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Investors' Risk Appetite and Global Financial Market Conditions

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Abstract

A structural vector autoregression model is developed to analyze the dynamics of bond spreads among a sample of mature and developing countries during periods of financial stress in the last decade. The model identifies and quantifies the contribution on bond spreads from global market conditions (including funding liquidity, market liquidity, as well as credit and volatility risks), contagion effects, and idiosyncratic factors. While idiosyncratic factors explain a large amount of the changes in bond spreads over the sample, global market risk factors are fundamental driving forces during periods of stress. The relative importance of the different risk factors changes substantially depending on the crisis episode. Contagion from emerging markets becomes small or non-existent when global financial market risks explicitly are taken into account.

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Contents Page

I. Introduction 3

II. The Concept of Risk Appetite 6

III. Variables in the Empirical Model 8
A. Bond Spreads 11
B. Global Financial Market Conditions 11
C. Contagion Effects 15

IV. Identification And Estimation...15

V. Forecast-Error Variance Decomposition 18

VI. Spread Decomposition...18
A. Empirical Results: Mean Spread Decomposition 19
B. Empirical Results: Spread Decomposition Over Time 25

VII. Conclusions 29

References...32

Appendix I. Dates of Financial Distress 34

Appendix II. Figures, Data, and Tables 37

> "When U.S. stocks are volatile, EMBI spreads widen. They narrow again when U.S. stocks calm down. That suggests that emerging market debt is not being driven by judgments of governments' creditworthiness."
>
> *Financial Times*, 10/26/07 (p. 15).

I. Introduction

The typical assumption is that spreads on sovereign bonds reflect the default risk of that country, which in turn are determined by its economic fundamentals. However, fundamentals do not change from one day to the other, unless new information is revealed periodically affecting the expectations about the underlying drivers of that particular economy. Yet spreads on sovereign bonds vary constantly, sometimes substantially over very short intervals of time. As quoted above by a leading international financial newspaper, observers have noticed that bond spreads generally tend to move with changes in global financial conditions, such as volatility in equity markets.

One observed regularity is that bond spreads tend to widen in a country facing financial stress, as investors price higher a risk in that country. But during periods of financial stress, spreads sometimes widen not only in the source crisis country but also across other countries that appear to be unrelated. Indeed, shocks can transmit rapidly across global financial markets. One possible channel is that conditions in global financial markets affect international investors' risk appetite, and changes in the latter may actually spread the original shock across global financial markets. Through this mechanism, seemingly unrelated asset markets across national boundaries may actually be affected by an otherwise unrelated shock.

As evidenced by the U.S. subprime mortgage and liquidity crisis that began in mid-2007, financial crises are not simply events from the past—although it has been several years since global financial markets experienced such a pervasive shock—and are not confined to emerging markets. This recent crisis was characterized by a drying up of liquidity across financial markets which was sparked by difficulties in the U.S. subprime mortgage market (see International Monetary Fund (2007)). Empirical analyses of this recent episode of global financial crisis are still scant, particularly in the context of other historical crises. A recent analysis on the U.S. subprime and liquidity crisis in mid-2007 is Dungey, Fry, González-Hermosillo, Martin and Tang (2007b), which found that the most acute episodes of global contagion across markets and countries in the past decade have been the Russia/LTCM crisis in 1998 and the U.S. subprime and liquidity squeeze in mid-2007. In both of these cases, the channel of contagion is primarily from credit markets to equity markets. They also find that there was contagion from U.S. credit markets to Russian and Argentinean credit markets, both of which had their central banks inject emergency liquidity during the U.S. subprime and liquidity crisis.[2]

[2] *Financial Times* (9/26/07) and *Fitch Ratings* (10/18/07).

There is a rich literature on financial contagion, which has tried to identify the channels through which shocks in one country transmit to financial markets in other countries (see Dornbusch, Park and Claessens (2000); Pericoli and Sbracia (2003) and Dungey, Fry, González-Hermosillo and Martin (2005), for surveys of this literature). The theoretical determinants of contagion are discussed in Kodres and Pritzker (2002). While most of the empirical literature on contagion has focused on emerging markets, a few exceptions have analyzed emerging markets and mature economies jointly for clues as to how shocks transmit globally during periods of financial stress, usually across the same asset market class (Kaminsky and Reinhart (2003); and Dungey, Fry, González-Hermosillo and Martin (2006) and (2007a)). Analyses of spillover and contagion effects across emerging markets and mature economies, as well as across different asset market classes are even less common (one exception is Dungey, Fry, González-Hermosillo, Martin and Tang (2007b)).

There may be several mechanisms for contagion whereby channels are established only during periods of stress that are over and above the market fundamental mechanisms, that link countries and asset markets during noncrisis periods. One such mechanism may be the presence of common international investors who react to a given shock by rebalancing their portfolios globally in assets and markets that would be otherwise seemingly unrelated. As investors become less willing to assume risk, they require a higher compensation for bearing such risk. This re-pricing of risk can effect the prices of other risky assets (Kumar and Persaud (2002)).

Observers often refer to this mechanism as investors' increased risk aversion or reduced risk appetite. However, these two concepts are conceptually different.[3] Risk aversion measures the subjective attitude of investors with regard to uncertainty. Since the degree of investors' risk aversion reflects entrenched preferences, it is usually assumed to be constant in asset pricing models. In contrast, the notion of investors' risk appetite is more broad as it is also influenced by the amount of uncertainty about the fundamental factors that drive asset prices. Thus, the risk premia embedded in asset prices are influenced by both risk aversion and the riskiness of the asset in question. One potential channel for shifts in investors' risk appetite is changes in global financial market conditions, a venue which is investigated empirically in this paper. Gauging the degree of investors' risk appetite is relevant from a global financial stability perspective as past episodes of brisk changes in risk premia, variations in market liquidity, and sharp movements in asset prices have been often associated with changes in investors' risk appetite.

Work analyzing the role of risk appetite as a transmission channel of financial crises include Kumar and Persaud (2002), Gai and Vause (2005), Coudert and Gex (2007), and Dungey, Fry, González-Hermosillo and Martin (2003). The first two papers analyze the relative importance of contagion due to shifts in risk appetite; the third paper analyzes the predictive power of several risk appetite indices; and the last one identifies the global market channels

[3] In practice, it is clearly difficult to disentangle risk appetite from risk aversion. An increase in either one causes asset prices to decline and risk premia to increase. This issue is examined in Bliss and Panigirtzoglou (2004).

of financial crises.[4] There is also a wide literature on the determinants of emerging market spreads. For example, Kashiwase and Kodres (2005) estimate a panel data model in which emerging market spreads are a function of liquidity risk and fundamental factors.

