond yields and spreads in first differences to ensure stationarity.

Before discussing our results, let us briefly note some computational issues. Good starting values are very important for the optimization procedure to converge. We use the findings from section two to set starting values for estimation.[15] For the variances of structural shocks we use the regime variances of the VAR residuals contained in the matrix $\Omega_{e,s}$ as starting values - this should ensure that the starting values are at least roughly of a realistic magnitude. For the variances of the common shock and coefficients in the vector Γ we use starting values of 1. We also constrain all variances to be positive, and impose constraints on some structural coefficients (for example, we constrain the feedback effects between US short- and long term government bond yields to be positive). This increases the efficiency of the estimation and also ensures that we choose the right "rotation" of the matrix A (see Ehrmann, Fratzscher and Rigobon, 2005). However we make sure to check that the constraints imposed are never actually binding. We estimate our model including constant, time trend and five lags in the VAR, and one common shock.[16]

Our estimation yields estimates for the structural-form parameters in A and Γ, as

[15] We use the built-in MATLAB constrained optimisation routine `fmincon`.

[16] The likelihood ratio test, final prediction error and Akaike information criterion suggest an optimal lag length of 5, while the Schwarz and Hannan-Quinn information criteria point to an optimal lag length of 3. Our intuition is that financial markets adjust to new information very quickly, and that including lagged values covering the past work week should be sufficient.

well as for the structural shock variances $\Omega_{\mu,s}$ and $\Omega_{z,s}$. The estimated coefficients in matrix A correspond to the *direct* contemporaneous effects of the various structural shocks on the endogenous variables, as described by the structural form equation (3): the coefficient $A(i,j)$ describes the direct effect of a shock to endogenous variable j on variable i. These coefficients therefore give information about the importance of various transmission channels. In order to judge the overall effect of a shock the variable j on variable i, one has to account for all simultaneous feedback effects. This is done in the reduced form model in equation (4) where it can be seen that the coefficients of A^{-1} determine the *overall* effects of structural shocks - that is, the cumulative effect of the different direct transmission channels.

The distribution and standard errors for the estimated parameters were obtained using bootstrap: the residuals in each regime are resampled and used to compute new covariance matrices. New parameters are then estimated using GMM. We repeat this procedure 500 times to obtain a set of all coefficients in the model, estimated 500 times. The significance of the estimated parameters can then be judged from the bootstrap p-value.

Table 3 reports the parameter estimates for both structural-form (matrix A with switched signs) and reduced-form (matrix A^{-1}) coefficients. Bold font indicates that coefficients are statistically significant at the 95% confidence level, according to the bootstrap p-value. Detailed bootstrap results on parameter significance can be found in appendix B.

Direct effects:

We first discuss direct feedback effects, presented in panel (a) of Table 3. Our results imply that a structural shock that increases EMBIG spreads will tend to decrease US government bond yields, where the effect is stronger for long term yields. Both coefficients are highly significant. This finding can be interpreted as reflecting a "flight to quality". The coefficients capturing the reverse effect, however, are close to zero and insignificant, positive for long-term US government bond yields but negative for short term yields. As noted earlier, we would expect a positive sign, as it is conventional wisdom that debt financing costs for risky borrowers tend to increase with risk-free interest rates. However, our finding that the effect is small (and in the case of short rates has the wrong sign) is consistent with the empirical literature on the determinants of sovereign spreads, which seems to be inconclusive as to whether US interest rates can explain the variation of EME credit spreads.[17] Indeed, it seems plausible to obtain negative effects if

[17] For example, Kamin and von Kleist (1999) regress emerging market bond spreads on a set of ex-

Table 3: Estimation results using threshold rule for regime choice

(a) **contemporaneous feedback effects: direct**

From... ...to	**US 3m**	**US 10y**	**US HY**	**EMBIG**
US 3m		**0.10**	-0.03	**-0.06**
US 10y	**0.17**		-0.06	**-0.11**
US HY	0.00	**–0.53**		**0.04**
EMBIG	-0.01	0.03	**0.20**	

(b) **contemporaneous feedback effects: overall**

From... ...to	$\boldsymbol{\mu}_{US3}$	$\boldsymbol{\mu}_{US10}$	$\boldsymbol{\mu}_{USHY}$	$\boldsymbol{\mu}_{EMBIG}$
US 3m	**1.02**	**0.13**	**-0.05**	**-0.07**
US 10y	**0.18**	**1.07**	**-0.10**	**-0.12**
US HY	**-0.10**	**-0.57**	**1.06**	**0.10**
EMBIG	-0.02	**-0.09**	**0.21**	**1.02**

Bold coefficients are significant at the 95% confidence level.
See Table 8 in appendix B for details.

interest rates in the US reflect stronger economic conditions there which in turn support economic performance in EMEs.

