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BRIC and the U.S. financial crisis: An empirical investigation of stock and bond markets

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ABSTRACT

We examine empirical evidence of the behavior of stocks and bonds from BRIC nations by using daily data from January 2003 to July 2010. We present unconditional and conditional empirical results depending upon a simple measure of U.S. financial stress. In the long term, BRIC bond markets deviate much more from the U.S. financial stress measure than the BRIC bonds and stocks that deviate among themselves. Stock and bond return correlations for Brazil and Russia are significantly large and negative. The own correlations are more important in determining the evolution of the conditional correlations relative to unexpected news. Dynamic conditional correlations between stock returns, bond returns and U.S. financial stress increase after the Lehman Brothers' event in September 2008, except for the bond returns in India.

1. Introduction

Brazil, Russia, India and China form a small group of countries, now known as the BRIC, that have called the attention of investors and academia in the new millennium. The reasons are multiple but the common theme is that they represent a class of middle-income emerging market economies of relatively large size that could potentially provide the needed steam to enhance economic growth in the world economy. In parallel, among many other shocks, the new millennium has witnessed one of the largest and most complex financial crisis to date. One of the main characteristics of the crisis was how

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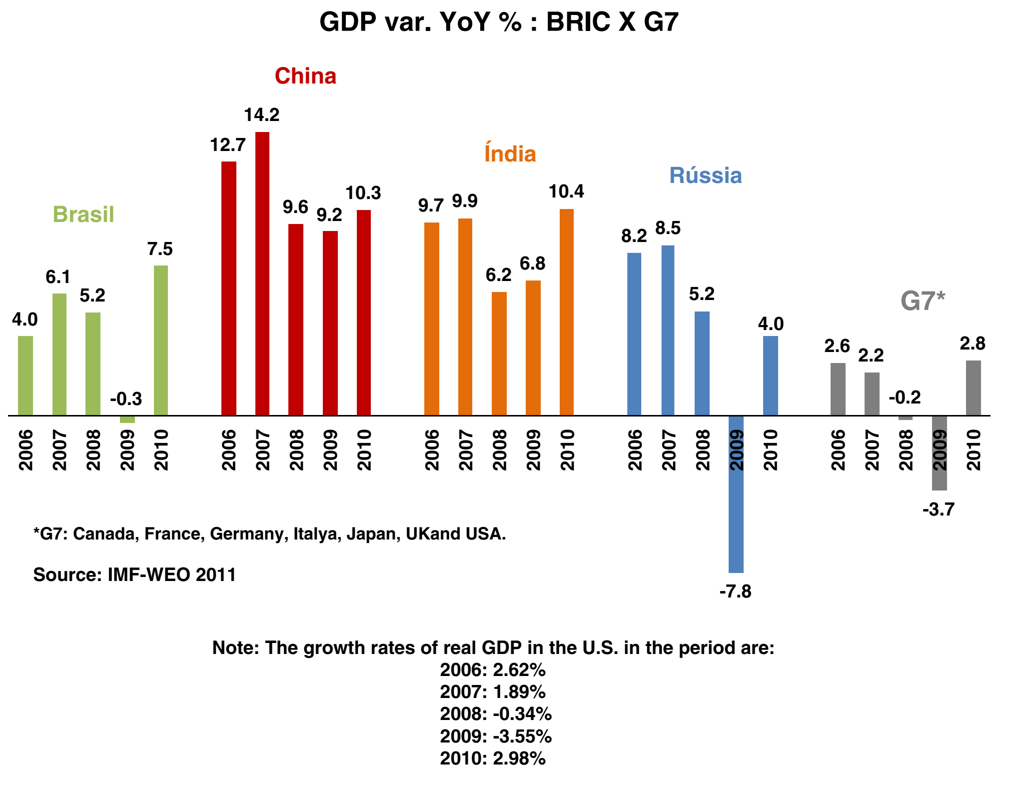

Fig. 1. GDP (var. % 2006–2010).

rapidly it spread from the U.S. housing market to its financial market and then to the rest of the world. According to the IMF (2009a,b), developed countries had gone through a gross domestic product drop of respectively 7.2% and 8.3% on the 4th quarter of 2008 and 1st quarter of 2009. Facing a weaker external demand and illiquid financial markets, developing countries – especially after the Lehman Brothers' bankruptcy episode on September 2008 – have suffered the consequences from the Subprime crisis, although in a less intense way when compared to the U.S. and Western Europe. Fig. 1 shows the GDP annual real growth of the G7 group and the BRIC, Brazil, Russia, India and China.