This paper quantifies the relative importance of potential determinants of spreads for emerging markets' sovereign bonds and mature markets' corporate bonds from 1998 through 2007, encompassing several episodes of financial market distress. A vector autoregression model is constructed to capture the dynamics of global bond spreads as a function of global market conditions, idiosyncratic factors, and contagion effects. The identification of the factors is made through long-run restrictions, which permit quantifying the contribution of the various factors to the bond spreads during various periods of financial stress.

In particular, four different global market risk factors are assumed to reflect the degree of risk appetite of international investors. The first risk factor is the *funding liquidity* premium, proxied by monetary conditions. The second risk factor is *default risk*. The third factor is *market liquidity risk*, as investors prefer liquid instruments which can be transformed into other assets without a significant loss of value during times of stress. Market liquidity may be an especially important systemic factor during financial crises if a liquidity squeeze forces a generalized sale of assets, depressing their prices and resulting in additional default risks which may feed back into even more illiquidity. The final aggregate risk factor considered reflects *volatility*, as measured in equity markets and in future interest rate contracts. The four aggregate global market risk factors are used to explain daily movements in the sovereign bond spreads for thirteen emerging markets and the spreads in BBB investment grade corporate bonds for four mature markets from January 2, 1998 through August 9, 2007 (one day before the European Central Bank began a round of liquidity injections into the financial system, which was followed a few days later by the easing of monetary policy in other central banks, including the U.S. Federal Reserve). In addition, idiosyncratic and contagion effects from emerging markets are also estimated in the model.

The results suggest that, while idiosyncratic factors explain a significant amount of the changes in bond spreads over time, global financial market conditions are fundamental driving forces at times of crisis. The relative importance of the various global risk factors depends on the crisis episode. An important result of this paper is that, once global financial market factors are explicitly considered, contagion from emerging markets becomes very small or essentially not existent, suggesting that investors' risk appetite may be the key

[4] The approach in this paper is similar to Dungey, Fry, González-Hermosillo, and Martin (2003), with several important differences. First, the proxies for global market conditions in this paper are different and chosen to reflect, where possible, some of the newer instruments in financial markets. Second, the choice of countries is different and expanded, as they only examine emerging markets, while mature markets are also introduced here as part of a more global framework. As highlighted during the 2007 subprime mortgage meltdown and liquidity squeeze, global financial crises can also originate in mature markets. Third, this paper covers a longer period, January 1998 to August 2007, with a larger number of episodes of financial stress including the recent turbulence sparked by the U.S. subprime mortgage crisis. In contrast, in Dungey, Fry, González-Hermosillo, and Martin (2003), only nine emerging markets' sovereign spreads are examined during three crises episodes (the Russian default (1998), the LTCM bail-out (1998), and the Brazilian devaluation (1999)).

channel of transmission of shocks across national boundaries and market classes, especially in increasingly integrated global financial markets.

The paper proceeds as follows: Section II discusses the conceptual basis of risk appetite. Section III surveys the variables which have been used in the empirical literature and by practitioners to proxy investors' risk appetite, and discusses the actual variables used in this paper. Section IV discusses the identification and estimation strategy. Section V examines the unconditional variance decomposition. Section VI discusses the spread decomposition and the empirical results. Section VII concludes and offers suggestions for future research. Appendix I details the crises dates. Appendix II contains an explanation of the Data Sources, as well as the Tables and Figures.

II. The Concept of Risk Appetite

The investors' degree of risk aversion reflects underlying preferences and, as such, it is expected to change infrequently over time. In contrast, risk appetite is likely to change more often as investors respond to changing levels of uncertainty in the macroeconomic environment. Thus, risk appetite depends on the subjective degree to which investors are willing to bear uncertainty *and* on the overall level of uncertainty about the fundamental factors which drive asset prices.

The standard treatment of asset pricing theory (e.g., Cochrane (2001) and also discussed in Gai and Vause (2005)) states that in an efficient market, with fully rational and informed investors, the current price of an asset, p_t, should equal the expected discounted value of its possible future payoffs, x_{t+1}. These payoffs comprise income (such as dividend payments) received over the long-run horizon, plus the ongoing value of the asset as implied by its future price. More formally,

$$p_t = E_t\left(m_{t+1} \cdot x_{t+1}\right) \tag{1}$$

where x_{t+1} denotes the payoff in period t+1, and m_{t+1} denotes the discount factor—the marginal rate at which the investor is willing to substitute consumption at time $t + 1$ for consumption at time t. Both x_{t+1} and m_{t+1} vary across states of the world. Indeed, m_{t+1} is usually referred to as the *stochastic* discount factor.

The basic asset pricing equation can also be expressed in terms of gross returns, R_{t+1}, by dividing equation (1) by current prices. Thus,

$$1 = E_t\left(m_{t+1} \cdot R_{t+1}\right) \tag{2}$$

Although, in general, different assets have different expected returns, all assets have the same expected *discounted* return in equilibrium (of unity). Since both the gross return and the stochastic discount factor are random variables, equation (2) can be written as

$$1 = \underbrace{E_t\left(m_{t+1}\right) \cdot E_t\left(R_{t+1}\right)}_{\text{risk-neutral component}} + \underbrace{cov_t\left(m_{t+1}, R_{t+1}\right)}_{\text{risk adjustment}} \tag{3}$$

The first term on the right-hand side of equation (3) reflects the mean return required by investors to hold the asset *if* they were indifferent to risk, the risk-neutral component. The second term is a risk adjustment required by risk-averse investors. Given that the gross risk-free rate can be denoted as $R^f_{t+1} = 1/E_t m_{t+1}$, we can rearrange (3) to obtain the familiar expression

$$\underbrace{E_t\left(R_{t+1}\right) - R^f_{t+1}}_{\text{risk premium}} = -R^f_{t+1} cov_t\left(m_{t+1}, R_{t+1}\right) \tag{4}$$

Equation (4) states that the expected return of a risky asset in excess of that available on a risk-free asset is proportional to *minus* the covariance of its state-contingent rate of return and the stochastic discount factor.

The risk premium can, in turn, be decomposed into the quantity of risk, β_i, inherent in each asset and the unit price of risk that is common across assets, λ_t. In particular,

$$E_t\left(R_{t+1}\right) - R^f_{t+1} = \underbrace{\frac{-cov_t\left(m_{t+1}, R_{t+1}\right)}{var\left(m_{t+1}\right)}}_{\beta_i} \cdot \underbrace{var\left(m_{t+1}\right) \cdot R^f_{t+1}}_{\lambda_t} \tag{5}$$

The price of risk, λ_t, is the expected excess return that, in equilibrium, investors require to hold each unit of risk. *Risk appetite*—the willingness of investors to bear risk—can therefore be defined as the inverse of the price of risk. So when an investor's risk appetite falls, they require larger expected excess returns to hold risky assets.