Our results also indicate strong comovement of US high yield spreads and EMBIG spreads; note that the influence of US high yields spreads on EMBIG is stronger than *vice versa.* The effect of a shock to US long-term interest rates on US high yield spreads is estimated to be strongly negative and highly significant. This result appears very counterintuitive. As mentioned in section two, one possible explanation might be that interest rates tend to increase when the economy is booming; this is likely to coincide with periods when the corporate sector is strong. The reverse effect of US high yield spreads on US interest rates is negative, which could again be interpreted as reflecting a "flight to quality". Finally, the influence of US short-term on long-term yields is stronger than *vice versa.*

Overall effects:

Now consider the overall effect of structural shocks on the endogenous variables, as given by the coefficients of the matrix A^{-1}. The parameter estimates are summarized in panel (b) of Table 3. Again we concentrate first on the relationship between US long-term

planatory variables and find that the effect of interest rates in industrialised countries on EME spreads is insignificant, and often has the wrong (negative) sign. See also Eichengreen and Mody (1998).

government bond yields and EME bond spreads. The overall effects of a shock to EMBIG spreads on US government bond yields are negative, and larger than the direct effects. This suggests that the various transmission channels tend to magnify the "flight to quality" effect. The reverse overall effect of US interest rates on EME bond spreads contradicts the intuitive financing cost/search for yield argument: the coefficients are estimated to be negative and the coefficient for long-term rates is significant. Again this could be explained by cyclical factors behind interest rate movements. All other coefficients have the same sign as the corresponding direct effects. Note that the coefficients on the diagonal are greater than one: the initial impact of a structural shock on EMBIG spreads is one, but this effect is magnified through the feedback effects of other variables so that the overall effect on EMBIG spreads is larger than one.

To summarise our results let us reconsider the two questions posed in the introduction. What is the relationship between US government bond yields and EMBIG spreads? We find that although there may be a weak positive effect of US interest rates on EME bond spreads - in line with the financing cost intuition - the overall effect, taking into account feedback effects through other variables, turns out to be negative. How can we explain this sign change from weakly positive to significantly negative? From panel (a) of Table 3, the most likely reason is the indirect feedback through US high yield spreads: a positive shock to US long-term rates will slightly increase EMBIG spreads, but also have a large negative effect on US high yield spreads which in turn influence EME bond markets.

The reverse effect of an EME shock to US interest rates is estimated to be negative and significant: thus, there is strong evidence of flight to quality. However, an EME shock is not necessarily good news for bond markets in mature economies. Structural shocks that raise EMBIG spreads will also raise US high yield spreads, constituting an important channel through which contagion may occur. In the other direction, shocks to the US corporate debt market - for example, the US auto sector shock in 2005 - will also tend to spill over to EMEs. One possible source underlying the comovement of EMBIG and US high yield spreads (in both directions) could be changes in investors' risk aversion and the associated portfolio shifts into less risky assets.

Table 4 presents the decomposition of the 10-period ahead forecast error variance. Note that both US short- and long-term government bond yields are explained largely by their own structural shocks (this actually holds for all forecast horizons, with some variations for short-term forecasts). However, a very different picture emerges for US high yield spreads and EMBIG spreads: for forecast horizons above 5 periods, the variances of

Table 4: Variance decomposition

	% of 10-period ahead forecast error variance of...			
	US 3m	**US 10y**	**US HY**	**EMBIG**
... explained by shocks to				
US 3m	84.6	1.6	1.6	11.5
US 10y	1.9	96.8	97.1	85.9
US HY	0.2	0.4	0.1	0.4
EMBIG	0.5	1.1	0.7	0.8
common shock	13	0.1	0.4	1.4

Regime choice using threshold rule.

the errors in forecasting US high yield and EMBIG spreads are both almost exclusively explained by structural shocks to US long-term government bond yields. This suggests that US long-term rates are of primary importance for explaining the developments of markets of more risky debt, at least in the medium run.

5 Robustness checks

5.1 Parameter stability

The fundamental assumption underlying our empirical methodology is that the structural parameters in the matrices A and Γ are stable. Unfortunately, within our methodology it is impossible to check whether parameters are stable across regimes. Given our limited sample it is not possible to estimate the reduced-form VAR in equation (4) separately for each regime and then test for whether the estimated coefficients are stable across regimes (the smallest regime contains only 72 observations). What we can test for, however, is whether parameters are stable across reasonably large subsets of our sample. We do so formally by using a multivariate version of the Chow test, which tests for stability of the reduced-form parameters, but not for stability of the structural shock variances. If the reduced form parameters, $B = A^{-1}\Pi$ are stable, then so should the structural parameters in matrix A. We therefore re-estimate the reduced-form VAR for two subsamples, from January 1997 up until summer 2000 and from summer 2000 until December 2006. The null hypothesis of parameter stability is not rejected.[18]

[18] Note however that results from the test may be biased because of heteroskedasticity of the structural shocks - see e.g. Toyoda (1974). Therefore, it is likely that the critical value is in fact lower than the one found from the χ^2 - distribution. However, our test results indicate that parameter stability is accepted by a wide margin.