Our main motivation stems from the impact of the financial crisis on the BRIC nations relative to the source of the crisis. The main focus is on the measurement of transmission of financial shocks from the U.S. to stock and bond markets of the BRIC countries. The importance of this line of inquiry is multiple. We would like to determine whether or not this group of emerging economies can be considered insulated from the financial stress of the U.S.; whether it can provide diversification opportunities; whether it can perform the role of the locomotive in sustaining world economic growth.[3]

The four BRIC countries vary in their structural characteristics, economic policies and geopolitical importance. China and India are economies with most population living in rural areas, and relatively closed and state-controlled capital markets. Their development strategy is export led, based on domestic industrialization for export markets. Meanwhile, Brazil and Russia have most of their population living in urban areas. Brazil and Russia are primarily natural resource-based economies and well known commodity exporters. Their capital markets, while developed at very different periods and pace, are much more open and currently subject to relatively lower state controls.

[3] In the context of this paper, see Aloui et al. (2011), Chittedi (2009), Morales (2011), Balakrishnan et al (2009). The recent papers by Bianconi and Yoshino (2010, 2012) focus on the economic effects of the U.S. on firm value worldwide and on real estate firm values in Brazil respectively.

Our empirical analysis uses daily data from January 2003 to July 2010 and is fourfold. First, we examine unconditional volatility measures of BRIC and U.S. markets and use the heat map tool developed by the IMF (2008, 2009a,b) to understand how volatility spreads across the BRIC nations over time. We use information from the heat maps to estimate simple short term VARs to understand the impact of a simple measure of financial stress, based upon the S&P500 volatility index VIX and the spread between the UK Libor and the U.S. federal funds rate, the TED spread, on the returns to stocks and bonds in the BRIC countries. Next, we use Johansen's (1988) cointegration framework to examine long term relationships among the BRIC countries and the U.S. financial stress measure.[4] Finally, conditional on our cointegration results, we use multivariate GARCH methods and dynamic conditional correlations of Engle (2002) to examine conditional dynamic volatility and correlations of the BRIC market returns, distinguishing between own autocorrelations and news effects.

In terms of the unconditional volatilities, we find that for stock returns the U.S. crisis spread through Brazil, Russia, China and India which gave an identification for a short term VAR. For bond returns, the U.S. crisis spread through Brazil, Russia, India and China. The cointegration results confirm some of the short term evidence above, but, most importantly, for the long term, stock index levels in Brazil and India are related to the U.S. financial stress measure, but not the stock levels in Russia and China. The multivariate GARCH and dynamic conditional correlation results show that neither news nor autocorrelation of correlations plays a predominant role in the case of the dynamic conditional correlations of stock returns.[5] The dynamic conditional correlations among the stock returns of all BRIC nations have increased since the beginning of the financial crisis in September 2008. In terms of bond returns, all the BRIC countries display significant conditional heteroskedasticity with Russia as the most responsive country to conditional volatility news, while China does respond and shows signs of volatility instability in its bond returns index. In this case, the own correlations are more important in determining the evolution of the conditional correlations of bond returns relative to the unexpected news.[6] The dynamic conditional correlations among bond returns of all the BRIC nations have increased after the September 2008 event, but not for India-EMBI which is seen to be insulated and uncorrelated to other BRIC countries.

For the joint behavior of the stocks and bonds, they are significantly negatively correlated for Brazil and Russia, but not significant for China and India. The returns of stocks in Brazil are significantly negatively correlated with Russia and China and bond returns in Brazil are negatively correlated with the stock returns in Russia and India. The bond returns in Russia are significantly negatively correlated with the stock returns in India. The largest correlations are between Brazil and Russia.[7]

The reminder of this paper is as follows. Section 2 provides a literature review. Section 3 briefly describes the data. Section 4 presents simple preliminary statistical and short term VAR analysis of the data while Section 5 extends to long term analysis and dynamic correlation analysis. Section 6 provides a summary and concludes.

