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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 using daily data from prior to the East Asian crisis through to the early stages of the current global financial crisis. We exploit the changing volatility of the data to fully identify a structural VAR, without imposing *ad hoc* restrictions. We find that shocks that widen emerging market sovereign debt (EMBIG) spreads have a negative effect on US interest rates in the short run (consistent with 'flight to quality' effects), while shocks that increase US interest rates raise EMBIG spreads over longer horizons (consistent with 'financing cost' or 'search for yield' effects). We also find that shocks that increase EMBIG spreads tend to widen US high-yield spreads and *vice versa*, constituting an important contagion channel through which crises in emerging market economies can affect mature markets. Forecast error variance decompositions show that shocks to US long rates can explain around 60%–70% of the variation of EMBIG and US high-yield spreads.

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Contents

Summary

With an increasingly integrated global financial system, we frequently observe that shocks to individual asset markets affect not only other asset markets in the same country but also the ones in other countries. Such spillover effects were noticeable during several past financial crises episodes in emerging market economies (EMEs) and have been also prevalent during the current global financial crisis which started in developed countries. From a central banking perspective, understanding the mechanisms through which shocks are transmitted across financial markets is important for gauging the impact that financial crises and volatilities in EMEs can have on the financial systems in developed countries, and *vice versa*.

Using daily data from prior to the east Asian crisis through to the early stages of the current global financial crisis, this study analyses the relationships between bond markets in the United States and EMEs. How do shocks — such as financial disruptions — in EME bond markets affect interest rates in the United States? And how do changes in US interest rates in turn affect EME bond markets? A key challenge in answering these questions is to identify a shock to a specific asset. For example, interest rates paid on risky US corporate debt and the rates paid on EME debt exhibit a high positive correlation: they tend to move in the same direction. However, we do not know whether this positive correlation is caused by EME shocks being transmitted to the United States, by US shocks affecting EMEs, or merely the result of a common shock.

Many studies deal with this problem by imposing some *ad hoc* restrictions; for example, assuming that the causality runs in only one direction. In this paper, we use a method developed by Rigobon and his co-authors, which allows us to capture all feedback effects. This method identifies a shock to a specific asset market as a period when volatility in this asset market is uniquely high; ie volatilities in other asset classes are low. Then the period can be used to identify the feedback effects from this market to other asset markets. The period of shocks identified in this way for EME bond markets capture all the known EME sovereign crises over the past decade (such as in Argentina, Brazil, Russia and Turkey).

We find that adverse shocks to EME sovereign bond spreads lead to a short-run fall in US interest. This finding supports a stylised fact that, at the time of stress, investors shift their investment away from risky assets into risk-free assets which causes prices of the risk-free assets

to rise, and thus their rates to fall. This is often described as a ‘flight to quality’. An adverse shock to EME bond spreads also leads to a widening in US high-yield spreads, and *vice versa*. This constitutes an important contagion channel through which crises in emerging markets can affect mature economies. What is the overall contemporaneous effect of a shock to EMEs on mature economies? On the one hand, mature economies might benefit from strong ‘flight to quality’, driving down the financing costs for risk-free bonds. On the other hand, an EME shock is not necessarily good news for mature economies as it will widen the spreads on other risky bonds, leading to a higher financing cost for risky corporates. In the other direction, we also find that an increase in financing costs of US riskier corporates — as happened in the early stages of the current financial crisis — can lead to a sizable increase in financing cost of EME sovereigns (although by much less than if shocks originate in EMEs themselves).

We also examine the speed and duration of shock transmission. For example, shocks that raise US interest rates initially *decrease* US high-yield and EME bond spreads for a very short period, but eventually widen the spreads of risky debt with a lag of about two days. Since both EME sovereign bonds and US high-yield bonds are priced as spreads over risk-free US Treasury yields with similar maturities, a rise in the US interest rates will automatically increase the interest rates paid on these risky bonds, ie higher financing cost for emerging market (EM) sovereigns and US corporates. The reverse is also true: a fall in US interest rates is likely to lead to a fall in EM and US high-yield bond spreads. This is consistent with the stylised fact that, when the safe rates are low, investors search for higher return by purchasing riskier bonds, which push up the prices and bring down the spreads on these assets. Therefore, our results support the existence of the ‘financing cost’ and ‘search for yield’ channels, but they work with a lag.

We then ask how much of the forecast error variance of each variable can be explained by shocks from other variables. We find that both US short and long-term government bond yields are explained largely by their own structural shocks, across all forecast horizons. However, a very different picture emerges for US high-yield and EM bond spreads: at longer forecast horizons the variances of the errors in forecasting US high-yield and emerging market sovereign debt spreads are both largely explained by structural shocks to US short and long-term rates. In particular, shocks to US long-term government bond yields explain 60% and 75% of the forecast error variance in EM bond spreads for 5-day and 20-day ahead forecasts. This suggests that US interest rates are of primary importance for explaining the developments in markets for more risky debt, at least in the medium run.

1 Introduction

Financial markets worldwide have become increasingly integrated. One consequence of this integration is that we observe a large degree of comovement across financial markets, as shocks to individual markets or countries are transmitted internationally. Such spillover effects were notable during past financial crises in emerging market economies (EMEs) and have been prevalent during the current global financial crisis which started in developed countries. 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 EMEs can affect the financial systems in developed countries, and *vice versa*.

Using daily data from prior to the east Asian crisis through to the early stages of the current global financial crisis, the aim of this paper is to quantify the linkages between bond markets in the United States and EMEs, and across government and high-yield debt markets.[1] How do shocks to one market or asset class affect other markets? And how fast are shocks transmitted through different channels? To answer these questions we estimate a structural vector autoregressive (VAR) model which is identified using the changing volatility in the data, following Rigobon (2003). We use daily data on US government bond yields, EME bonds spreads, and US high-yield spreads. The estimated coefficients of the structural model describe how the underlying structural shocks are transmitted across markets in the very short run (intraday), while the effects of shocks over longer horizons can be analysed using impulse response functions and forecast error decompositions.

We find that in the short run — over a horizon of one or two days — shocks that widen emerging market sovereign debt (EMBIG) or US high-yield spreads decrease US government bond yields, consistent with 'flight to quality' effects. While the effect of shocks to US interest rates on EME and US high-yield spreads is negative over very short horizons, we find that shocks to US interest rates increase spreads of risky debt with a lag of about two days: a positive shock to US short or long rates leads to wider spreads on risky debt, which could be interpreted as reflecting an increase in the default risk following higher financing costs; and the effect of lower US interest rates leading to more narrow spreads could reflect the market's 'search for yield'. We also find that shocks to EME spreads tend to widen US high-yield spreads, and *vice versa*: this comovement is particularly important because it represents one possible channel through which

[1] For a related study using data on UK bond markets see Felices, Hoggarth and Madouros (2008).

crises in EMEs might negatively affect mature markets.

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 made popular by Rigobon (2003), 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. The crucial assumption underlying this methodology is that while the volatility of the underlying shocks is allowed to change across time, the coefficients describing the comovement of the endogenous variables are constant over the whole sample period: our results should therefore be thought of as capturing average, long-run effects.

While the assumption of heteroskedastic underlying shocks is appropriate for the bond market data in our sample, assuming that parameters are stable across the sample period is more problematic. 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 whether parameters are stable across volatility periods. 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 across the first and second part of the sample is not rejected in a standard multivariate Chow test.

A crucial step in our estimation procedure is to identify periods in which the volatility of the underlying unobserved structural shocks changes. We employ two different methods to identify such volatility 'regimes'— an *ad hoc* threshold rule and a regime-switching model — and check whether our results are robust to the particular volatility periods chosen. We also discuss how our choice of volatility regimes corresponds to actual events, such as 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,[2] 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 financial contagion, typically defined as an increase in the correlation between markets in times of crises.[3] Research 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 (for example Forbes and Rigobon (2002)), and tests whether the probability of a crisis in one market, conditional on a crisis in another market, is higher than the unconditional probability (for example Pesaran and Pick (2007). 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 non-linearities 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.

While most empirical work on asset price comovements has looked at stock markets, studies analysing bond markets and in particular 'flight to quality' effects are scarce.[4] Hartmann, Straetmans and de Vries (2004) study the relationship of stocks and government bonds in times

[2]Examples include the correlated information channel (King and Wadhwani (1990)), portfolio rebalancing (Kodres and Pritsker (2002)), herd behaviour (Calvo and Mendoza (2000) and Chari and Kehoe (2003)), wealth effects (Kyle and Xiong (2001)), and the role of information markets (Veldkamp (2006)).