Table 5: Structural-form coefficients in two subsamples

	first sample (pre-2000)			
From...	**US 3m**	**US 10y**	**US HY**	**EMBIG**
...to				
US 3m		0.0284	-0.1882	-0.0512
US 10y	0.1941		**-0.2132**	-0.1499
US HY	0.1004	**-0.4676**		0.0734
EMBIG	-0.0218	0.0476	**0.1108**	
	second sample (post-2000)			
From...	**US 3m**	**US 10y**	**US HY**	**EMBIG**
...to				
US 3m		0.1462	-0.0370	0.0413
US 10y	**0.1138**		-0.0382	-0.1603
US HY	-0.0237	**-0.5352**		0.1235
EMBIG	-0.0293	-0.0732	**0.2232**	

Bold coefficients are significant at the 95% confidence level.
For details see Tables 9 and 10 in appendix B.

To investigate further whether the parameters of the structural model change across time, we split our dataset into two samples and reestimate our model. For the estimation of the model in the two subsamples we use the same regime periods as before, chosen from the analysis of the whole dataset. The estimation in the subsamples is complicated by the fact that regime periods are spread unevenly across the sample: for example, most EMBIG-regime periods are in the first half of the sample (corresponding to the observation that EMBIG volatility has declined substantially in recent years), while US high yield regime periods are mostly in the middle/second half of the sample. We split the sample around summer 2000 to ensure that all regimes in both samples contain enough observations for the model to be identified. However, from the results in Tables 5 and 6 it is seen that even with this split most estimated coefficients remain insignificant because the number of observations in some high volatility regimes remains too small to guarantee robust identification.

The estimated structural coefficients corresponding to direct spillover effects are reported in Table 5. Most of the structural coefficients estimated for both subsamples have the same sign as in the benchmark estimation in Table 3. Moreover, most coefficients are even quantitatively similar. The only exceptions are that the effect of US long-term government bond yields on EMBIG spreads turns negative for both parts of the sample,

Table 6: Reduced-form coefficients in two subsamples

		first sample (pre-2000)		
From...	**US 3m**	**US 10y**	**US HY**	**EMBIG**
...to				
US 3m	1.0045	0.1303	-0.2265	-0.0876
US 10y	0.1948	1.1369	-0.3015	**-0.2025**
US HY	0.0089	-0.5190	**1.1267**	**0.1601**
EMBIG	-0.0117	-0.0062	0.1154	**1.0100**
		second sample (post-2000)		
From...	**US 3m**	**US 10y**	**US HY**	**EMBIG**
...to				
US 3m	**1.0202**	**0.1710**	-0.0421	0.0095
US 10y	**0.1300**	**1.0779**	-0.0857	-0.1780
US HY	-0.1014	**-0.6080**	**1.0775**	0.2264
EMBIG	-0.0621	**-0.2196**	**0.2481**	**1.0633**

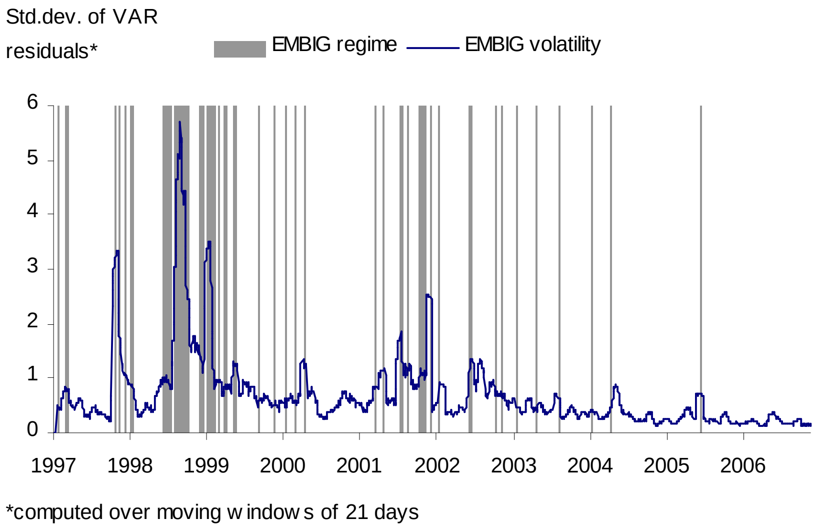
Bold coefficients are significant at the 95% confidence level.
For details see Tables 9 and 10 in appendix B.

while the effect of US short-term rates on US high yield spreads turns negative in the second part of the sample (however, in both cases the coefficients remain insignificant). The comovement of EMBIG and US high yield spreads increases in the second part of the sample, although only the effect from US high yield to EMBIG is significant.