It is apparent from equation (5) that risk appetite reflects variation in the stochastic discount factor, $var(m_{t+1})$. Since the stochastic discount factor specifies the marginal rate at which the investor is willing to substitute uncertain future consumption for present consumption, risk appetite depends on the *degree* to which investors dislike uncertainty about their future consumption and on factors that determine the overall *level* of uncertainty surrounding consumption prospects. The degree to which investors dislike uncertainty corresponds to *risk aversion*. Accordingly, risk aversion reflects innate preferences over uncertain future consumption prospects—the curvature of individuals' utility functions—that are unlikely to vary significantly over time.

The factors underpinning risk appetite can also be examined by imposing some structure on the stochastic discount factor. For example, if consumption growth is log-normally distributed with variance, $\sigma^2_t\left(c_{t+1}\right)$, and investors have power utility functions, then the price of risk is

$$\lambda_t = \gamma \sigma^2_t\left(c_{t+1}\right) \tag{6}$$

where γ is the coefficient of absolute risk aversion.[5] So a rise in γ would mean a fall in risk appetite. But risk appetite will also fall if the uncertainty about future consumption growth (the expected volatility of future consumption) is amplified. The expected volatility of future consumption may depend on factors such as unemployment prospects, the stance of macroeconomic policy, global prospects and, more generally, global financial market conditions. In general, one would expect that the periodic shifts in market sentiment witnessed over time are more likely to be driven by the macroeconomic environment rather than by changes in the risk aversion of investors.

III. Variables in the Empirical Model

Investors' risk appetite is, nevertheless, not directly observable. Yet, risk appetite is frequently cited as a factor explaining asset price movements and several indicators are typically used by market participants to measure it. These measures are often amalgamations of an array of different market-based indicators which are aggregated to produce a single index of "risk appetite." Box 1 details some of the key market-based indicators typically used to gauge investors' risk appetite.[6]

This plethora of market-based indicators are used routinely by market participants.[7] However, they are less than ideal for analytical purposes as they essentially add up all the potential risk factors into a mix that creates an index of risk appetite. In addition, they do not generally examine potential linkages among the different risk components.

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[5] This is a standard result in asset pricing. See Cochrane (2001) for a detailed exposition.

[6] The group of indicators summarized in Box 1 include: CBOE's Volatility Index (VIX); JP Morgan's Risk Tolerance indices −one global (JPM G-10 RTI) and another one for emerging markets (JPM EM RTI); UBS FX Risk Index (UBS FX); Westpac's Risk Appetite Index (WP); Bank of America's Risk Appetite Monitor (RAM); Merrill Lynch's Risk Aversion Indicator (ML RAI); Dresdner Kleinwort's Aggregate Risk Perception Index (ARPI); and Lehman Brothers' Market Risk Sentiment Index (MARS).

[7] In addition to market-based indicators, another strand of the literature has examined financial CAPM−type models in a single financial market. These include the Goldman Sachs Risk Aversion Index and the Credit Suisse Global Risk Appetite Index. They are not considered here because they tend to rely on macroeconomic data only available in monthly or quarterly data frequencies, whereas the approach in this paper is to focus on financial market high frequency data. For a survey of these indicators, see European Central Bank (2007).

Box 1. Survey of Market-Based Indicators of Risk Appetite

Index	Components	Method
VIX	• Implied volatility of S&P500 Index	Based on a weighted average of the implied volatility from eight calls and puts on the index.
JPM G-10 RTI	• US swap spread (liquidity risk) • VIX (equity market risk) • EMBI+ (credit risk in emerging markets) • Trade-weighted Swiss franc (risk appetite in currency markets)	Constructed as an equally weighted average after having standardized the four components.
JPM EM RTI	• VIX • EMBI+	A weighted average after standardizing the two components (weights: 30% VIX, 70% EMBI+).
UBS FX	• US Treasury relative to the U.S. stocks • Three-month foreign exchange option implied volatility (USD/JPY and EUR/USD) • Gold in EUR and USD • VIX • EMBI+ • US Treasury spread • Differences in stock returns between the S&P financials and utilities • High-yield corporate spreads relative to the US Treasury	An arithmetic average of the normalized values of market variables.
WP	• An average of the three-month implied volatility for six major currencies • VIX index • US ten-year bond-swap spread • JP Morgan emerging markets bond spread • US BB1 industrial bond spread	A 60-day z-score[1)] of a base index calculated in three steps: the first step calculates the daily percentage change of each variable, then the figures obtained are averaged, and finally the index values are indexed to 100 on 1 January 1998.
RAM	• EMBI spread • Carry AUD/JPY • Corporate bond spread BB • Carry EUR/CHF • Spread MSCI EM Lccy	The correlation (over a rolling six-week period) among a large sample of emerging economies for each of the three asset classes, multiplying them by a market direction measure (in order to distinguish between bullish or bearish periods). Finally, the correlation coefficients are aggregated with an equally weighted average.
ML RAI	• US high-yield spreads (US higher yield spread over Treasuries, expressed as % yield) • VIX implied volatility • TED spreads (three-month euro-dollar deposits minus three-month T-bills) • US ten-year swap spreads, emerging market bond spreads (ML USD Emerging Markets Sovereign 'Plus' Index yield) • The trade-weighted Swiss franc, and emerging market equities (USD) • US small cap stock	For each item, this takes the standard deviations from 52-week moving averages. Then it sums the standard deviations of US high-yield spreads, VIX implied volatility, TED spreads, US ten-year swap spreads, emerging market bond spreads and the trade-weighted Swiss franc, while it subtracts those of EM equities and US small cap stock.
ARPI	Based on high-frequency data (mainly spreads and implied volatilities) from five asset classes: • Fixed income basket (global and political risk) • Equity basket (equity investment risk) • Liquidity basket (liquidity risk) • Commodity basket (energy risk) • Credit basket (credit risk)	Based on a two-step principal component analysis (PCA), firstly within the baskets, and secondly between the principal components of these baskets.
MARS	• Market volatility (one-year FX implied volatility and equity implied volatility) • EM event risk (EM CDS spreads and EM equities) • Market liquidity (G3 swap spread) • Risk appetite ratios (equity to bond returns, gold price to gold equity returns, and US equity P/E ratio).	Built on a four-step process: input transformation a rank transformation of each risk input relative to its past 20 day values), data aggregation (a simple equally weighted average), transformation of the average rank into a score between 0 and 1, and finally a computation of the two-day moving average of the aggregate index.

1) The X-day z-score is defined as the value of a base index, net of its X-day mean, and divided by its X-day standard deviation.

Source: European Central Bank (2007)

Thus, for example, it is not clear how to examine analytically measures of risk appetite which throw into the mix sovereign bond spreads for emerging markets, movements in commodity prices, in equity prices, in fixed income markets, and in exchange rate markets, in addition to measures of volatility and liquidity and other market data. The approach adopted in this paper is more fundamental, based on a few representative variables that are viewed to reflect the key risk factors in global financial markets. In particular, the model includes sovereign bond spreads in representative emerging markets and roughly comparable investment grade BBB corporate bonds in mature economies, several risk premia in global financial markets that are assumed to represent the compensation that international investors demand to accept risk, idiosyncratic factors proxying for "fundamentals," and any additional contagion effects from emerging markets.