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

[4]For a comprehensive empirical study of bond markets see Borio and McCauley (1996).

of market turmoil. Using an extremal dependence measure, they calculate the probability of joint stock market crashes and of 'flight to quality', conditional on a crash in one market. Baur and Lucey (2006) study the relationship of bond yields, stock prices and gold prices and investigate whether gold acts as a hedge for bonds and stocks in normal times, and as a 'safe haven' in times of market turmoil. However, they only analyse the effects of shocks to bond and stock markets on the price of gold, without taking into account possible feedback from gold to other markets. Gonzalo and Olmo (2005) develop a copula to describe different patterns of dependence across stock and bond markets.

The contribution of this paper is to analyse the relationships between bond markets in EMEs and the United States, including both US high-yield debt and US government debt, and to identify how shocks are transmitted across markets without imposing unrealistic restrictions. The inclusion of US corporate debt spreads adds important insights that have been missing from the previous literature of financial market comovement, as widening credit spreads on risky debt are an important channel through which EME shocks can affect mature markets and *vice versa*. To our knowledge, this study is the first to analyse comovement between financial markets in EMEs and developed countries using the Rigobon (2003) methodology.

The remainder of this paper is structured as follows. The next section sets out the intuition for how variables in our sample might be related, and reviews some stylised facts about the correlations of the data for tranquil and crises periods. This is 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 estimation strategy. The fourth section then presents the results. Section 5 discusses robustness; 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.

2 Comovement of international bond markets: intuition and stylised facts

Before we begin with the formal empirical analysis it is useful to outline possible channels through which shocks could be transmitted across bond markets, and to look at some simple

Table A: Correlations

(a) Full sample, 1997-2008

	US 3m	US 10y	US HY	EMBIG
US 3m	1.00			
US 10y	0.27	1.00		
US HY	-0.24	-0.60	1.00	
EMBIG	-0.12	-0.29	0.33	1.00

(b) Russian/LTCM crisis, 1.8.1998-31.10.1998

	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.

statistics of the raw data to get an idea of the relevant stylised facts.

Our data set includes daily data from 1 January 1997 to 30 May 2008. We use US short (three-month) and long-term (ten-year) government bond yields as a measure of risk-less debt, and the Merrill Lynch High Yield Master II index ('US high-yield'), a benchmark index for the broad US high-yield debt market, as a measure of US corporate debt spreads. As a measure of emerging market debt spreads we use the JPMorgan Emerging Markets Bond Index Global ('EMBIG'), a benchmark for emerging market dollar-denominated debt.[5] For the compilation of the EMBIG index, JPMorgan uses information collected at 3 pm New York time. Therefore all data can be treated as being generated in the same time zone. Data is obtained from Bloomberg, Merrill Lynch and JPMorgan.

What comovements should we expect across bond market in the United States and EMEs? First consider the comovement of US short and long-term government bond yields. The economic theory of the term structure of interest rates suggests that US short and long rates should be positively related on most occasions. However, a fall in short-term interest rates could also induce an increase in long rates if markets take lower short rates as a signal of higher inflation in the future. Panel (a) of Table A reports contemporaneous correlations of the differenced raw data, computed over the whole sample period.[6] Note that US short and long-term government

[5]Since the EMBIG was introduced only in 1999, the JPMorgan Emerging Markets Bond Index (EMBI) is included up to 1998.

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

bond yields are indeed positively correlated.

Next consider the comovement of high-yield markets in the United States and EMEs. Intuitively, we would expect US high-yield spreads and EMBIG spreads to be positively related. For example, consider the case of a financial crisis in some emerging market economy, which could be captured through a shock to EMBIG spreads. We often observe that the reaction to such an event is a sell-off not only in the assets that are directly affected, but also in other risky and high-yielding markets. Such sell-offs could be driven by increased risk aversion, or margin calls forcing investors to sell risky debt following losses on some investments. From panel (a) of Table A we see that EMBIG and US high-yield spreads are positively correlated across the sample period.

US government bond yields, EMBIG and US high-yield spreads could be related through several distinct channels. First, risky debt is typically priced at a spread over risk-less rates. Therefore higher US interest rates should raise the financing costs of EMEs, which could increase their default risk and thus the spreads of EME sovereign bonds. Moreover, since spreads are computed as the difference between the yields of risky and risk-less assets with corresponding maturity they should be increasing in risk-less rates for simple 'mathematical' reasons.[7] Furthermore, falls in risk-less rates are often thought to be associated with a 'search for yield', as investors shift into more risky assets such as EME debt in order to earn higher returns, thus driving the prices of these assets up and their yield spreads over risk-less debt down. These 'financing cost' and 'search for yield' channels suggest that an increase (decrease) in US interest rates should lead to higher (lower) spreads on risky debt.

However following a rise in US government bond yields, US high-yield and EMBIG spreads could also move in the opposite direction. The spread of risky bonds is determined by the probability of default and the loss given default. Both factors have countercyclical characteristics. During a recession, the probability of default and the loss given default are likely to pick up, so does the spread. Therefore, the spread on risky assets is believed to be countercyclical (see for example Duffie and Singleton (2003). If an increase in US interest rates is associated with or signals strong economic growth in the United States,[8] it could hence lead to

[7]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 $i - r = (1 + r)(1 - p)/p$ which is increasing in r.

[8]Indeed, the simple statistical correlation between GDP growth and US ten-year government bond yields is around 0.4 for our sample

a *decrease* in US high yield spreads. Moreover, given that the United States is an important trading partner of most countries in the EMBIG index, a rise in US interest rates could induce a fall in EMBIG spreads as well. We call this the 'growth effect'.

Furthermore, financial crises episodes 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: therefore, an increase in EME spreads could lead to a fall in US government bond yields. In short, the 'growth effect' and the 'flight-to-quality effect' suggest a negative correlation between US interest rates and US high-yield spreads and EMBIG.

From panel (a) of Table A we see that US interest rates, EMBIG and US high-yield spreads are negatively correlated. One possible interpretation of this finding is that at least in the contemporaneous relationship between US interest rates and yields on risky debt, 'flight to quality' and 'growth' effects dominate the 'financing cost' and 'search for yield' channels.[9] Previous empirical studies have failed to find clear evidence of a positive effect of US interest rates on EME bond spreads (see for example Eichengreen and Mody (1998) and Kamin and von Kleist (1999), and only few studies have sought to quantify the reverse influence of EMEs on financial markets in mature economies.[10] One of the main contributions of this paper is to shed light on the causal relationship between US interest rates and EME bond spreads.

It is interesting to also look at how correlations change during periods of financial market turmoil. As an example, panel (b) of Table A 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'.

period.

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

[10]For example, Sáez, Fratzscher and Thiemann (2007) identify shocks originating in emerging markets from data on news announcements and analyse their effect on global equity markets, including equity markets in mature economies. Kaminsky and Reinhart (2003) find that emerging market shocks spreads globally if they affect the financial centres in mature economies. Moschitz (2004) is the only study that we are aware of that analyses the relationship of bond markets in EMEs and the US corporate debt market, as well as US stock markets, using a reduced-form regime-switching model. In contrast, we are also able to identify the contemporaneous relationships across markets.