Next we turn to the reduced-form coefficients, corresponding to the overall contemporaneous effects of structural shocks on the endogenous variables. These are reported in Table 6. There are three main changes between the estimated transmission channels for the first and the second sample. The strength of the "flight-to-quality" effect decreases in the second part of the sample, and the influence of EMBIG on US high yield spreads is stronger than the reverse effect in the first part of the sample, while the opposite is true in the second sample. A further change occurs in the effect of US government bond yields on EMBIG spreads: the estimated coefficients change from roughly zero in the first part to strongly negative in the second part of the sample.

These changes in coefficients between the two samples may partly reflect difficulties in identification, since due to the rarity of EME crises in recent years there are only very few observations in the EMBIG-volatility regime of the second sample. However, it is also possible that there are more fundamental reasons. Over the years, the composition of the EMBIG index has changed: while in the 1990s the fraction of investment-grade

Figure 4: EMBIG high volatility regime periods with multivariate mixture model



debt in the EMBIG was about 10%, this number has increased to about 50% in recent years. Therefore, the nature of EME bonds as an asset class - including their relationship with other macroeconomic indicators - may have changed.

5.2 Alternative methods of regime choice

The results presented in the previous sections were derived using a simple threshold rule to choose volatility regimes. This rule is very easy to implement and works well in practice. However, one may feel uncomfortable with regime choice using an apparently "ad-hoc" rule. As a robustness check, we present here results using an alternative method which involves estimating a regime switching model to describe the behavior of the residuals/structural shocks. We assume that the stochastic process through which structural shocks are generated is governed by an underlying unobserved variable which we call the state. Thus, if the system is in state $s_t = 1$, structural shocks are assumed to have a covariance matrix Ω_1, in state $s_t = 2$ shocks have a covariance matrix Ω_2 and so forth. The covariance matrices for each state, as well as the probability that any given observation of the residuals is generated by an underlying state $s_t = j$ can be estimated and in this way volatility regimes can be chosen endogenously. Because of the dimensionality of the problem, we use a multivariate mixture model, rather than a more standard Markov model. Therefore, we only need to estimate the unconditional

Table 7: Estimation results using endogenous regimes

(a) **contemporaneous feedback effects: direct**

From... ...to	**US 3m**	**US 10y**	**US HY**	**EMBIG**
US 3m		**0.22**	**-0.11**	-0.04
US 10y	**0.08**		0.03	**-0.14**
US HY	0.02	**-0.55**		**0.06**
EMBIG	**-0.15**	**0.07**	**0.08**	

(b) **contemporaneous feedback effects: overall**

From... ...to	μ_{US3}	μ_{US10}	μ_{USHY}	μ_{EMBIG}
US 3m	**1.03**	**0.28**	**-0.11**	**-0.08**
US 10y	**0.99**	**1.01**	0.01	**-0.14**
US HY	**-0.04**	**-0.55**	**1.00**	**0.14**
EMBIG	**-0.16**	-0.02	**0.10**	**1.01**

Bold coefficients are significant at the 95% confidence level.
See Table 11 in appendix B for details.

probabilities of each state and their means and covariances, but no transition matrix. Details are given in appendix A.

Figure 4 plots the regimes periods chosen for the case of EMBIG spreads, together with the volatility of EMBIG residuals (computed over moving windows of 21 days). Note that the regime periods chosen differ greatly from the previous threshold-method: individual regime periods often only last for two or three days, and are spread out more across the sample. Again, the most important EME crises events are picked up in the EMBIG high volatility regime. Note that the bond market sell-off in May/June 2006 is included as well (in contrast to the regime choice with threshold rule).

Estimation results are presented in Table 7. Although most coefficients are equal in sign and similar in magnitude to the previous results, there are two differences: the direct effect of US long-term government bond yields on EMBIG spreads is estimated to be positive, and now also significant, while the corresponding overall effect is again negative, but now insignificant. Furthermore, we again find that the financing cost argument holds only for US long-term, but not for short-term rates (if indeed it holds at all). A further difference is that the effect of US high yield spreads on US long rates is now estimated to be positive, although close to zero and insignificant.

6 Conclusion

This paper has analysed how shocks are transmitted across bond markets in emerging market economies and mature markets. Our main contribution was to use a recently developed method, "Identification through Heteroskedasticity", to identify all parameters in a structural model of bond markets in the US and EMEs, without imposing ad-hoc assumptions. This allowed us to quantify not only the overall spillover effects, but also the importance of alternative transmission channels.

We found strong evidence for the "flight to quality" phenomenon, while the "financing cost channel" was estimated to be insignificant, or significant but with negative sign in the case of overall effects. An alternative explanation for this negative sign is that interest rates in the US are procyclical such that they actually support economic growth in EMEs. Concerning the comovement of US high yield spreads and EMBIG spreads we found that spill over effects in both ways are equally important. Therefore, the feedback between EME bond markets and markets for risky debt in developed countries appears to be an important channel through which crises in EMEs can negatively affect mature markets.

We carried out robustness checks to show that our results are not sensitive to the exact choice of the regime windows, using a multivariate mixture model to choose volatility regimes endogenously. We also tested for parameter stability by te-estimating the model for two subsamples of our dataset.