2. Literature review

According to Claessens et al. (2000), contagion between countries can be defined as a significant increase in the links between international markets after a shock in a country or a group of countries. Forbes and Rigobon (2000) show that the links between countries can be measured by many different statistics such as correlation in asset returns, the probability of a speculative attack, or even the transmission of shocks or volatility and bilateral relations of trade in goods. In this paper, we use simple unconditional volatility measures, vector autoregressions (VAR), cointegration, and conditional volatility and correlations among stock and bond returns to study the spread of the U.S. financial crisis to the BRIC nations.[8]

[4] Bhar and Nikolova (2009a,b) explore the cointegration of the BRIC with their respective regions and the world.

[5] Our results are closely related to Mun and Brooks (2012); but Bunda et al (2009) find alternative results.

[6] The terminology own correlations refers to the autocorrelations of the correlations themselves.

[7] Chittedi (2009) shows that India is far less integrated with the global markets. Also note that BRIC countries compete for foreign investment in world capital markets and those movements may reflect investor preferences for Brazil over Russia and China; e.g. Buchanan et al (2011) discuss the large portfolio capital inflows into high growth emerging markets in the new millennium. Aizenman and Sengupta (2011) present a comparative analysis of China and India during the recent crisis. See also Aloui et al. (2011).

[8] De Santis and Imrohoro lu (1997) is an early contribution studying the dynamics of the expected stock returns and volatility in the emerging financial markets. They did not find support for a potential claim that market liberalization increased price volatility in their sample.

Regarding the recent financial crisis, the early studies of Eichengreen and Park (2008) and Eichengreen et al. (2009) pointed to the inability of the emerging markets to steer clear of the U.S. financial crisis. Dooley and Hutchinson (2009) show that, at the beginning of the Subprime crisis from June 2007 to August 2008, the emerging economies' response was limited; a result compatible with Llaudes et al. (2010). This became known as the decoupling versus coupling debate. First, with an early period where developed and developing countries' growth rates seemed to be heading in opposite directions, then, after the Lehman Brother's bankruptcy in the U.S. in September 2008, the crisis got to its most critical period and its transmission to emerging markets started to be felt more intensely. This is illustrated in Fig. 2 by comparing the MSCI Index evolution for both BRIC countries and developed countries.[9]

More recently, Aloui et al. (2011) study the co-movements between the BRIC stock markets and the U.S. during the period of the global financial crisis. They find that dependency on the U.S. is higher and more persistent for Brazil–Russia than for China–India; and we also find similar results here. By using daily return data from Brazil, Russia, India, China (BRIC markets) and the U.S., their empirical results show strong evidence of dependence between each of the BRIC markets and the U.S. markets, but stronger for the commodity-price dependent markets. Chittedi (2009) found the cointegration relationships between the BRIC countries and the U.S., UK and Japan. Chittedi shows that India is far less integrated with the global markets. Our results in this paper show that for the bond markets, India is insulated from the other BRIC nations.

On the other hand, Morales (2011) finds evidence of weak integration among Chinese financial markets, energy markets and the U.S. stock market. Morales shows that the Brazilian, Indian and Russian markets are more sensitive to international shocks arisen from U.S. markets and also to oil market instability. Bhar and Nikolova (2009a,b) explored the cointegration of the BRIC with their respective regions and the world in the post-liberalization period. They found that India has the highest level of integration on regional and world levels among the BRIC countries followed by Brazil, Russia and lastly China. They found the existence of diversification opportunities for China, given its closed nature of the financial system.[10] Our results highlight the fact that the cointegration relationships among the BRIC nations and the U.S. measure of financial stress depend very much on the nature of asset class in consideration, in our case the stocks versus the bonds, or the joint behavior of the stocks and bonds.

Our results regarding the multivariate GARCH models and dynamic conditional correlations shed light on Mun and Brooks (2012) who explore the roles of news and volatility in explaining the changes in correlations between the national stock markets during the global financial crisis. They show that the majority of the correlations are better explained by volatility rather than by news. We find that for stock returns, news and volatility are equally important, but for the bond returns and stocks and bonds jointly, the role of news is less important than the volatility for the BRIC nations in the 2005–2010 period.[11]

Our focus on the stocks and bonds brings about a long literature on stock and bond correlations as well. Those are two different classes of assets where bonds usually have seniority over stocks and serve as a more short term hedge against volatility in stock markets. Baur (2007) shows empirically that, in emerging markets, the level of stock–bond correlation depends more on cross country influences than on the stock and bond market interaction. Aslanidisy and Christiansenz (2011) examine the realized stock–bond correlation based upon high frequency returns and find that correlation dependence behaves differently when the correlation is large negative and large positive.[12]

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[9] The MSCI BRIC Equity Index was launched by MSCI Barra in December, 2005. The index currently consists of 229 constituents (as of January 31, 2007), and has history back to 30 December, 1994. The index is market capitalization weighted and combines the components of the MSCI Brazil, MSCI Russia, MSCI India and MSCI China Equity Indices. MSCI Index is an index consisting of a wide selection of stocks traded in 23 developed countries. It is weighted for market capitalization and is considered an important benchmark of the state of global stock markets. It is managed by MSCI and has existed since 1969.