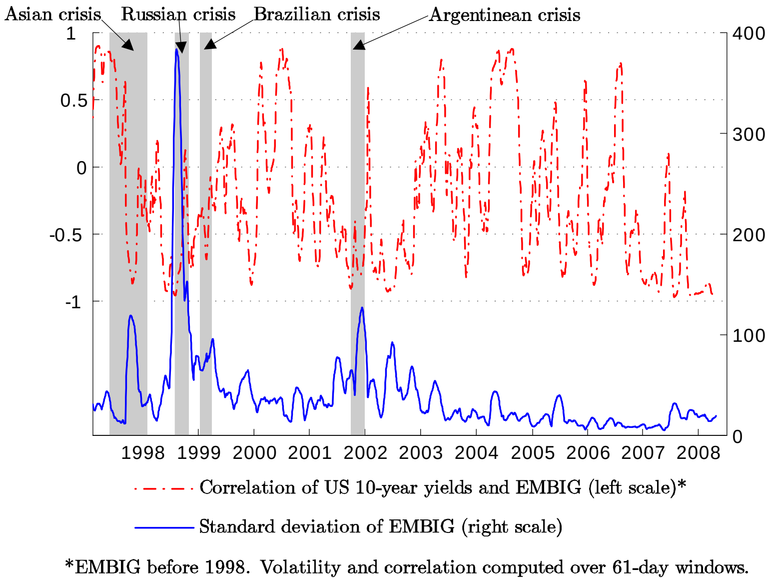

Chart 1: Correlation of US ten-year government bond yields and EMBIG spreads

Chart 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. Several financial crises episodes are marked by spikes in EMBIG volatility, and by a corresponding fall in 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 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 times 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 of 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. For example, a high correlation between EMBIG spreads and US government bond yields could be caused by EMBIG spreads affecting US interest rates (eg, 'flight to quality'); by US interest rates affecting EMBIG spreads (eg, the 'financing costs' channel); or causation could run through some third factor such as US high-yield spreads (eg, a financial crisis in an 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). Moreover, apart from the contemporaneous correlations presented in Table A, shocks to one variable could be transmitted more slowly, affecting other variables only with a lag. 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. As an example, Chart 1 shows that episodes of EME crises are clearly marked by higher EMBIG volatility. This heteroskedasticity of the data can be exploited to identify the structural model, following Rigobon (2003).[11]

To illustrate this identification method consider a simple example with only two endogenous variables — say, EMBIG spreads and US government bond yields — which are related as follows:

$$EMBIG_t = \alpha \cdot i_{US,t} + \epsilon_t \quad \textbf{(1)}$$

$$i_{US,t} = \beta \cdot EMBIG_t + \eta_t \quad \textbf{(2)}$$

where ε_t and η_t are structural shocks. Following the intuition from the previous section we might expect $\alpha > 0$ (the 'financing cost channel') and $\beta < 0$ ('flight to quality' effects). This situation is captured in panel (a) of Chart 2. A data set of observations on EMBIG and US interest rates might look like the scatterplot on the right panel (b) of Chart 2. Clearly, it is very difficult to separately identify the two relationships in **(1)** and **(2)**. More formally, estimating equations **(1)** and **(2)** separately will yield biased coefficients because of simultaneous equation bias.

Now, suppose that we can distinguish periods in which the volatility of one variable increases,

[11] See also Wright (1928) and Sentana and Fiorentini (2001).

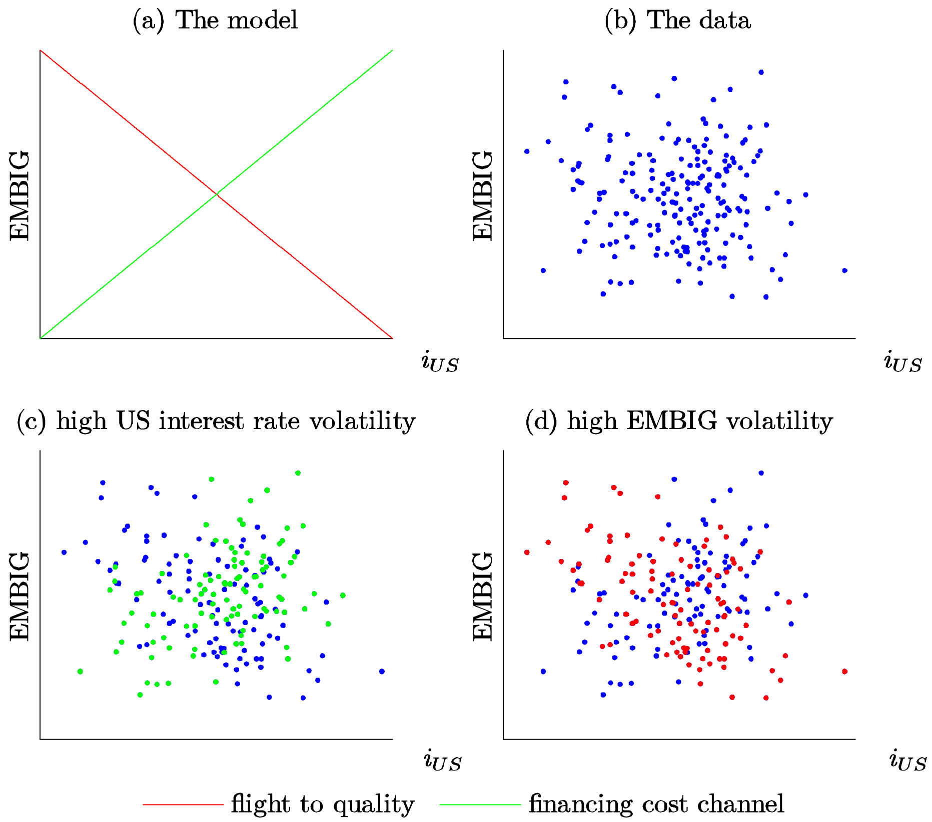

Chart 2: Illustration of identification procedure

while the volatility of the other variable stays constant or increases only slightly. We could interpret the heteroskedasticity observed in EMBIG spreads and US interest rates as stemming from varying volatility of the underlying structural shocks ε_t and η_t. Then during periods when US interest rate shocks are very volatile the relationship in equation **(1)** is traced out, as shown in panel (c) of Chart 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 — 'volatility regimes' — can help to identify the model.

Note that the choice of volatility 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 Chart 2. The next section introduces our empirical model and explains identification through heteroskedasticity more formally.

3.2 The empirical model

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

$$\mathbf{A}\mathbf{y}_t = \boldsymbol{\vartheta}(t) + \Pi(L)\,\mathbf{y}_{t-1} + \gamma z_t + \boldsymbol{\mu}_t \tag{3}$$

where $\mathbf{y}_t$ is a vector of endogenous variables, z_t is a common shock, and $\boldsymbol{\mu}_t$ is a vector of structural shocks, $\mathbf{A}$ and $\Pi(L)$ are parameter matrices with L denoting the lag operator, γ is a vector of parameters, and the vector $\boldsymbol{\vartheta}(t)$ includes both constants and a time trend. The diagonal elements in $\mathbf{A}$ and the first element in γ are normalised to one. Of particular interest to us is the matrix $\mathbf{A}$, which determines the contemporaneous feedback effects among the endogenous variables. We make the following assumptions:

$$\begin{aligned} E(\boldsymbol{\mu}_t) &= E(\boldsymbol{\mu}_t z_{t-k}) = \mathbf{0} \\ E(z_t) &= E(z_t z_{t-j}) = 0 \\ E(\boldsymbol{\mu}_t \boldsymbol{\mu}'_{t-i}) &= \mathbf{0} \end{aligned}$$

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

To capture the changing volatility of the 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 $s = 1, \ldots, S$ volatility periods or regimes, and that the shock variances are constant within each regime, but differ across regimes. For each regime s we have

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

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 $\mathbf{A}^{-1}$. This yields

$$\mathbf{y}_t = \mathbf{B}_0 (t) + \mathbf{B}_1 (L) \mathbf{y}_{t-1} + \mathbf{u}_t \tag{4}$$

where $\mathbf{B}_0 (t) \equiv \mathbf{A}^{-1} \boldsymbol{\vartheta} (t)$, $\mathbf{B}_1 (L) \equiv \mathbf{A}^{-1} \Pi(L)$ and

$$\mathbf{u}_t \equiv \mathbf{A}^{-1} \gamma z_t + \mathbf{A}^{-1} \boldsymbol{\mu}_t \tag{5}$$

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 in $\mathbf{B}_0 (t)$ and $\mathbf{B}_1 (L)$.[12] However, we want to go further and identify the structural parameters in $\mathbf{A}$ and γ. To do this we can use 'identification through heteroskedasticity', implemented through general methods of moments (GMM) estimation. The residuals from the regression in **(4)** will reflect the underlying shocks $\boldsymbol{\mu}_t$ and z_t. Therefore it is natural to use these residuals to determine volatility regimes. How this can be done is described in the next section.