Given that the price and the quantity of risk that investors are willing to assume are not distinguishable from each other in the data, the observed risk premium demanded by investors is assumed to reflect their risk appetite. The overall risk premium in global financial markets, itself also not directly observable in one single indicator, is assumed to have several key components: a funding liquidity premium, a credit risk premium, a market liquidity premium and a market volatility premium.[8] In addition to these aggregate global factors, bond spreads can be also influenced by fundamental factors which are idiosyncratic and, potentially, by additional sources of contagion from emerging markets which are not already captured by the global financial market conditions that are assumed to condition investors' risk appetite.

Economic fundamentals are modeled rather simplistically in this paper; essentially, as everything else that is not encompassed by the aggregate market factors or by the additional sources of contagion, discussed in more detail below, emanating from emerging markets. This trade-off is accepted because the objective is to analyze the role of changes in global market conditions based on high frequency data, whereas measures of economic fundamental drivers rely on monthly or quarterly data. Indeed, the objective of this paper is to determine the relative importance of aggregate risk factors during periods of financial stress, rather than to provide a model that best fits bond spreads. Moreover, because bond spread across countries tend to be more strongly correlated during periods of stress (Dungey, Fry, González-Hermosillo, and Martin (2005)) than during tranquil periods, common factors are likely to be particularly important during periods of stress.[9]

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[8] There is no theoretical model for the global transmission of shocks to guide the choice of the appropriate "global" variables for this paper. However, the actual selection of variables is based on the analysis of the financial position of a representative banking firm in González-Hermosillo and Li (2008, forthcoming) where market, liquidity, and credit risks are viewed as fundamental. In addition, volatility risk is essential in equity and derivatives markets, while funding liquidity is related to credit conditions and the level of the risk-free interest rate.

[9] Of course, the interpretation that idiosyncratic factors represent what is not explained by common global factors or other sources of contagion requires caution since its appropriateness depends on the quality of the proxies used to measure those risk factors.

Below follows a more detailed discussion of the data and the proxies used for the various components determining the risk premia required by global investors.

A. Bond Spreads

The data for bond spreads in emerging markets are based on JP Morgan's EMBI+ country-specific indices. These indices contain U.S. dollar-denominated Brady bonds, Eurobonds and other traded loans issued by sovereigns, rated Baa1/BBB+ or below, and which satisfy certain maturity and liquidity conditions.[10] The spreads are calculated as the difference between the yield on the instruments and the yield on U.S. Treasury bonds of similar maturity. The sovereign spreads include Brazil, Bulgaria, Colombia, Ecuador, Mexico, Panama, Peru, Philippines, Russia, South Africa, Turkey, Ukraine, and Venezuela. For mature markets, the representative bond spread is constructed as the difference between the yields on 10-year BBB-rated corporate bond indices and government bond indices of similar maturity and currency.[11] The mature markets analyzed are the United States, Canada, Japan, and the Eurozone.

B. Global Financial Market Conditions

The choice of variables that reflect global financial markets is constrained by the need to have a parsimonious set of variables that is still able to reflect "global" market conditions. They are discussed below.

Funding Liquidity Premium

The first aggregate market risk factor considered is the funding liquidity premium or a proxy to measure the amount of credit availability in the global financial system. Finding proxies to measure funding liquidity is particularly troublesome after 2004, as long-term interest rates have stayed relatively constant even as a number of central banks have increased short-term interest rates. In addition to traditional monetary aggregates like M1 and M2, more appropriate proxies for funding liquidity would need to also include measures of credit availability, fund flows, asset prices, and leverage (Warsh (2007)). In addition to the fact that it would be extremely difficult to construct proxies for those broad liquidity conditions, most of them would not exist on the daily frequency needed in this model.[12]

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[10] In particular, the instruments must have a maturity greater than two and a half years, meet certain liquidity conditions and have a minimum issue size of US$500 million.

[11] The corporate bond indices are computed by Bloomberg, whereas the government bond indices are computed by DataStream.

[12] It is difficult to get a satisfactory proxy for global liquidity funding conditions reflected in daily data, especially for recent years as financial innovation has led to extraordinary leverage in financial markets. Estimates based on monthly frequency of the data have included monetary aggregates plus foreign official reserve holdings (Rasmus and Stracca (2006)).

In this paper, the *3-month-ahead federal funds futures rate* is used as a measure of global funding liquidity or monetary conditions.[13] The federal funds rate is the instrument used by the U.S. Federal Reserve to affect monetary conditions. This rate can affect risk spreads through two channels. A decline in the federal funds rate implies a lower cost of borrowing and therefore an rising level of funding liquidity in the economy. In addition, it reduces the return from safer assets. Everything else constant, these two channels would be expected to result in international investors seeking higher returns in risky assets. In contrast, higher expected interest rates make borrowing more expensive and drains funding liquidity from the system, increasing the probability that creditors will face difficulties. In this paper, funding liquidity conditions are proxied by the implied federal funds rate in futures markets, rather than the actual federal funds rate, because the former captures the effects of anticipated changes in monetary policy at the time when they are anticipated, rather than when they actually take place. Another advantage of focusing on the 3-month ahead federal funds futures rate is that it implicitly captures a segment of the yield curve that is longer than the spot overnight federal funds rate, while also exhibiting more daily variation than the actual federal funds policy rate.

Credit risk Premium

Two different measures of aggregate credit or default risk are examined. The most direct one, because it prices in the cost of buying insurance against default, is credit default swaps. In particular, the *10-year Itraxx Europe Crossover index* is examined in this paper and it measures the cost of buying insurance against default by European firms whose ratings are between investment and speculative grade.[14] Because credit default swap indices only exist after 2004, we also need to rely on other proxies of credit risk that cover a longer period.

The proxy used to measure aggregate default risk over the longer sample is the *10-year USD swap spread* which is the difference between the 10-year swap rate and the 10-year U.S. Treasury bond ($s_{10,t} - i_{10,t}$).[15] [16] In a swap contract, one party agrees to pay a fixed interest rate in return for received an adjustable rate from another party. When an investor enters a swap agreement as a fixed receiver in a fixed-for-floating swap, the investor is promised to receive from the counterparty a series of semi-annual fixed payments in exchange for paying the

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[13] Kashiwase and Kodres (2005) also choose this proxy for funding liquidity.

[14] There are many Itraxx indices and derivatives on Itraxx. The Itraxx crossover Europe index was chosen because of its relative liquidity and the fact that the 35 companies on which it is based are closer substitutes to emerging market bonds than other higher-rated indices. A similar index exists for U.S. corporations (CDX), which moves similarly to Itraxx. Because most of the other "global" variables are largely U.S.-based, the choice of the Itraxx crossover Europe was thought to give the analysis a more global balance.