Apart from providing some interesting new evidence on financial transmission channels between emerging and mature bond markets, our analysis can hopefully be of further use for monitoring the development of international financial markets. Comparing how estimated coefficients change as the sample grows might lead to interesting insights into how the importance of different transmission channels has changed. This can help to evaluate the risk that shocks to EMEs could spill over to mature markets.

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7 Appendices

A Estimating regimes using a multivariate mixture model

This appendix provides more detailed information on how volatility regimes can be estimated using a multivariate mixture model.[19] Let be $\mathbf{e}_t$ a vector containing the period t VAR residuals,

$$\mathbf{e}_t = \left[\begin{array}{cccc} e_{us3m,t} & e_{us10y,t} & e_{ushy,t} & e_{embig,t} \end{array} \right]'$$

and assume that for each period t, $\mathbf{e}_t$ is drawn from a different probability distribution, depending on the current realization of an underlying, unobserved variable s_t which we call the state (some realizations of s_t will later correspond to our volatility regimes). Assume that there are M states, so that $s_t = \{1, 2, ..., M\}$. Let the unconditional probability that a given state, say $s_t = j$, is realized in t be given by

$$p\left(s_t = j; \boldsymbol{\theta}\right) = \pi_j,$$

where $\boldsymbol{\theta}$ is a vector that contains all parameters of the model, as defined below. If the underlying state in t is $s_t = 1$ our residuals $\mathbf{e}_t$ are assumed to have been drawn from a multivariate normal distribution with mean $\boldsymbol{\mu}_1$ and covariance matrix $\boldsymbol{\Sigma}_1$; if the current state is $s_t = 2$, the residuals are drawn from a normal distribution with mean $\boldsymbol{\mu}_2$ and covariance matrix $\boldsymbol{\Sigma}_2$. In general, we have

$$\mathbf{e}_t | s_t = j; \boldsymbol{\theta} \sim N\left(\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j\right)$$

The corresponding probability density function (conditional on $s_t = j$) is denoted by $f\left(\mathbf{e}_t | s_t = j; \boldsymbol{\theta}\right)$. The vector $\boldsymbol{\theta}$ summarizes all parameters in our model. Thus $\boldsymbol{\theta}$ will contain the unconditional probabilities of the M states, $\pi_1, ..., \pi_M$, the elements of the mean vectors $\boldsymbol{\mu}_j$ for each state $j = 1, ..., M$, and the unique elements of the M covariance matrices $\boldsymbol{\Sigma}_j$.

The idea is then to choose the parameters in $\boldsymbol{\theta}$ such that the probability of observing our sample of residuals is maximized. To compute the likelihood function, consider first the joint probability of observing $\mathbf{e}_t$ while the underlying state is $s_t = j$. This is given

[19] For an introduction into the formulation and estimation of univariate mixture distributions see Hamilton (1994), chapter 22.

by

$$p(\mathbf{e}_t, s_t = j; \boldsymbol{\theta}) = f(\mathbf{e}_t | s_t = j; \boldsymbol{\theta}) \cdot \pi_j$$

Summing over all possible states M, the unconditional density of $\mathbf{e}_t$ is then

$$f(\mathbf{e}_t; \boldsymbol{\theta}) = \sum_{j=1}^{M} p(\mathbf{e}_t, s_t = j; \boldsymbol{\theta})$$

From this, the log likelihood is computed as

$$L(\boldsymbol{\theta}) = \sum_{t=1}^{T} \log f(\mathbf{e}_t; \boldsymbol{\theta})$$

where T is the number of observations in the sample. The likelihood function is then maximized with respect to $\boldsymbol{\theta}$ using the EM algorithm. This algorithm has the advantage that it increases the value of the likelihood function in each iteration; thus, if the algorithm converges, we have found the maximum of the likelihood function. The estimation is performed using the MATLAB toolbox *h2m*, written by Cappé (2001).

Once the parameters have been estimated, we can compute the probability that the underlying state in some period t is $s_t = j$. This is done using Bayes' rule:

$$p(s_t = j | \mathbf{e}_t, \boldsymbol{\theta}) = \frac{p(\mathbf{e}_t, s_t = j; \boldsymbol{\theta})}{f(\mathbf{e}_t; \boldsymbol{\theta})}$$

We then say that the underlying state in period t is j if this is the state which has the highest conditional probability: formally, $s_t = j$ if $p(s_t = j | \mathbf{e}_t, \boldsymbol{\theta}) > p(s_t = i | \mathbf{e}_t, \boldsymbol{\theta})$ for all i.

Next, we need to decide which of the M states correspond to our volatility regimes. Recall that for identification purposes, we would like to choose $N = 1 + n$ regimes: one "tranquility" regime, and n regimes where only one variable is volatile, while the others have a low volatility. Thus we pick those of the M states that best match this description.