From equation **(5)** the variance-covariance matrix of the error term $\mathbf{u}_t$ for regime s is computed as

$$\boldsymbol{\Omega}_{u,s} = \mathbf{A}^{-1} \gamma \gamma' \sigma^2_{z,s} \mathbf{A}^{-1\prime} + \mathbf{A}^{-1} \boldsymbol{\Omega}_{\mu,s} \mathbf{A}^{-1\prime} \tag{6}$$

While $\boldsymbol{\Omega}_{u,s}$ is unknown, we can compute the variance-covariance matrix of the VAR residuals $\boldsymbol{\Omega}_{e,s}$ separately for each regime s. Substituting $\boldsymbol{\Omega}_{e,s}$ as a proxy for $\boldsymbol{\Omega}_{u,s}$ into **(6)** and rearranging leads to GMM conditions, which are given by

$$\mathbf{A} \boldsymbol{\Omega}_{e,s} \mathbf{A}' = \gamma \gamma' \sigma^2_{z,s} + \boldsymbol{\Omega}_{\mu,s} \tag{7}$$

Note that $\boldsymbol{\Omega}_{\mu,s}$ is diagonal since we have assumed that the structural shocks are uncorrelated. If there are n endogenous variables $\boldsymbol{\Omega}_{e,s}$ will have $N = n \cdot (n+1)/2$ distinct elements, so that equation **(7)** delivers N moment conditions for each regime which we summarise in the column vector $\mathbf{m}_s$. Therefore, with S regimes, we obtain $N \cdot S$ moment conditions which can be used for GMM estimation. There are in total $n^2 - 1 + S(n+1)$ structural parameters which need to be estimated: $n(n-1)$ non-normalised parameters in $\mathbf{A}$, $n-1$ non-normalised parameters in γ, and the variances of the $n+1$ shocks for the S regimes. The model is identified if there are at least as many moment conditions as unknown parameters. Therefore we need to find at least

$$S \geq 2 \cdot \frac{n-1}{n+2} \tag{8}$$

[12]See eg Enders (2003), page 270.

volatility regimes for the model to be identified. Let $\boldsymbol{\theta}$ denote a vector containing all unknown structural parameters. We choose $\boldsymbol{\theta}$ to minimise the objective function

$$\min_{\boldsymbol{\theta}} \mathbf{m}'\mathbf{m} \tag{9}$$

with

$$\mathbf{m} = \left[\begin{array}{cccc} m_1 \cdot \frac{T_1}{T} & m_2 \cdot \frac{T_2}{T} & \ldots & m_S \cdot \frac{T_S}{T} \end{array} \right]'$$

where T_s denotes the number of observations in regime s and T denotes 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 can be summarised as follows. First, we estimate the reduced-form model given in equation **(4)** using OLS, including US short- and long-term government bond yields, US high-yield spreads and EMBIG spreads as endogenous variables. 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 **(7)**. Finally, GMM is used to identify the structural form parameters of the original VAR.

3.3 Choosing volatility regimes

Some previous studies applying 'identification through heteroskedasticity' have used straightforward economic intuition to identify volatility regimes. For example, Rigobon and Sack (2004) analyse the effect of US monetary policy on asset prices. They use two regimes, one including periods of Federal Open Market Committee meetings and Fed chairman's testimonies to congress, and another including all other periods. The idea is that 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 (2008) 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.

In our case no such natural, exogenous events are available to identify volatility regimes. While some events can be identified — for example, financial crises in emerging markets could be interpreted as shocks to EMBIG spreads, tightening cycles in US monetary policy could represent shocks to US short-term government bond yields, and the US auto sector turmoil in 2005 could be captured through shocks to US high-yield spreads — it is often not straightforward to map such events into volatility regimes because many events may be associated with shocks to several variables at once. Therefore we instead use two alternative methods to choose regimes. The first method uses a simple threshold rule, following 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 5.

Recall from Chart 2 that volatility regimes should be chosen such that the relative volatilities of different structural shocks vary significantly across regimes. To achieve identification 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' can be decided by defining a reasonable volatility threshold. Thus 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

$$mean(\sigma_{i,t}) + c \cdot st.dev(\sigma_{i,t}) \qquad \textbf{(10)}$$

where we set $c = 1$. Whenever $\sigma_{i,t}$ is above this 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, so that from equation **(8)** the model is overidentified. In regime one we include periods where the residuals of all endogenous variables are tranquil. In addition, 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.[13]

Chart 3 plots the volatility of EMBIG residuals and the threshold which is used to 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

[13] Increasing c in equation **(10)** will decrease the number of volatility periods and therefore typically also the number of *unique* high-volatility periods, making identification more difficult. Decreasing c will increase the number of high-volatility periods; however, it is then also more likely that the volatility of more than one variable is above the threshold for any period t, so that the number of periods not used for GMM estimation rises.

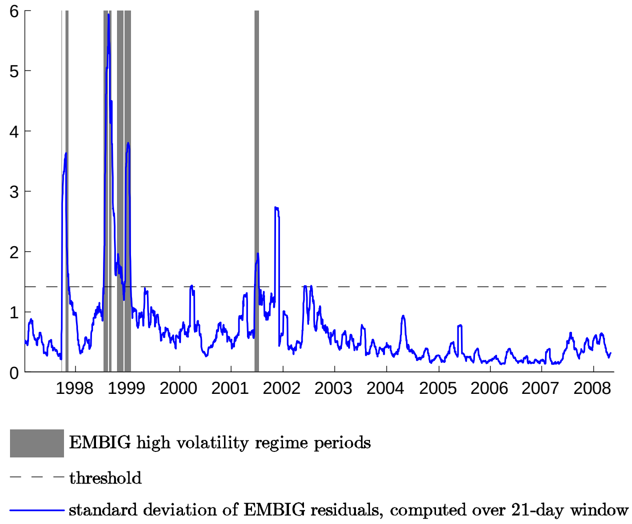

Chart 3: EMBIG high-volatility regime periods with threshold rule

Brazilian (beginning of 1999) and Argentine (2001/02) crises. However, as indicated in the chart, 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.[14]

The threshold rule delivers sensible results. Nevertheless, we also combined the threshold rule with economic intuition to define regimes. For example we allowed for a longer period of the Asian crisis (according to the threshold rule, the high EMBIG volatility lasts only from mid-November to December 1997), attributed all of the Russian crisis period to the EMBIG 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. The resulting covariances of the residuals within each volatility regime were not very different from the corresponding covariances within volatility regimes chosen with the threshold rule, and the GMM estimates for the structural coefficients were also very similar. Therefore we only report the results from the regime choice using the threshold rule below.[15]

[14] With the threshold rule, regime 1 (tranquility) includes 2,182 observations, while regime 2 (US three-month volatility) has 112, regime 3 (US ten-year volatility) 150, regime 4 (US high-yield volatility) has 79 and finally regime 5 (EMBIG volatility) 130 observations.

[15] Rigobon (2003, proposition 3) analyses the conditions under which estimation by 'identification through heteroskedasticity' remains

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)**, including the coefficients in the matrices **A** and γ and the (co)variances of the underlying shocks in $\mathbf{\Omega}_{\mu,s}$ and $\sigma^2_{z,s}$. This makes it possible to analyse the effects of the underlying *structural* shocks on the endogenous variables, and to assess the importance of various transmission channels across different time horizons. We use data on bond yields and spreads in first differences to ensure stationarity,[16] and include constants, time trend and five lags in the VAR.[17]

Before discussing the results let us briefly note some computational issues. Good starting values are important for the optimisation procedure to converge. We use the findings from Section 2 to set starting values for estimation.[18] For the variances of structural shocks we use the regime variances of the VAR residuals contained in the matrix $\mathbf{\Omega}_{e,s}$ 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 one. Furthermore we impose sign restrictions on some structural coefficients to ensure that we choose that 'rotation' of matrix **A** which is economically meaningful (see Ehrmann, Fratzscher and Rigobon (2005) for a discussion).[19] We also constrain all variances to be positive. Since the model is already identified through exploiting the changing volatility of the underlying shocks, these additional constraints are overidentifying restrictions whose validity can be tested, and we make sure to check that they are never actually binding.

4.1 Transmission of shocks in the short run

From the structural model in equation **(3)** it is clear that the contemporaneous effects (occurring within one day) of structural shocks can be found by examining the coefficients in the matrix

consistent even if the volatility regimes are misspecified.

[16] Augmented Dickey-Fuller tests show that all variables are clearly non-stationary. However, cointegration test results using the Johansen (1988) procedure are not clear-cut. Nevertheless, we also analysed the data in a cointegrated vector error correction model; the estimated structural coefficients were very similar to the results presented below.

[17] 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 working week should be sufficient.