[10] Modi et al. (2010) found that the correlation of BSE (India) with BVSP (Brazil), MXX (Mexico), FTSE100 (UK), DJIA and NASDAQ (US) is low. Therefore, they conclude that these combinations provide attractive portfolio diversification opportunities for Indian investors.

[11] Owyong and Iyer (2010) show that the behavior of the emerging market bonds depends on their relationships with developed market sovereigns and with equity volatility, and on the relative performance of the emerging market assets in fixed income and equity markets. Buchanan et al. (2011) find high returns and high volatility for a BRIC portfolio index.

[12] Yang et al. (2009) use monthly stock and bond return data in the past 150 years (1855–2001) for both the U.S. and the UK, and documents time-varying stock–bond correlations over the business cycle, the inflation environment and monetary policy stance. Ciner et al. (2010) investigate five major financial asset classes, examining how each acts as a hedge or a safe haven to each other. They find that gold acts as a safe haven for most assets, except oil. See also Gupta (2011).

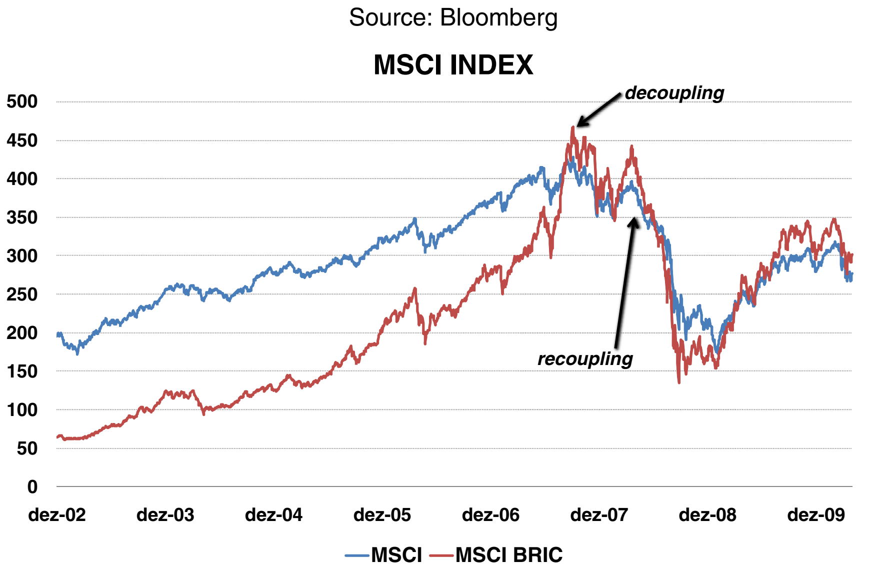


Fig. 2. MSCI × MSCI — BRIC.

In regard to the bond markets, our results are comparable to Bunda et al. (2009) who empirically assess the comovements in the emerging market bond returns relating to the external and domestic factors during episodes of heightened market volatility. Between 2003 and 2008, they find that the comovement of the emerging market bond returns appears to be driven more by external events, and that contagion in bond markets during this period was very low. However, we find that news play a less important role than the own autocorrelation of volatility and correlations in explaining bond returns and the joint behavior of the bonds and stocks. The discrepancy may be due to our use of a more recent sample period of 2005–2010 for the bond sample, and our focus on the BRIC nations. Siklos (2011) examines the determinants of the bond yield spreads for 22 emerging markets in the period 1998–2009. He finds that the global financial crisis raised yield spreads in all emerging markets, except in Asia, which suggests that bond markets in that region were decoupled from those in other parts of the world. Our findings regarding the insulation of India's bond market are consistent with Siklos' findings.