[15] Regarding the notation, the first subscript indicates the maturity of the instrument, while the second indicates the time period. Both the maturity and the period are denominated in years.

[16] A large universe of fixed-income securities, including corporate bonds and mortgage-backed securities, use interest rate swap spreads as a key benchmark for pricing and hedging.

counterparty a series of semi-annual floating payments. While the fixed payments are determined at the outset of the swap agreement, the floating payments are to be determined at later dates, based on the relevant maturity of the LIBOR rates prevailing at the beginning of each payment period.[17] The swap rate is the fixed payment on the notional amount. The swap rate examined here is based on contracts in which the variable rate is the 3-month LIBOR rate ($l_{1/4,t}$), and payments are made semi-annually. Ignoring liquidity premiums, the swap rate must be the expected average of future default-risky LIBOR rates.

$$s_{10,t} = E_t\left[\frac{l_{1/4,t} + l_{1/4,t+1/4} + \ldots + l_{1/4,t+10}}{40}\right] \tag{7}$$

Similarly, the 10-year US Treasury note must be the expected path of default-free 3-month Treasury bills.

$$i_{10,t} = E_t\left[\frac{i_{1/4,t} + i_{1/4,t+1/4} + \ldots + i_{1/4,t+10}}{40}\right] \tag{8}$$

The difference between the yield on a Treasury note and the LIBOR rate is a short-term default-risk premium (DR). Thus the 10-year swap spread is the expected average of future short-term default premiums, reflecting not only current but also expected future default risk.

$$s_{10,t} - i_{10,t} = E_t\left[\frac{DR_{1/4,t} + DR_{1/4,t+1/4} + \ldots + DR_{1/4,t+10}}{40}\right] \tag{9}$$

The empirical literature on swap spreads has found that they also contain a liquidity premium. However, the liquidity premium component of swap spreads appears to be much more persistent than the default premium component (Liu, Longstaff, and Mandell (2006)), so most of the variation in swap spreads is expected to be caused by variations in default risk.[18] A proxy for movements in the market liquidity premium is discussed below.

Market Liquidity Premium

The measure of market liquidity premium examined here is the *difference between the yield on the 20-year U.S. Treasury bond and the yield on the 10-year U.S. Treasury note*. Since

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[17] The LIBOR rate is the rate at which banks lend to each other and it is recorded by the British Banking Association (BBA) each day at 11 a.m. London time. The composite rate is calculated based on quotes provided by a basket of reference banks selected by the BBA.

[18] It is worth noting that another potential candidate to measure credit risk could have been the TED spread, or the difference between the 3-month U.S. dollar LIBOR and the yield on the 3-month U.S. Treasury bill. This spread behaves similarly to the 10-year USD swap spread discussed above, except that it captures only short-term movements and it is particularly difficult to separate the component originating from credit risk vs. that related to market liquidity.

these two bonds are default-free, their yield is simply the expected average of future yields on Treasury bills plus a liquidity premium. Their difference must then be equal to:

$$i_{20,t} - i_{10,t} = E_t\left[\frac{i_{1,t+10} + \ldots + i_{1,t+20}}{10}\right] + LP_{20,t} - LP_{10,t} \tag{10}$$

It is reasonable to assume that the first term of the RHS is fairly constant because of the long horizon of the interest rates at these maturities, given the current information (i.e., the expected U.S. Treasury bond rates for 10-year and 20-year maturities are approximately the same in practice). Thus, movements in this spread will be largely driven by movements in liquidity premiums (LP). In particular, 10-year U.S. Treasury notes are usually used as a benchmark in the pricing of other financial assets and therefore are more liquid than 20-year bonds. In fact, yields on 20-year U.S. Treasury bonds have been some times been above those on 30-year U.S. Treasury bonds (which is also fairly liquid), which could be hardly explained if not by the relative illiquidity of 20-year bonds over other more liquid benchmark maturities.[19] [20]

Market Volatility Premium

The measure of market volatility used in this analysis is the *Chicago Board of Options Exchange (CBOE) Volatility Index*, known as VIX. It measures the implied volatility from option prices on the S&P 500 equity index.[21]

Another measure examined that also captures volatility risk is the uncertainty about the future path of interest rates. This is proxied by the *implied interest-rate volatility from swaptions* with maturities between one and six months.[22]

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[19] For example, during the LTCM crisis in the fall of 1998, spreads between the 30- year U.S. Treasury bond and the 29-year U.S. Treasury bond were unusually large, signaling market liquidity pressures (Committee on the Global Financial System (1999)). Yields on the 30-year U.S. Treasury bond are not used here because this maturity was discontinued for several years during the period examined.

[20] Another commonly used measure of liquidity is the difference between the yields of "on-the-run" and "off-the-run" U.S. Treasury bonds. However, this measure has the disadvantage that it exhibits important variations caused directly by the timing of the auctions, and therefore it is not examined.

[21] This volatility index is largely U.S.-based, but it is widely used to measure global market volatility. One disadvantage of using this index is that it is based on an average of a few observations that are out-of-the-money (the so-called "volatility smile"), rather than using all of the possible volatility and out-of-the-money strike price combinations. The problem with the way in which this index is calculated is that it does not take into account changes in the shape of the volatility smile that lead to a different curvature or a shift in the curve. There are other volatility indices, including the VDAX for the German stock market and various volatility indices for foreign exchange contracts. However, VIX was chosen because of its common use as representative of "global" volatility.

[22] A swaption is an option to enter into a swap contract.

C. Contagion Effects

As discussed earlier, the empirical literature has identified contagious effects during some of the recent crises (surveyed in Dornbusch, Park, and Claessens (2000); Pericoli and Sbracia (2003); and Dungey, Fry, González-Hermosillo, and Martin (2005)). This literature identifies the transmission mechanisms that propagate shocks from the source country across national borders and across financial markets, where channels over and above the market fundamental mechanisms that link countries and asset markets during noncrisis periods appear only during a crisis. In particular, an increase in a country's spread can lead to extraordinary increases in the spreads of other countries. This transmission can happen through different channels. For example, a deterioration in the fundamentals of a particular country, or a certain shock (e.g., a terrorist attack, a natural disaster, etc.), can cause a generalized increase in the investors' degree of risk aversion, requiring higher spreads in markets all across the globe. This is an increase in the price of risk, and should be captured by the aggregate risk variables discussed earlier.

But spreads can also increase for other reasons. The discovery of bad news about one country may cause investors to revise their expectations about the fundamentals of other specific countries which share similar features (i.e., not a generalized effect across the globe, as in the case of a decline in risk appetite). This other channel works through an increase in the (perceived) quantity of idiosyncratic risk.

In order to measure the contagion effects from emerging markets to a particular country, it is not practical to include spreads in other countries or an aggregate index of emerging market spreads directly into the model because this would induce multicollinearity. Instead, as a proxy for this country-specific contagion effect, for each country we construct the *difference between the spread in the composite (aggregated) EMBI+ index for all emerging markets and the bond spread of the country in question*. This variable is meant to measure how a particular bond spread is affected by the *relative* performance of bonds spreads in other similar countries.