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

[19] For example, we constrain the feedback effects between US short and long-term government bond yields to be positive. While this restriction does not necessarily always hold in theory, it is not rejected for our sample.

Table B: Estimation results using threshold rule for regime choice

contemporaneous feedback effects (matrix $\mathbf{A}^{-1}$)

From... ...to	μ_{US3m}	μ_{US10y}	μ_{USHY}	μ_{EMBIG}
US 3m	1.0129^{***} [0.0000]	0.1783^{***} [0.0000]	-0.0086 [0.1450]	-0.0805^{***} [0.0030]
US 10y	0.0823^{*} [0.0840]	1.0952^{***} [0.0000]	-0.1643^{***} [0.0050]	-0.1392^{***} [0.0000]
US HY	-0.0408^{*} [0.0840]	-0.5524^{***} [0.0000]	1.0956^{***} [0.0000]	0.1401^{***} [0.0000]
EMBIG	-0.0023 [0.4920]	-0.0923^{***} [0.0000]	0.1986^{***} [0.0000]	1.0239^{***} [0.0000]

***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Bootstrap p-values in parentheses. See Table E in appendix B for details. Sample includes daily data from January 1997 to May 2008.

$\mathbf{A}^{-1}$: the (i, j)th coefficient in $\mathbf{A}^{-1}$ determines the contemporaneous effect of a shock to endogenous variable j on variable i. Table B reports the parameter estimates; parameter significance is judged using bootstrap p-values.[20] Note that the coefficients on the diagonal are greater than one: the initial impact of, for example, a structural shock to EMBIG spreads is normalised to 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.

Our results imply that structural shocks that increase EMBIG and US high-yield spreads will tend to decrease US government bond yields, where the effect is stronger for long-term yields. This finding can be interpreted as reflecting a 'flight to quality', as discussed in Section 2. As for the reverse effect, the overall effect of shocks that raise US interest rates — especially long rates — is to *decrease* US high-yield and EMBIG spreads, although the effect of short-term yields on EMBIG spreads is insignificant. 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. These results might be interpreted as reflecting the 'growth effect'. 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*. Finally, US short and long-term interest rates are positively related, with the influence of US long-term on short-term yields being stronger than

[20]Following Kilian (1998), the standard bootstrap procedure introduced by Runkle (1987) to VAR analysis is amended to a 'bootstrap after bootstrap' procedure with 1,000 + 1,000 replications to correct for a potential bias in the OLS estimation of the reduced-form VAR. Following Rigobon (2003), the residuals in each of the regimes are then bootstrapped to obtain a distribution of covariance matrices $\mathbf{\Omega}_{e,s}$ for each regime s, from which confidence intervals for the structural parameters in $\mathbf{A}^{-1}$ are estimated. Detailed results on parameter significance can be found in Appendix B.

the reverse effect.

What is the overall contemporaneous effect of a shock to EMEs on mature economies? On the one hand, mature economies might benefit from strong 'flight to quality', driving down the financing costs of low-risk borrowers. On the other hand, an EME shock is not necessarily good news for bond markets in mature economies since it will widen the spreads on other risky debt as well, thus causing problems for more risky borrowers in mature markets. 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.

4.2 Transmission of shocks over longer horizons

From Table B it appears as if EMEs have a stronger influence on the United States than *vice versa*. However the strength of these transmission channels is determined not only by the coefficients describing the contemporaneous effects, but also by the average size of the shocks and effects occurring through lagged terms. These effects of shocks over longer horizons can be analysed using impulse response functions and forecast error decompositions. Note that since we have estimated all structural parameters in equation **(3)**, impulse responses and variance decompositions can be computed directly and are not sensitive to the ordering of the variables, as in most other VAR studies.

Chart 4 plots the responses of the endogenous variables (in columns) to one standard deviation shocks (in rows). Consistent with the 'flight to quality' channel, shocks to US high-yield and EMBIG spreads decrease US government bond yields only in the very short run: these shocks are incorporated into US interest rates very quickly. Concerning the reverse effects, note that shocks to US government bond yields decrease US high-yield and EMBIG spreads only in the very short run; but these shocks strongly widen the spreads of risky debt with a lag of about two days. This suggests that 'financing cost' and 'search for yield' channels do exist, but work with a lag. The contagion channel between bond markets in EMEs and the United States appears to work only in the short term: shocks that raise EMBIG spreads significantly widen US high-yield spreads, and *vice versa*, in the short run, with the effect turning negative after two days. A shock to US short-term (long-term) rates has an immediate (intraday) positive effect on US long (short) rates; this effect dies off over the following days. Thus, US short and long rates tend to move together.

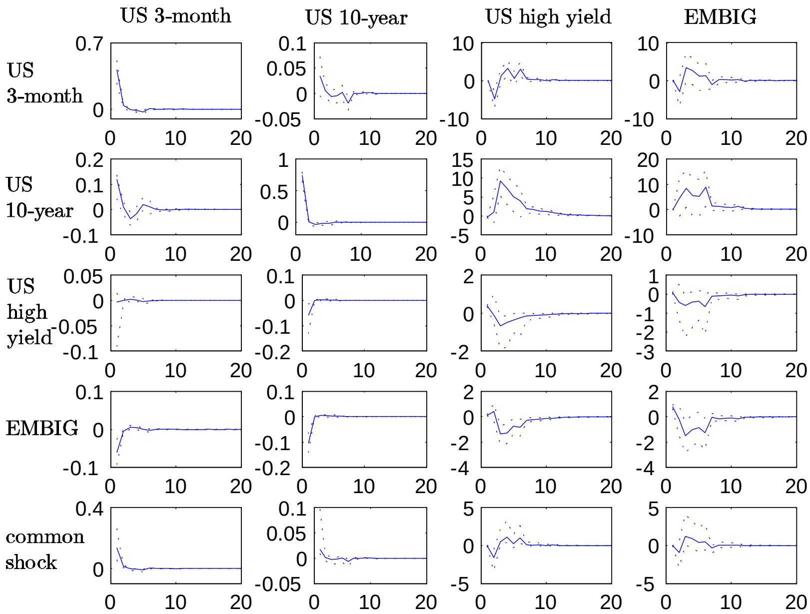

Chart 4: Impulse response functions

Response of the variables listed in the columns to one standard deviation shocks listed in the rows. Dotted lines are 95% confidence bands obtained from 1,000 + 1,000 bootstrap replications. Regime choice using threshold rule. Sample includes daily data from January 1997 to May 2008.

These results are supported by the forecast error variance decompositions shown in Chart 5, which shows the contribution of individual structural shocks (in rows) to the forecast error variances of the endogenous variables (in columns), at various forecast horizons. Both US short and long-term government bond yields are explained largely by their own structural shocks, across all forecast horizons. However, a very different picture emerges for US high-yield spreads and EMBIG spreads: while the forecast error variances of US high-yield and EMBIG spreads are largely explained by their own structural shocks in the short run, at longer forecast horizons the variances of the errors in forecasting US high-yield and EMBIG spreads are both almost exclusively explained by structural shocks to US short and long-term government bond yields. When forecasting the value of EMBIG spreads one day ahead, shocks to US long-term government bond yields explain 0.72% of the forecast error variance; for 5-day and 20-day ahead forecasts this percentage increases to 61.32% and 74.95%. The corresponding contributions of US short-term yields to the forecast error variance of EMBIG 5 days and 20 days ahead are 21.49% and 16.65%. This suggests that US interest rates are of primary importance for explaining the developments in markets for more risky debt, at least in the medium run.