3. Data

We use daily data from January 2, 2003 to July 21, 2010 for the stock market variables. The stock returns for the BRIC countries we use are: Brazil — IBOVESPA: São Paulo Stock Exchange Index; Russia — Russian Trading System; India — Bombay Stock Exchange; and China — Shanghai Stock Exchange. The stock measures are the local market indices. Our daily series of the Emerging Market Bond Indexes (EMBI) for the BRIC countries is based on the JPMorgan Bank index as the benchmark government bond yields for the emerging markets and are from January 31, 2005 to July 21, 2010. The sovereign bond indices are in U.S. dollars. The U.S. variables are the daily Chicago Board of Trade VIX implied volatility index and the spread between the LIBOR and the US Fed funds rate, known as the TED spread.[13]

[13] We had a lack of data availability for the India EMBI bonds prior to January 2005. The TED spread is the difference between the interest rates on interbank loans and short-term U.S. government debt ("T-bills"). TED is an acronym formed from T-Bill and ED, the ticker symbol for the Eurodollar futures contract. The TED spread is an indicator of the perceived credit risk in the financial intermediation sector. Data sources are from the respective providers of the indexes, and the TED spread is from the U.S. Federal Reserve Board.

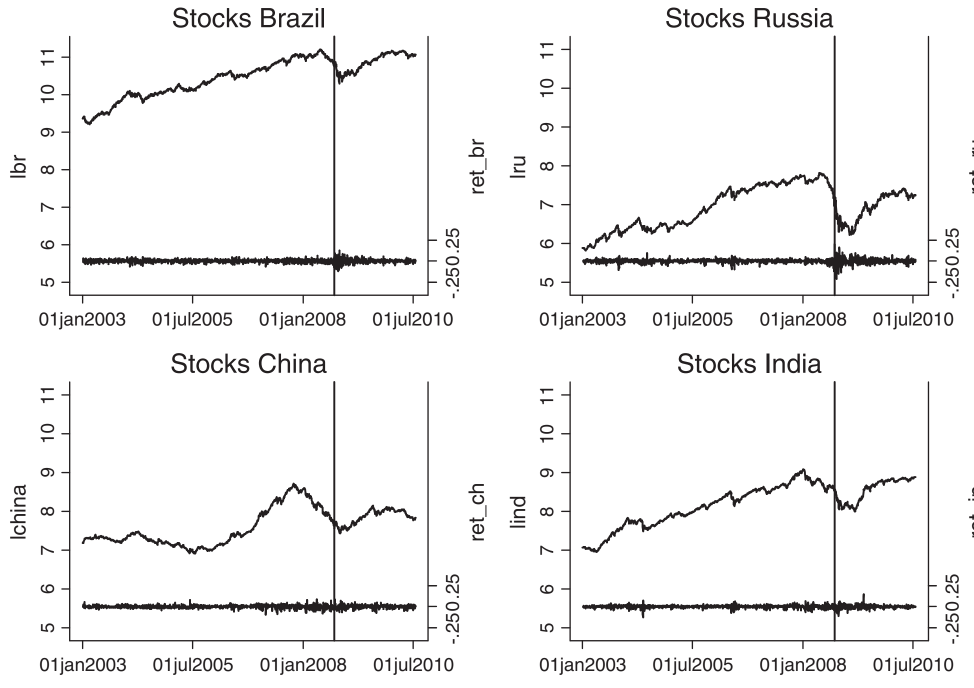


Fig. 3. BRIC stock markets — (log) levels and volatility.

4. Transmission of financial crisis and short term VARs

In this section we focus on a simple data driven examination of the spread of the U.S. financial crisis among the BRIC nations by using heat maps and short term VARs.

4.1. Heat map

The heat map is a simple tool elaborated by the IMF (2009a,b, 2010a,b) to show the evolution of financial stress by an index that identifies periods in which the financial variables being studied reach higher levels of unconditional volatility. Our main use here is to show the transmission of the crisis across the BRIC countries. The index is based on a simple computation of z-scores basically taking the number of standard deviations away from the mean for a base period.[14] As Blanchard (2008) points out, the larger the change in the price of the asset or index, or the higher the volatility of the price or index, the higher the value of the index.