How should the number of states, M, be determined? We take $M = n^2$ to cover all possible volatility combinations that can arise if each variable is either volatile or not.[20] For example there could be one state where only US short rates are volatile, another

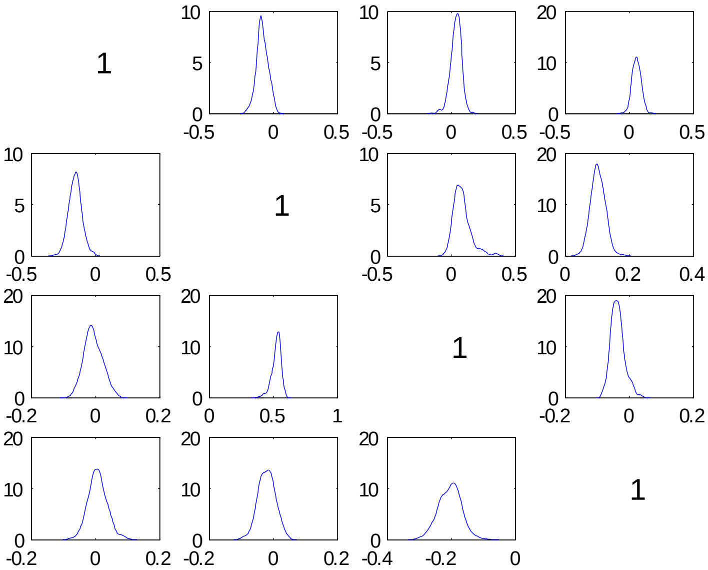
[20] Of course, the estimated variances do not need to confirm intuition; for example, one variable could be estimated to have a low variance in all states, while another variable exhibits several different levels of volatility across states. However, allowing for a greater number of states would further increase the dimensionality of the maxization problem.

state where US short and long rates are volatile, a third state where US short rates and US high yield spreads are volatile and so forth. We set starting values for the EM algorithm to point estimation in the direction of such volatility combinations.

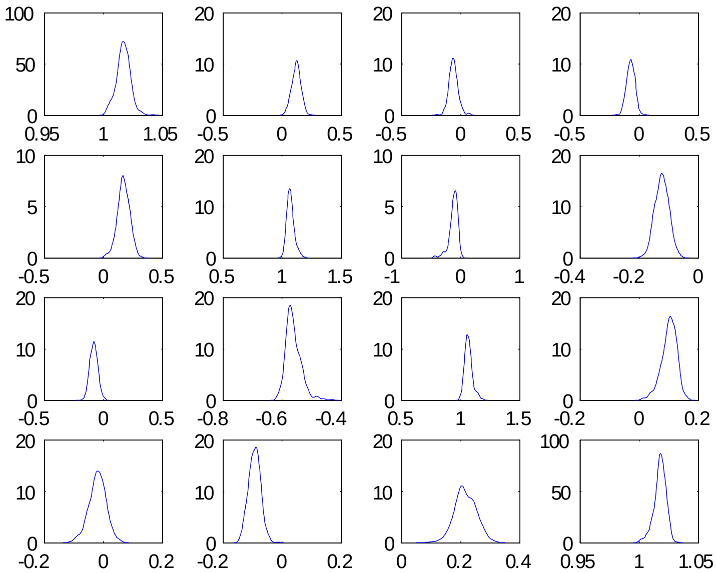
It is worth noting that the dimension of the problem can become quite large, so that the algorithm may take long to converge. Convergence is significantly faster if the covariance matrices $\mathbf{\Sigma}_j$ are diagonal. Unfortunately this is unrealistic as the VAR-residuals will be correlated (unlike the underlying structural shocks which we are trying to uncover).[21] Alternatively we could also work with the standard deviations of the residuals - however, in this case it is not clear whether or not it is reasonable that, for example, $\sigma^2_{us10,t}$ and $\sigma^2_{embig,t}$ will be correlated in a given state.

[21] Recall that $e_t = A^{-1}(\Gamma z_t + \mu_t) + \varepsilon_t$, where ε_t represents the error in estimating our reduced-form parameters $A^{-1}\Pi(L)$.

B Tables and graphs



Distribution of structural coefficients (matrix A) from 500 bootstrap replications



Distribution of reduced-form coefficients (matrix A^{-1}) from 500 bootstrap replications

Table 8: Bootstrap results for benchmark specification (threshold rule)

Estimated structural-form coefficients (matrix A)

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
US 3m→US 10y	-0.1709***	-0.1571	0.0501	0
US 3m→US HY	-0.0018	-0.0090	0.0264	0.3660
US 3m→EMBIG	0.0064	0.0091	0.0293	0.3920
US 10y→US 3m	-01001**	-0.0905	0.0506	0.0440
US 10y→US HY	0.5316***	0.5217	0.0383	0
US 10y→EMBIG	-0.0209	-0.0221	0.0254	0.1840
US HY→US 3m	0.0270	0.0358	0.0408	0.1580
US HY→US 10y	0.0606*	0.0804	0.0678	0.0640
US HY→EMBIG	-0.2030***	-0.2048	0.0319	0
EMBIG→US 3m	0.0552**	0.0571	0.0361	0.0380
EMBIG→US 10y	0.1048***	0.1048	0.0216	0
EMBIG→US HY	-0.0379**	-0.0359	0.0191	0.0480