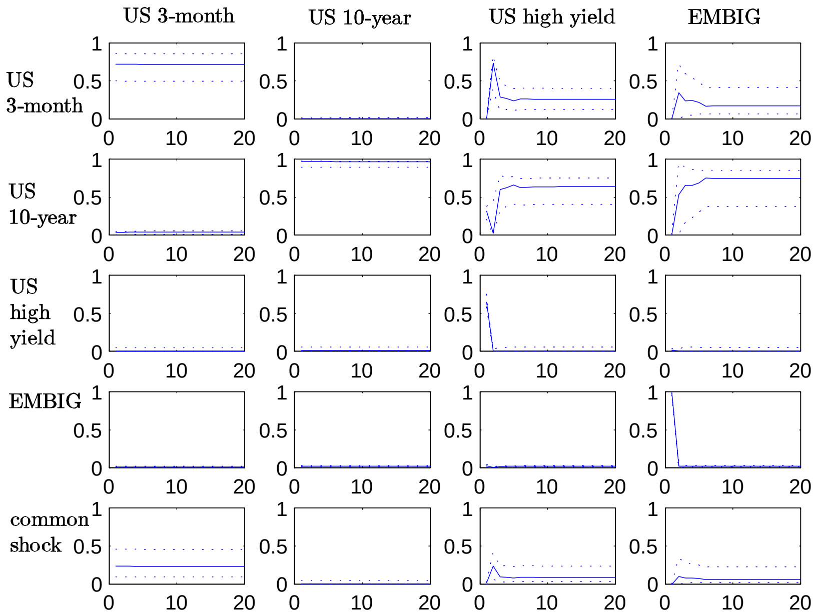

Chart 5: Forecast error decomposition **Fraction of forecast error variance of the variables listed in the columns, explained by shocks listed in the rows. Dotted lines are 95% confidence bands obtained from 1,000 + 1,000 bootstrap replications. Regime choice using threshold rule. Sample includes daily data from January 1997 to May 2008.**

5 Robustness checks

5.1 Parameter stability

The fundamental assumption underlying our empirical methodology is that the structural parameters in $\mathbf{A}$ and γ are stable. Unfortunately, within our methodology it is impossible to check whether parameters are stable across volatility periods. 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 79 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 $\mathbf{B}_0(t) = \mathbf{A}^{-1}\vartheta(t)$ and $\mathbf{B}_1(L) = \mathbf{A}^{-1}\Pi(L)$ are stable, then so should the structural parameters in $\mathbf{A}$. We therefore re-estimate the reduced-form VAR for two subsamples, from January 1997 up until May 2001 and from May 2001 until May 2008. The null hypothesis of parameter stability is not rejected.[21]

To investigate further whether the parameters of the structural model change across time, we split our data set into two samples and re-estimate our model. As a robustness check, we use the same regime periods as before, chosen from the analysis of the whole data set, for the estimation of the model in the two subsamples. 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 and second half of the sample. We split the sample in May 2001 to ensure that all regimes in both samples contain enough observations for the model to be identified. The results are reported in Table C, where it is seen that even with this early split date some estimated coefficients remain insignificant because the number of observations in some high-volatility regimes remains too small to guarantee robust identification. Most of the structural coefficients estimated for both subsamples have the same sign as in the benchmark estimation in Table B. Moreover, most coefficients are even quantitatively similar. Where parameters are different between the first and second subsample, those parameters are typically insignificant in at least one of the subsamples. Charts 7 to 10 in Appendix B show that impulse responses and variance decompositions are also very similar for both subsamples.

The 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 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.

[21] Note however that results from the test may be biased because of heteroskedasticity of the structural shocks — see eg 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 not rejected by a wide margin.

Table C: Contemporaneous feedback effects (matrix A^{-1}) in two subsamples

first sample (pre-2001)

From... / ...to	**US 3m**	**US 10y**	**US HY**	**EMBIG**
US 3m	1.0499^{***} [0.0000]	0.2620^{**} [0.0260]	0.1024 [0.4000]	-0.0844^{***} [0.0000]
US 10y	0.3118 [0.1350]	1.1030^{***} [0.0000]	-0.0673^{**} [0.0130]	-0.1428^{***} [0.0000]
US HY	-0.0235 [0.4800]	-0.5442^{***} [0.0030]	1.0255^{***} [0.0000]	0.1441^{***} [0.0000]
EMBIG	-0.1948^{*} [0.0730]	-0.0534 [0.1770]	0.0815 [0.1470]	1.0040^{***} [0.0000]

second sample (post-2001)

From... / ...to	**US 3m**	**US 10y**	**US HY**	**EMBIG**
US 3m	1.0219^{***} [0.0000]	0.2167 [0.1170]	0.1315 [0.1190]	0.1363 [0.2000]
US 10y	0.1028^{*} [0.0790]	1.2318^{**} [0.0380]	-0.3771^{*} [0.0610]	-0.2134 [0.1490]
US HY	-0.1040^{**} [0.0590]	-0.6276^{**} [0.0380]	1.1846^{**} [0.0360]	0.1161 [0.1780]
EMBIG	0.0597^{**} [0.0420]	-0.1674^{**} [0.0390]	0.2263^{*} [0.0610]	1.0444^{***} [0.0050]

***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Bootstrap p-values in parentheses. See Tables G and H in appendix B for details. Regime choice using threshold rule. The first sub-sample includes daily data from January 1997 to May 2001; the second sub-sample includes daily data from May 2001 to May 2008.

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 behaviour of the residuals, as a proxy for the underlying 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 $\mathbf{\Omega}_1$, in state $s_t = 2$ shocks have a covariance matrix $\mathbf{\Omega}_2$ 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 of

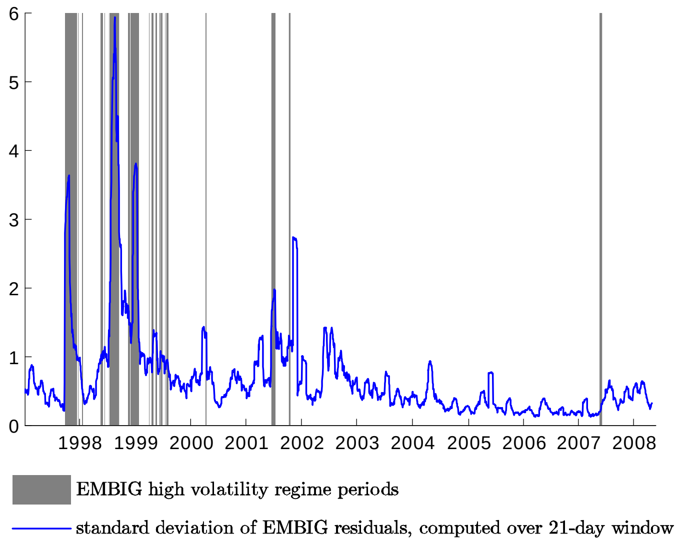

Chart 6: EMBIG high-volatility regime periods with multivariate mixture model

normal distributions model, rather than a more standard Markov model. Therefore, we only need to estimate the unconditional probabilities of each state and their means and covariances, but no transition matrix. Details are given in Appendix A.

Chart 6 plots the regime 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, and are spread out more across the sample. Again, the most important EME crises episodes are picked up in the EMBIG high-volatility regime. Estimation results concerning the overall effects of structural shocks on the endogenous variables, corresponding to the coefficients in matrix $\mathbf{A}^{-1}$, are reported in Table D. All coefficients are equal in sign and similar in magnitude to the benchmark results in Table B. Impulse responses and forecast error variance decompositions are not reported, but are virtually identical to the benchmark results presented in Charts 4 and 5. This suggests that our empirical results are robust to alternative specifications of the volatility regimes that are used for identification of the structural model.

Table D: Estimation results using multivariate mixture model for regime choice

contemporaneous feedback effects (matrix $\mathbf{A}^{-1}$)				
From... ...to	μ_{US3m}	μ_{US10y}	μ_{USHY}	μ_{EMBIG}
US 3m	1.0104*** [0.0000]	0.1673** [0.0200]	−0.0743 [0.3390]	−0.0994* [0.0850]
US 10y	0.0583* [0.0930]	1.0765*** [0.0060]	−0.1004** [0.0120]	−0.1714*** [0.0050]
US HY	−0.0394 [0.6200]	−0.6035*** [0.0060]	1.0631*** [0.0060]	0.1548*** [0.0070]
EMBIG	−0.0230 [0.1830]	−0.1592** [0.0340]	0.1267** [0.0500]	1.0328*** [0.0000]

***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Bootstrap p-values in parentheses. See Table F in appendix B for details. Sample includes daily data from January 1997 to May 2008.

6 Conclusion

Using daily data from the start of 1997 through to end-May 2008, this paper analysed how shocks are transmitted across bond markets in emerging market economies and mature countries. Our main contribution was to exploit the heteroskedasticity of the data, following Rigobon (2003), to identify all parameters in a structural model of bond markets in the United States and EMEs, without imposing *ad hoc* restrictions. This allowed us to quantify the importance of alternative transmission channels.