IV. Identification And Estimation

The variables in the model can be expressed as the following expression:

$$Z_{it} = \left\{ FF_t, DR_t, ML_t, MV_t, IV_t, \log\left(Spread_{EMBI+,t} / Spread_{it}\right), \log\left(Spread_{it,}\right)\right\} \qquad (11)$$

where i indicates a particular bond spread, FF stands for the funding liquidity (or monetary conditions) proxy, DR stands for default risk, ML stands for market liquidity, MV stands for market volatility, and IV for interest-rate volatility.

The dynamics of each of the variables is captured by estimating a vector autoregression (VAR) model in which all seven variables are endogenous. This implies that there is immediate feedback among all variables in the short-run. The structural innovations are identified by imposing restrictions on the long-run effects of the variables, as in Blanchard and Quah (1989). In particular, it is assumed that in the long-run: (i) bond spreads have no permanent effect on funding liquidity or on any other aggregate global market risk factor; (ii) feedback effects among default risk, market liquidity risk, and market and interest rate volatility risks are temporary;[23] and (iii) the contagion effects from emerging markets are temporary.

The aggregate global market factors and bond spreads follow the following stationary process

$$\Delta Z_t = \chi + \sum_{j=0}^{\infty} C(j) e_{t-j} \qquad (12)$$
$$e \sim N\left(0, I\right)$$

where ΔZ_t is the vector of variables in first differences, e_t is the vector of structural innovations, and I is the identity matrix.

In order to estimate the innovations, the following reduced-form VAR(p) is first estimated:

$$\sum_{j=0}^{p} A(j) \Delta Z_{t-j} = \alpha + v_t \qquad (13)$$
$$A(0) = I$$
$$v \sim N\left(0, \Omega\right)$$

We can invert (13) to obtain its moving-average representation

$$\Delta Z = \chi + \sum_{j=0}^{\infty} B(j) v_{t-j} \qquad (14)$$

where $\sum_{j=0}^{\infty} B(j) = \left(\sum_{j=0}^{p} A(j)\right)^{-1}$ and $\chi = \sum_{j=0}^{\infty} B(j)\alpha$. Since $A(0) = I$, $B(0) = I$, it follows that $v_t = C(0)e_t$. Therefore, identification of $C(0)$ allows us to recover the structural shocks from the residuals of the estimated VAR. In order to identify $C(0)$ we first notice that $Var(v) = C(0)Var(e)C(0)'$, which implies

$$\Omega = C(0)C(0)' \qquad (15)$$

Second, since $C(j) = B(j)C(0)$, it follows that

$$\sum_{j=0}^{\infty} C(j) = \left(\sum_{j=0}^{\infty} B\left(j\right)\right) C(0) \qquad (16)$$

[23] The long-term feedback effects of funding liquidity risk are not restricted *a priori* to be zero over the long-term. The intuition is that funding liquidity effects may be more permanent than the other global factors.

Some restrictions are imposed on the matrix of long-run multipliers, the LHS of (16), which is denoted by H. In particular, the identification restrictions discussed earlier imply that H must satisfy the following matrix:

$$H = \begin{bmatrix} h_{11} & h_{12} & h_{13} & h_{14} & h_{15} & 0 & 0 \\ h_{21} & h_{22} & 0 & 0 & 0 & 0 & 0 \\ h_{31} & 0 & h_{33} & 0 & 0 & 0 & 0 \\ h_{41} & 0 & 0 & h_{44} & 0 & 0 & 0 \\ h_{51} & 0 & 0 & 0 & h_{55} & 0 & 0 \\ h_{61} & h_{62} & h_{63} & h_{64} & h_{65} & h_{66} & h_{67} \\ h_{71} & h_{72} & h_{73} & h_{74} & h_{75} & 0 & h_{77} \end{bmatrix} \tag{17}$$

where h_{ik} is the long-run multiplier of an innovation to variable k on variable i. The order of the variables follows that in (11). Once we have $\hat{C}(0)$, we can construct estimates of e_t as $\hat{e}_t = \hat{C}(0)^{-1}\hat{v}_t$.

The reduced-form VAR in equation (13) is estimated by ordinary least squares. We use 5 lags, as suggested by the AIC criteria. Then the estimated coefficients $\hat{A}(j)$ and the residuals $\hat{v}_t$ are used to estimate $C(0)$ and H using the identifying restrictions (15) and (17). Since the model is over-identified, we estimate the parameters in $C(0)$ through maximum likelihood. The log-likelihood function is given by:

$$\ln L = -\sum_{t=1}^{T}\left(\frac{N}{2}\ln(2\pi) + \frac{1}{2}\ln|\Omega| + \frac{1}{2}v_t'\Omega^{-1}v_t\right) \tag{18}$$

The model is estimated using two different samples. The first sample covers the period between January 2, 1998 and August 9, 2007.[24] The bond spreads analyzed are sovereign spreads from Brazil, Bulgaria, Ecuador, Mexico, Panama, Peru, Russia, and Venezuela, and the corporate spreads are from the United States and Canada. The proxy used for default risk is the 10-year USD swap spread.

The second sample starts in mid-September 2004. Here, we are able to use newer financial instruments that did not exist before (a credit default swap index) to gauge default risk directly. In addition, we are able to analyze a larger number of developing countries and mature markets. The additional sovereign bond spreads correspond to Colombia, the

[24] The sample ends one day before the European Central Bank injected €95 billion into the financial system, marking the first policy intervention aimed at bringing to an end the U.S. subprime mortgage and liquidity crisis.

Philippines, South Africa, Turkey, and Ukraine. The additional corporate bond spreads in mature markets correspond to Japan and the Eurozone.

V. Forecast-Error Variance Decomposition

The analysis proceeds by decomposing the unconditional variance of the bond spreads. The h-step ahead forecast error of ΔZ_t is

$$\Delta Z_{t+h} - E_t\left(\Delta Z_{t+h}\right) = \sum_{j=0}^{h-1} C(j) e_{t+h-j} \tag{19}$$

Given the independence of the innovations, the h-step ahead forecast error variance of ΔZ_t is

$$\operatorname{var}_t\left(\Delta Z_{t+h}\right) = \sum_{0}^{h-1} C(j) C(j)' \tag{20}$$

We can obtain the variance due to a particular innovation k as

$$\operatorname{var}_{k,t}\left(\Delta Z_{t+h}\right) = \sum_{0}^{h-1} C(j) I_k C(j)' \tag{21}$$

where I_k is a matrix with 1 in its (k,k) cell and zeros elsewhere. Taking the limit of these expressions we can compute the unconditional variance decomposition. The results are presented in Tables 2 and 14.