Estimated reduced-form coefficients (matrix A^{-1})

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
μ_{us3m} →US 3m	1.0221***	1.0170	0.0061	0
μ_{us3m} →US 10y	0.1828***	0.1684	0.0511	0
μ_{us3m} →US HY	-0.0962***	-0.0798	0.0337	0.0040
μ_{us3m} →EMBIG	-0.0223	-0.0221	0.0294	0.2260
μ_{us10y} →US 3m	0.1273***	0.1227	0.0443	0
μ_{us10y} →US 10y	1.0662***	1.0708	0.0326	0
μ_{us10y} →US HY	-0.5701***	-0.5601	0.0285	0
μ_{us10y} →EMBIG	-0.0943***	-0.0921	0.0200	0
μ_{ushy} →US 3m	-0.0498**	-0.0615	0.0372	0.0420
μ_{ushy} →US 10y	-0.0950***	-0.1207	0.0769	0.0100
μ_{ushy} →US HY	1.0585***	1.0668	0.0340	0
μ_{ushy} →EMBIG	0.2132***	0.2162	0.0334	0
μ_{embig} →US 3m	-0.0717**	-0.0733	0.0363	0.0200
μ_{embig} →US 10y	-0.1254***	-0.1262	0.0227	0
μ_{embig} →US HY	0.1052***	0.1019	0.0230	0
μ_{embig} →EMBIG	1.0192***	1.0178	0.0045	0

*,** and *** denote significance at the 90%, 95% and 99% level, respectively. Results from 500 bootstrap replications. Regime choice using threshold rule.

Table 9: Bootstrap results for first subsample (pre-2000)

Estimated structural-form coefficients (matrix A)

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
US 3m→US 10y	0.1941	0.2584	0.4876	0.2180
US 3m→US HY	0.1004	-0.0630	0.5382	0.7960
US 3m→EMBIG	-0.0218	-0.0361	0.1353	0.2840
US 10y→US 3m	0.0284	0.1599	0.3262	0.3140
US 10y→US HY	-0.4676***	-0.4435	0.1222	0.0040
US 10y→EMBIG	0.0476	0.0604	0.0806	0.1140
US HY→US 3m	-0.1882	-0.1991	0.1790	0.1180
US HY→US 10y	-0.2132***	-0.3407	0.2454	0.0060
US HY→EMBIG	0.1108***	0.1309	0.0976	0.0080
EMBIG→US 3m	-0.0512	-0.0228	0.0802	0.3320
EMBIG→US 10y	-0.1499*	-0.1209	0.0763	0.0820
EMBIG→US HY	0.0734	0.0588	0.0626	0.1260

Estimated reduced-form coefficients (matrix A^{-1})

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
μ_{us3m} →US 3m	1.0045	0.7308	2.4302	0.1180
μ_{us3m} →US 10y	0.1948	-0.2513	3.9427	0.5800
μ_{us3m} →US HY	0.0089	0.3565	3.8658	0.2360
μ_{us3m} →EMBIG	-0.0117	0.0159	1.3741	0.6000
μ_{us10y} →US 3m	0.1303	0.1193	1.2692	0.2040
μ_{us10y} →US 10y	1.1369	0.9804	1.6499	0.1140
μ_{us10y} →US HY	-0.5190	-0.3503	1.2805	0.1200
μ_{us10y} →EMBIG	-0.0062	-0.0152	0.5584	0.5260
μ_{ushy} →US 3m	-0.2265	-0.0878	1.7015	0.1520
μ_{ushy} →US 10y	-0.3015	-0.1062	2.8583	0.1180
μ_{ushy} →US HY	1.1267**	0.8440	3.0454	0.0360
μ_{ushy} →EMBIG	0.1154*	0.0682	0.9345	0.0600
μ_{embig} →US 3m	-0.0876*	-0.0827	0.0619	0.0760
μ_{embig} →US 10y	-0.2025***	-0.1918	0.0733	0.0040
μ_{embig} →US HY	0.1601**	0.1469	0.0721	0.0200
μ_{embig} →EMBIG	1.0100***	1.0080	0.0256	0

*,** and *** denote significance at the 90%, 95% and 99% level, respectively. Results from 500 bootstrap replications. Regime choice using multivariate mixture model.