We found that shocks that widen EME and US high-yield spreads tend to lower US government bond yields in the short run, consistent with the 'flight to quality' phenomenon. Concerning the reverse effect we found that shocks to US interest rates tend to widen high-yield spreads with a lag of about two days, which could be interpreted as reflecting higher financing cost for risky borrowers or 'search for yield' effects. Shocks that increase US high-yield spreads widen EMBIG spreads, and *vice versa*, in the short run; 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 and *vice versa* as has occurred, to some extent, during the current financial crisis.

We carried out robustness checks to show that our results are not sensitive to the exact choice of the volatility periods. To do this we used a multivariate mixture model to choose volatility regimes endogenously. We also tested for parameter stability by re-estimating the model for two subsamples of our data set.

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. In face of adverse shocks, this can help to better quantify the interaction of financial asset prices in developed countries and EMEs.

Appendix 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.[22] Let be $\mathbf{e}_t$ a vector containing the period t VAR residuals,

$$\mathbf{e}_t = \begin{bmatrix} e_{us3m,t} & e_{us10y,t} & e_{ushy,t} & e_{embig,t} \end{bmatrix}'$$

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

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

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 Σ_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 Σ_2. In general, we have

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

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

The idea is then to choose the parameters in $\boldsymbol{\theta}$ such that the probability of observing our sample of residuals is maximised. 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 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 N, the unconditional density of $\mathbf{e}_t$ is then

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

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

From this, the log likelihood is computed as

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

The likelihood function is then maximised 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 was performed using the MATLAB toolbox *h2m*, written by Oliver Cappé.

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 $i \neq j$. Next, we need to decide which of the N states correspond to our volatility regimes. Recall from subsection 3.3 that for identification purposes, we would like to choose $1 + n$ 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 N states that best match this description.

How should the number of states, N, be determined? We let $N = n^2$, where n denotes the number of endogenous variables in the VAR, to cover all possible volatility combinations that can arise if each variable is either volatile or not.[23] For example, there could be one state where only US short rates are volatile, another 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 Σ_j are diagonal. Unfortunately, the VAR-residuals will be correlated (unlike the underlying structural shocks which we are trying to uncover). 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.

[23] Of course, the estimated variances do not need to confirm this 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 maximisation problem.

Appendix B: Tables and charts

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

contemporaneous feedback effects (matrix $\mathbf{A}^{-1}$)

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
μ_{us3m} →US 3m	1.0129***	1.0083	0.0102	0.0000
μ_{us3m} →US 10y	0.0823*	0.0774	0.0572	0.0840
μ_{us3m} →US HY	-0.0408*	-0.0683	0.0515	0.0840
μ_{us3m} →EMBIG	-0.0023	-0.0002	0.0264	0.4920
μ_{us10y} →US 3m	0.1783***	0.1316	0.0423	0.0000
μ_{us10y} →US 10y	1.0952***	1.0910	0.0413	0.0000
μ_{us10y} →US HY	-0.5524***	-0.5446	0.0370	0.0000
μ_{us10y} →EMBIG	-0.0923***	-0.0917	0.0210	0.0000
μ_{ushy} →US 3m	-0.0086	-0.0896	0.0993	0.1450
μ_{ushy} →US 10y	-0.1643***	-0.1852	0.1119	0.0050
μ_{ushy} →US HY	1.0956***	1.1006	0.0461	0.0000
μ_{ushy} →EMBIG	0.1986***	0.2008	0.0366	0.0000
μ_{embig} →US 3m	-0.0805***	-0.0795	0.0251	0.0030
μ_{embig} →US 10y	-0.1392***	-0.1371	0.0223	0.0000
μ_{embig} →US HY	0.1401***	0.1378	0.0277	0.0000
μ_{embig} →EMBIG	1.0239***	1.0228	0.0046	0.0000

***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Results from 1000+1000 bootstrap replications, following Kilian (1998) and Rigobon (2003). Regime choice using threshold rule. Sample includes daily data from January 1997 to May 2008.

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

contemporaneous feedback effects (matrix $\mathbf{A}^{-1}$)

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
μ_{us3m} →US 3m	1.0104***	1.0092	0.0335	0,0000
μ_{us3m} →US 10y	0.0583*	0.0604	0.0573	0.0930
μ_{us3m} →US HY	-0.0394	0.0070	0.0980	0.6200
μ_{us3m} →EMBIG	-0.0230	-0.0285	0.0409	0.1830
μ_{us10y} →US 3m	0.1673**	0.8092	11.1890	0.0200
μ_{us10y} →US 10y	1.0765***	2.8488	34.1474	0.0060
μ_{us10y} →US HY	-0.6035***	-2.0762	30.1229	0.0060
μ_{us10y} →EMBIG	-0.1592**	-0.4024	5.3423	0.0340
μ_{ushy} →US 3m	-0.0743	-0.7055	13.0522	0.3390
μ_{ushy} →US 10y	-0.1004**	-2.2860	39.7169	0.0120
μ_{ushy} →US HY	1.0631***	2.8603	34.4809	0.0060
μ_{ushy} →EMBIG	0.1267**	0.4168	6.2835	0.0500
μ_{embig} →US 3m	-0.0994*	-0.0898	0.1972	0.0850
μ_{embig} →US 10y	-0.1714***	-0.1784	0.4014	0.0050
μ_{embig} →US HY	0.1548***	0.0801	2.2058	0.0070
μ_{embig} →EMBIG	1.0328***	1.0892	1.7123	0.0000

***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Results from 1000+1000 bootstrap replications, following Kilian (1998) and Rigobon (2003). Regime choice using multivariate mixture model. Sample includes daily data from January 1997 to May 2008.

Table G: Bootstrap results for first subsample (threshold rule)

contemporaneous feedback effects (matrix $\mathbf{A}^{-1}$)

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
μ_{us3m} →US 3m	1.0499***	1.0080	0.0325	0.0000
μ_{us3m} →US 10y	0.3118	0.1749	0.1493	0.1350
μ_{us3m} →US HY	0.0235	-0.0061	0.1055	0.4800
μ_{us3m} →EMBIG	0.1948*	0.2520	0.1267	0.0730
μ_{us10y} →US 3m	0.2620**	0.2586	0.1356	0.0260
μ_{us10y} →US 10y	1.1030***	1.1270	0.0436	0.0000
μ_{us10y} →US HY	-0.5442***	-0.4648	0.0826	0.0030
μ_{us10y} →EMBIG	-0.0534	-0.0407	0.0447	0.1770
μ_{ushy} →US 3m	-0.1024	-0.0481	0.1543	0.4000
μ_{ushy} →US 10y	-0.0673**	-0.2374	0.1648	0.0130
μ_{ushy} →US HY	1.0255***	1.0878	0.0433	0.0000
μ_{ushy} →EMBIG	0.0815	0.0788	0.0735	0.1470
μ_{embig} →US 3m	-0.0844***	-0.0869	0.0242	0.0000
μ_{embig} →US 10y	-0.1428***	-0.1423	0.0229	0.0000
μ_{embig} →US HY	0.1441***	0.1425	0.0271	0.0000
μ_{embig} →EMBIG	1.0040***	0.9968	0.0078	0.0000

***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Results from 1000+1000 bootstrap replications. Regime choice using threshold rule. Sample includes daily data from January 1997 to May 2001.

Table H: Bootstrap results for second subsample (threshold rule)

contemporaneous feedback effects (matrix A^{-1})

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
μ_{us3m} $\rightarrow$US 3m	1.0219***	1.0087	0.0474	0.0000
μ_{us3m} $\rightarrow$US 10y	0.1028*	0.0776	0.0945	0.0790
μ_{us3m} $\rightarrow$US HY	-0.1040*	-0.0911	0.0951	0.0590
μ_{us3m} $\rightarrow$EMBIG	0.0597**	-0.0380	0.0300	0.0420
μ_{us10y} $\rightarrow$US 3m	0.2167	0.1018	4.4070	0.1170
μ_{us10y} $\rightarrow$US 10y	1.2318**	1.9282	31.4776	0.0380
μ_{us10y} $\rightarrow$US HY	-0.6276**	-2.0798	47.7696	0.0380
μ_{us10y} $\rightarrow$EMBIG	-0.1674**	-0.4499	9.5248	0.0390
μ_{ushy} $\rightarrow$US 3m	0.1315	-0.0310	4.4449	0.1190
μ_{ushy} $\rightarrow$US 10y	-0.3771*	-0.5070	21.2091	0.0610
μ_{ushy} $\rightarrow$US HY	1.1846**	1.8930	30.8741	0.0360
μ_{ushy} $\rightarrow$EMBIG	0.2263*	0.3067	6.4118	0.0610
μ_{embig} $\rightarrow$US 3m	0.1363	-0.1378	0.1907	0.2000
μ_{embig} $\rightarrow$US 10y	-0.2134	-0.1454	0.6107	0.1490
μ_{embig} $\rightarrow$US HY	0.1161	0.1691	0.6257	0.1780
μ_{embig} $\rightarrow$EMBIG	1.0444***	1.0336	0.3167	0.0050

***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Results from 1000+1000 bootstrap replications. Regime choice using threshold rule. Sample includes daily data from May 2001 to May 2008.