The results suggest that, overall, the aggregate global market factors account for a relatively small fraction of the total variance over the 1998–2007 period (Table 2). The extent ranges from only 8 percent in the United States, up to a maximum of 27 percent in Mexico. Contagion from emerging markets is generally very small (accounting for a maximum of 12 percent in the case of Bulgaria).

For the 2004–2007 sample (Table 14), aggregate global market factors explain a more significant fraction of the variance for some of the emerging markets, accounting for around 50 percent for Brazil, Colombia, Mexico, and the Philippines. However, aggregate market factors during this period explain a smaller fraction for some of the other bond spreads, with the smallest contribution being in the case of mature markets (7 percent for Japan, and approximately 15 percent for the United States and the Eurozone). Contagion effects from emerging markets are very small (accounting for less than 4 percent of the variance).

These results suggest that idiosyncratic factors are generally the main drivers of bond spread changes over extended periods of time. We now turn to examining these trends, but for shorter periods known to have been distressful.

VI. Spread Decomposition

For each period of financial stress (Appendix I details each period), the spreads are further decomposed into a benchmark spread, equal to the conditional expectation of the spreads during the period given information available before the start of the period, and the contributions of the structural innovations to the spreads during the period of stress. The purpose of this exercise is to examine how the different aggregate global market factors contribute to the bond spreads, relative to what they would have been if the crisis had not taken place.

Let T denote the first date of a crisis period. The change in the benchmark spread at date $T+h$, given the pre-crisis information is

$$E_{T-1}\left[\Delta Z_{T+h}\right] = \chi + \sum_{i=h+1}^{\infty} C(i) e_{T-2+h-i} \tag{22}$$

We can then decompose the changes in spreads into their pre-crisis conditional expectation and their forecast error, which is given by

$$\Delta Z_{T+h} - E_{T-1}\left[\Delta Z_{T+h}\right] = \sum_{i=0}^{h} C(i) e_{T+h-i} \tag{23}$$

The contribution of error k to the total forecast error is

$$\sum_{i=0}^{h} I_k C(i) e_{T+h-i} \tag{24}$$

Because some crises are preceded by a period which may already show a certain degree of financial stress, in most cases we compute conditional expectations using information up to several days or weeks before the start of the crisis.

A. Empirical Results: Mean Spread Decomposition

The results are presented in the tables containing the mean spread decompositions (Tables 3-13 examine the 1998–2007 period, and Tables 15–18 the 2004–2007 period). The first three columns in these tables show the mean actual spread during the crisis episode, the mean benchmark spread during the same period,[25] and their difference or the mean forecast error. The columns that follow indicate the contribution of each factor innovation to the forecast error.[26] The cases examined comprise the main episodes of financial stress from 1998 to 2007. Some particular episodes were excluded from the empirical analysis if they had a relatively small impact on global financial markets, despite having an important repercussion domestically; some examples are Ecuador's currency collapse (1999–2000), Argentina's debt default (2001) and Iceland's financial crisis (2006). The episodes of

[25] Recall that benchmark spreads are computed as the conditional expectation, given pre-crisis information.

[26] Note that while actual and benchmark spreads are presented in basis points, the forecast error is $\log\left(Spread_{it}\right) - E_{T-1}\left[\log\left(Spread_{it}\right)\right]$, and thus the contributions to the forecast error are presented in terms of the differences in the logarithms of basis points, or percentage point contribution.

financial stress examined include the Russian default and the subsequent near-collapse of Long-Term Capital Management (1998), the devaluation of the Brazilian currency (1999), the NASDAQ bubble burst (2000), the Turkish crisis (2001), the terrorist attacks on September 11 (2001), the Brazilian elections and the WorldCom accounting scandal (2002), the beginning of the tightening cycle of the Federal Funds rate (2004), the rating downgrades of Ford and General Motors (2005), the Turkish crisis (2006), the Chinese stock market correction (2007), and the U.S. subprime mortgages and liquidity crisis (2007). The specific dates used to define the episodes are described in Appendix I.

Russia's Default and the LTCM Crisis (1998)

In the first episode analyzed, the 1998 Russian default and the LTCM near-collapse are modeled jointly because of the proximity of the two events (Russia defaulted on August 17, and the Fed-orchestrated rescue plan of LTCM was publicly disclosed on September 23). The results in Table 3 suggest that the main aggregate global financial market factors behind the increase in the spreads of all the countries considered in the sample, relative to their conditional expectations or benchmarks, are funding liquidity (proxied by U.S. monetary policy expectations), market volatility and default risk, which together account for almost 40 percent of the forecast error for some of the emerging markets and 23 percent for Canada. Among the three global financial market factors, volatility risk is the most important (accounting for up to 18 percent of the forecast error). The contribution of contagion from emerging markets is negligible for all countries, while the contribution of idiosyncratic factors account for 58–85 percent of the forecast error.

Given that Brazil was the next country to experience a crisis in early January 1999, a few months after the Russian/LTCM crisis, it is interesting to examine the results during the August–October 1998 period but for the particular case of Brazil (Table 3). This is of particular interest because several empirical studies have found evidence of contagion from the Russian/LTCM crises to Brazil (Baig and Godfajn (2001), and Dungey, Fry, González-Hermosillo, and Martin (2006, 2007a)).[27] The results here suggest that global financial market conditions, proxying for investors' risk appetite, accounted for about 42 percent of the difference between the conditional expectation of Brazil's sovereign bond spread and its actual mean value. This difference represents 307 basis points, accounting for almost one-quarter of Brazil's 1,295 basis point actual mean spread against the equivalent U.S. Treasury bond during that period. The idiosyncratic component (the residual in this specification) accounted for another 431 basis points (58.5 percent of the forecast error). These results are consistent with the view that the contagion that was formerly found in previous studies may have been largely accounted for by the role of global investors' risk appetite. At the same time, it appears Brazil's fundamentals may have been reassessed, as captured by the significant size of the idiosyncratic component. Finally, contagion from emerging markets that is not already captured by global financial market conditions was negligible. However, it

[27] In particular, Dungey, Fry, González-Hermosillo, and Martin (2006) provide evidence that the Brazilian bond market was impacted by the Russian crisis, while the results in Dungey, Fry, González-Hermosillo, and Martin (2007a) suggest that Brazil's equity markets were affected by the near-collapse of LTCM.

is somewhat puzzling that the Brazilian results are not that different from other emerging markets, most of which did not have a full-blown crisis in the months that followed the Russian/LTCM crisis.

Brazil's Crisis (1999)

We now turn to examine the next crisis period marked by the devaluation of Brazil's Real on January 12, 1999 (Table 4). During this period, market volatility and funding liquidity are the main factors contributing to the forecast errors in emerging markets. Russia is unusual as the idiosyncratic contribution to the forecast error (the residual) is slightly negative, suggesting that the global market financial factors more than fully accounted for the forecast error. The effect from volatility risk, funding liquidity and default risk combined may have accounted for more than the 350 basis point forecast error in Russia. One interpretation is that the Russian and the Brazilian crises were so close in time that there were actually feedback effects from the latter to the former through a decline in investors' appetite for risk, reflected in the global financial market factors.