Table 10: Bootstrap results for second sub-sample (post-2000)

Estimated structural-form coefficients (matrix A)

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
US 3m→US 10y	0.1138**	0.1235	0.0758	0.0440
US 3m→US HY	-0.0237	-0.0246	0.0805	0.3760
US 3m→EMBIG	-0.0293	-0.0144	0.0746	0.4660
US 10y→US 3m	0.1462*	0.1304	0.1044	0.0680
US 10y→US HY	-0.5352***	-0.5221	0.0541	0
US 10y→EMBIG	-0.0732	-0.0593	0.1009	0.2820
US HY→US 3m	-0.0370	-0.0305	0.1772	0.3200
US HY→US 10y	-0.0382	-0.0665	0.1025	0.2320
US HY→EMBIG	0.2232**	0.2359	0.1425	0.0420
EMBIG→US 3m	0.0413	0.0431	0.1165	0.3220
EMBIG→US 10y	-0.1603*	-0.1598	0.1121	0.0840
EMBIG→US HY	0.1235	0.1159	0.1221	0.1580

Estimated reduced-form coefficients (matrix A^{-1})

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
μ_{us3m} →US 3m	1.0202***	1.0053	0.0301	0
μ_{us3m} →US 10y	0.1300**	0.1378	0.0826	0.0480
μ_{us3m} →US HY	-0.1014	-0.1013	0.0954	0.1020
μ_{us3m} →EMBIG	-0.0621	-0.0457	0.0822	0.2260
μ_{us10y} →US 3m	0.1710***	0.1488	0.0532	0.0040
μ_{us10y} →US 10y	1.0779***	1.0808	0.0490	0
μ_{us10y} →US HY	-0.6080 ***	-0.5906	0.0379	0
μ_{us10y} →EMBIG	-0.2196***	-0.2053	0.0672	0.0020
μ_{ushy} →US 3m	-0.0421	-0.0381	0.1635	0.2920
μ_{ushy} →US 10y	-0.0857	-0.1180	0.1247	0.1140
μ_{ushy} →US HY	1.0775***	1.0629	0.0729	0
μ_{ushy} →EMBIG	0.2481 **	0.2549	0.1455	0.0440
μ_{embig} →US 3m	0.0095	0.0164	0.1129	0.4580
μ_{embig} →US 10y	-0.1780*	-0.1799	0.1211	0.0680
μ_{embig} →US HY	0.2264*	0.2168	0.1402	0.0780
μ_{embig} →EMBIG	1.0633***	1.0375	0.0415	0

*,** and *** denote significance at the 90%, 95% and 99% level, respectively. Results from 500 bootstrap replications. Regime choice using multivariate mixture model.

Table 11: Bootstrap results for regime choice with multivariate mixture model

Estimated structural-form coefficients (matrix A)

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
US 3m→US 10y	-0.0764***	-0.1307	0.0501	0.0020
US 3m→US HY	-0.0206	-0.0089	0.0264	0.4500
US 3m→EMBIG	0.1542***	0.1606	0.0293	0
US 10y→US 3m	-0.2206***	-0.2495	0.0100	0
US 10y→US HY	0.5476***	0.5306	-0.0541	0
US 10y→EMBIG	-0.0673***	-0.1055	-0.0779	0.0060
US HY→US 3m	0.1105***	0.1236	0.1236	0
US HY→US 10y	-0.0280	-0.0541	-0.0541	0.1080
US HY→EMBIG	-0.0785**	-0.0779	-0.0779	0.0400
EMBIG→US 3m	0.0338	0.0201	0.0361	0.1480
EMBIG→US 10y	0.1348***	0.1371	0.0216	0
EMBIG→US HY	-0.0633***	-0.0647	0.0191	0.0060

Estimated reduced-form coefficients (matrix A^{-1})

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
μ_{us3m} →US 3m	1.0317***	1.0526	0.0214	0
μ_{us3m} →US 10y	0.0986***	0.1553	0.0533	0
μ_{us3m} →US HY	-0.0426**	-0.0825	0.0330	0.0460
μ_{us3m} →EMBIG	-0.1558***	-0.1576	0.0488	0
μ_{us10y} →US 3m	0.2838***	0.3181	0.0433	0
μ_{us10y} →US 10y	1.0089***	1.0118	0.0341	0
μ_{us10y} →US HY	-0.5478***	-0.5331	0.0286	0
μ_{us10y} →EMBIG	-0.0188	-0.0132	0.0384	0.4100
μ_{ushy} →US 3m	-0.1124***	-0.1187	0.0292	0
μ_{ushy} →US 10y	0.0064	-0.0228	0.0519	0.3920
μ_{ushy} →US HY	1.0003***	0.9928	0.0289	0
μ_{ushy} →EMBIG	0.0963***	0.0991	0.0451	0.0080
μ_{embig} →US 3m	-0.0803***	-0.0723	0.0264	0.0080
μ_{embig} →US 10y	-0.1390***	-0.1398	0.0309	0
μ_{embig} →US HY	0.1386***	0.1389	0.0397	0
μ_{embig} →EMBIG	1.0139***	1.0076	0.0078	0

*,** and *** denote significance at the 90%, 95% and 99% level, respectively. Results from 500 bootstrap replications. Regime choice using multivariate mixture model.