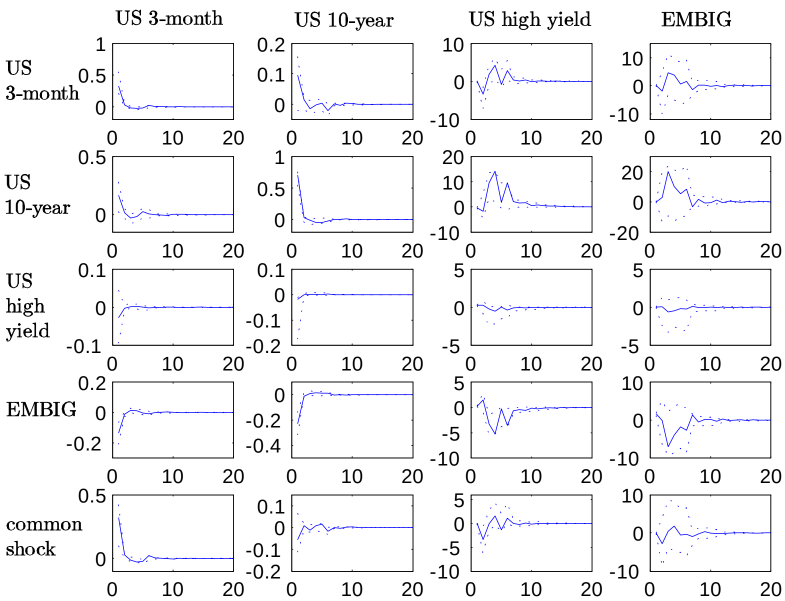

Chart 7: Impulse response functions for first subsample.

Response of the variables listed in the columns to one-standard deviation shocks listed in the rows. Dotted lines are 95% confidence bands obtained from 1000+1000 bootstrap replications. Regime choice using threshold rule. Sample includes daily data from January 1997 to May 2001.

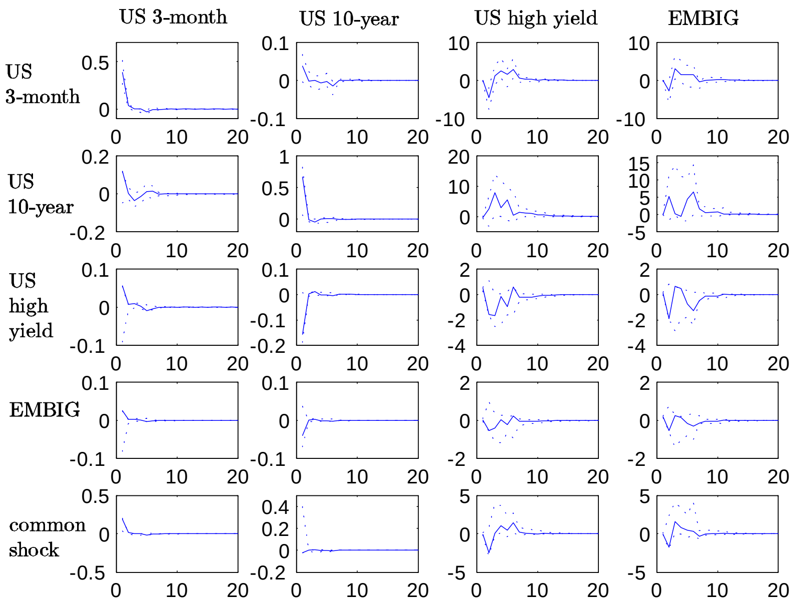

Chart 8: Impulse response functions for second subsample.

Response of the variables listed in the columns to one-standard deviation shocks listed in the rows. Dotted lines are 95% confidence bands obtained from 1000+1000 bootstrap replications. Regime choice using threshold rule. Sample includes daily data from May 2001 to May 2008.

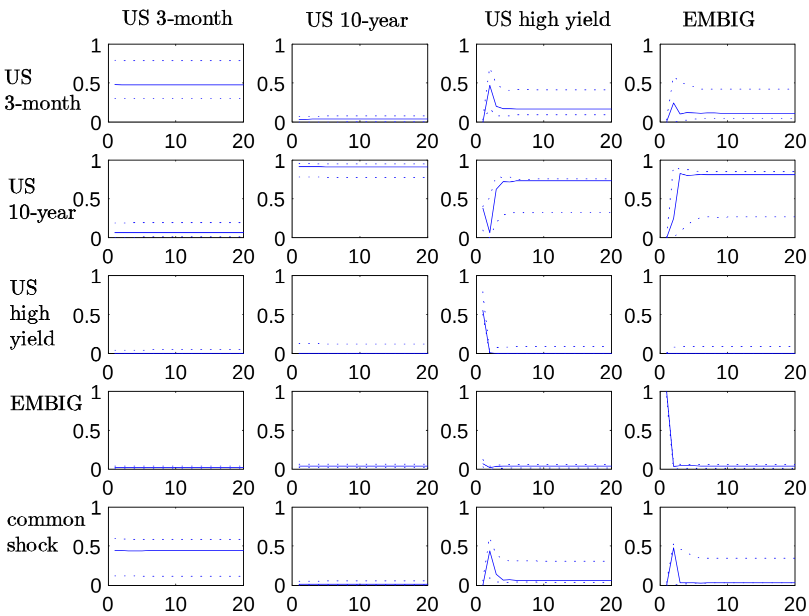

Chart 9: Forecast error decomposition for first subsample.

Fraction of the forecast error variance of the variables listed in the columns, explained by shocks listed in the rows. Dotted lines are 95% confidence bands obtained from 1000+1000 bootstrap replications. Regime choice using threshold rule. Sample includes daily data from January 1997 to May 2001.

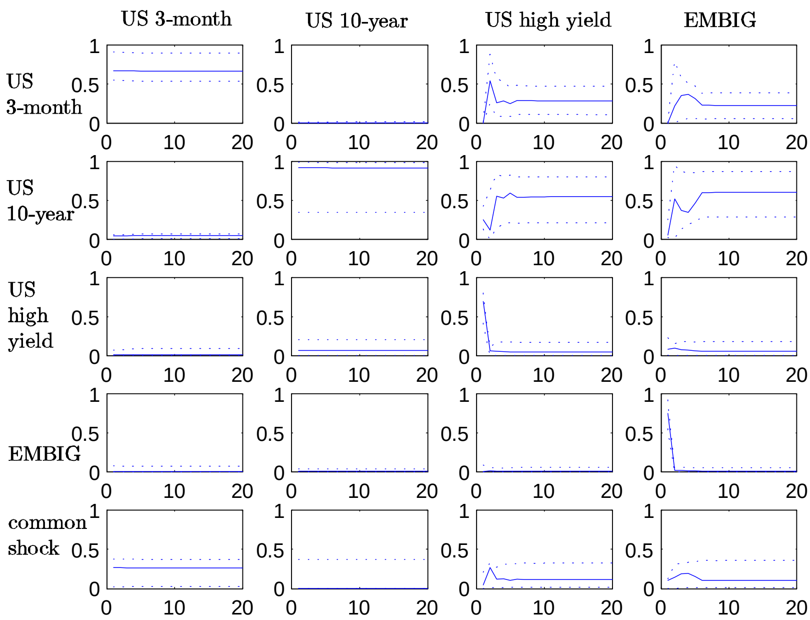

Chart 10: Forecast error decomposition for second subsample.

Fraction of the forecast error variance of the variables listed in the columns, explained by shocks listed in the rows. Dotted lines are 95% confidence bands obtained from 1000+1000 bootstrap replications. Regime choice using threshold rule. Sample includes daily data from May 2001 to May 2008.

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