Another interesting observation during this period is that mature markets were essentially unaffected by global financial factors, as their benchmark spreads are close to the actual spreads. These results support the view that the Brazilian crisis did not importantly affect other markets, as the forecast errors are generally much smaller during this period, particularly in the case of mature economies. Once again, contagion from emerging markets (not already accounted for by the common global financial market factors) is negligible.

NASDAQ Bubble Burst (2000)

During the NASDAQ bubble burst in 2000, default and funding liquidity risks are the main factors explaining most of the forecast errors considered (Table 5). It is interesting that volatility risk became very small during this period, in contrast to the previous periods of stress considered. The forecast errors are generally small for all the countries considered, except for Ecuador which was still suffering from its own financial crisis.[28] Also noteworthy is the result pointing to a negative forecast error for Russia during this period, less than two years after facing its own crisis. The model suggests that the improvement in Russia's spreads during this period was not so much due to improved fundamentals (recall that in this model, the residual is treated as "fundamentals"), but largely resulting from an improved risk appetite for Russian assets (measured by the negative contributions to the forecast error coming from global market risk factors, despite some increased risk coming from interest volatility).

[28] Ecuador's economy experienced a contraction in real GDP of 7 percent, an inflation rate of 60 percent and a 67 percent depreciation of the Sucre in 1999. Ecuador adopted the U.S. dollar as the legal tender in January 2000. Amid political and economic uncertainty, Ecuador's Finance Minister resigned in May 24, 2000.

Turkey's crisis (2001)

During Turkey's crisis in 2001 (Table 6), all of the forecast errors become smaller as the benchmark conditional expectations are close to the actual spreads for most countries. Volatility is again an important risk factor and, indeed, all global market risk factors take increased importance during this period. In contrast, idiosyncratic factors often have the opposite effect, acting to reduce the spreads. The only exceptions are Bulgaria, Peru, and the United States.

September 11th (2001)

In the period following September 11 in 2001, the U.S. Federal Reserve and other central banks injected substantial amounts of liquidity into the financial system in anticipation of potential disruptions in global markets following the closing on the New York stock exchange after the attacks. This is reflected in a negative contribution to the premia coming from funding liquidity (Table 7). That, plus a reduction in the default risk helped to largely offset the increases in spreads caused by higher premia coming from market liquidity, market volatility and interest-rate volatility risks. All forecast errors are relatively modest. It is noteworthy that market volatility risk, in particular, surged during this period and became the single most important source of risk premia for all emerging markets. However, in the case of mature economies, the largest contributor to the spreads is due to market liquidity risk.

WorldCom Scandal and Brazil's Elections (2002)

The next period of turbulence examined is the WorldCom accounting scandal, which roughly coincided with a period of uncertainty in the run-up to Brazil's elections, during June-October 2002 (Table 8). During this period, Brazil's forecast error is quite large, at around 1,200 basis points (the actual spread is 1,904 basis points and the conditional expectation is 709 basis points). The forecast error is explained mostly by a large contribution of idiosyncratic factors, which is consistent with the fact that investors were nervous about the likely election of a seemingly "populist" Lula government.[29] The forecast errors during this period were also relatively large for other Latin American countries (especially Ecuador and Peru) which may have been influenced by the "Lula-effect." During this period, funding liquidity is the main contributor to the forecast errors, followed by volatility and market liquidity. This may reflect the expectation among market participants that the U.S. Federal Reserve was about to start a new tightening cycle, after an extended period of declines in policy interest rates since early-2000, and uncertainty as to exactly when the new cycle would begin. The results suggest that there were no other contagion effects coming from emerging markets that were not already captured through the international investors' risk appetite conduit.

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[29] Lula was in fact elected on October 29, 2002, but his presidency turned out to quite pragmatic and less populist than had been anticipated by financial markets.

U.S. Federal Reserve Begins Tightening Cycle (2004)

Indeed, the U.S. Federal Reserve began to tighten monetary conditions on June 30, 2004 when it increased the federal funds policy rate by 25 basis points. However, the run-up to the tightening of monetary policy in the United States appeared to be a period of uncertainty amid jitters in global financial markets. This episode, marking expectations and uncertainty about the forthcoming tightening in U.S. monetary policy, is assumed to begin following the release of a strong payroll data (for March) on April 2, 2004. Against increasing speculation and uncertainty as to when monetary conditions might be tightened, and in light of a scheduled FOMC meeting, emerging markets experienced a generalized sell-off on May 3, 2004. This spike in spreads was short-lived, however, as spreads resumed their overall downward trend (which had started in the early part of the 2000s) after June 30, 2004 when the U.S. Federal Reserve actually increased its federal funds rate by 25 basis points for the first time in more than four years. This episode of uncertainty about the exact timing of the monetary policy tightening is, therefore, assumed to end on June 30, 2004 when the U.S. Federal Reserve announced the change in its policy stance.

Table 9 decomposes the period during the run-up to the U.S. Federal Reserve switching to a tightening stance. This period is characterized by relatively small forecast errors as the benchmark conditional expectations are close to the actual spreads (less than 200 basis points for all countries). Most of the forecast errors are attributed to funding liquidity risk, though with a much smaller contribution than in the previous episode of stress in 2002 (Table 8). Default risk also plays a role, but market liquidity and volatility risks are generally very small or even negative (acting to offset the increase in spreads). Idiosyncratic factors are fairly large in most cases (the exceptions being Venezuela and Bulgaria). Interest-rate uncertainty does not seem to be a very important factor. This is somewhat surprising, but it may be explained by the funding liquidity risk already capturing some of this uncertainty. Other contagion channels from emerging markets are, again, minuscule.

Ford and General Motors Downgrades (2004)

The Ford and General Motors downgrades in the spring of 2004 coincided with a general moderate (and temporary) increase in bond spreads (Figures 1–3). During this period, the forecast errors are modest (less than 110 basis points for emerging economies and below 12 basis points for mature economies) for all the countries considered (Tables 10 for the 1998–2007 period and Table 15 for the 2004–2007 period). However, the funding liquidity and the default risk channels seem to be quite important. Interest rate risk is relatively small, but larger than in any other previous period. Other channels of contagion from emerging markets are, once again, tiny. Idiosyncratic factors vary.[30]

[30] Idiosyncratic factors move from positive during the 1998–2007 sample to negative in the shorter 2004–2007 sample based on the actual cost of default insurance. Since the idiosyncratic factors in the specification are essentially the residuals, negative contributions suggest that the contributions of other risks may be overestimated. However, the forecast errors are fairly small in most of the specifications where idiosyncratic factors contribute negatively to the difference between the actual spread and the benchmark, which reduces the importance of negative idiosyncratic factors.