4.1.1. Stock markets

The main BRIC and U.S. companies whose stocks compose the stock index for each country are as follows: (i) Brazil: Petrobras (Energy), Vale (Mining), Itaú — Unibanco (Banking), Ambev (Beverage) and Bradesco (Banking); (ii) Russia:[15] Gazprom (Energy), Sberbank (Banking), Rosneft (Energy), Lukoil (Energy) and

[14] The heat index is computed as the simple average of a z-score of the daily return of the stock or bond relative to the mean and standard deviation of the 2003–2006 period, and a z-score of the standard deviation of a 30-day moving average of the daily return relative to a mean standard deviation and standard deviation of the standard deviation of the 2003–2006 period. The heat maps are obtained as the one-month average of the heat index. See IMF (2008, 2009a,b and 2010a,b), Blanchard (2008).

[15] Kuznetsova et al. (2011) shows that from a modest start almost 20 years ago, the Russian financial market has emerged as a major force in Eastern Europe and Central Asia.

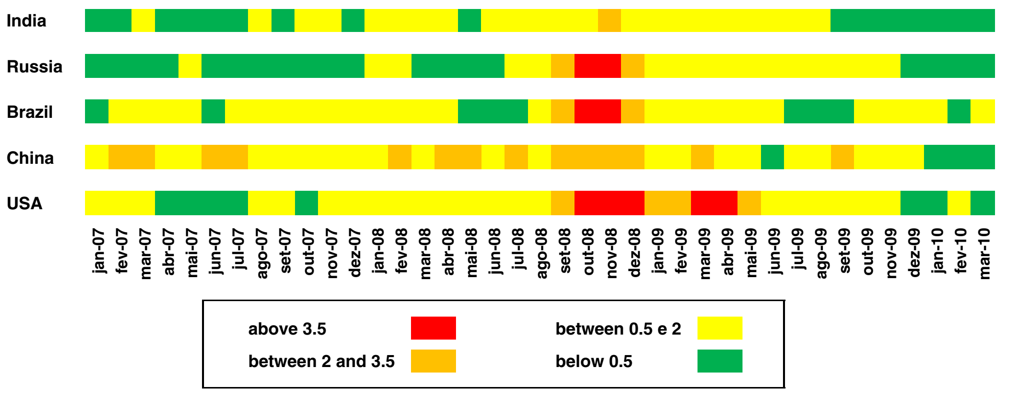


Fig. 4. Heat map stocks. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

Norilsk Nickel (Mining); (iii) China:[16] Petrochina (Energy), ICBC (Banking), China Construction Bank (Banking), Bank of China (Banking) and Agricultural Bank of China (Banking); (iv) India: Reliance Industries (Industry), Tata Consultancy Services (IT), Infosys Technologies (IT) and State Bank of India (Banking); and (v) U.S.: Exxon Mobil (Energy), Apple (Computer Technology), Microsoft (Computer Technology), Berkshire Hathaway (retail, baking, among others) and Walmart (Retail).

Fig. 3 shows the log levels and volatility of the stock markets of the BRIC nations in the sample period. The vertical dark vertical line is the failure of the Lehman Brothers on September 18, 2008. Markets in Brazil, Russia, China and India were in decline before the September 18 date. Afterwards all markets rebound. Volatilities in Brazil and Russia increase sharply after the Lehman failure, but not in China and India.

In Brazil, the stock market is more concentrated. In January 2011, the five companies listed above represented 48% (or US$ 700 billion) of the total market value of the companies that compose the stock index. Although two of those companies (Vale and Petrobrás) are commodity producers, they alone correspond to 30% of this total.

Like Brazil, Russia's stock index also presents a high concentration of commodity producing companies. That is expected given the importance of this sector to the country's economy. Among the five main companies listed above, only one of them is not specialized in producing metal or hydrocarbon, the bank Sberbank representing financials.

While financial companies dominate China's stock index, India is the country among the BRIC with the most similarities with the U.S. in what concerns its stock index, as its composition is more diversified, with stocks from manufacturing industries such as Reliance Industries, financial companies like State Bank of India, energy with ONGC, and information technology like Infosys.[17]

Fig. 4 shows the stock index heat map. As the heat index increases, the color goes from green to yellow to orange and then to red corresponding to under 0.5, from 0.5 to 2, from 2 to 3 and above 3.5 standard deviations respectively, so orange and red should be seen as rare events. We note that the BRIC stock markets have had a very volatile period during the crisis, with a peak between September 2008 and December 2008, after the Lehman Brother's bankruptcy. The contagion process goes from the U.S. to Brazil, Russia, China and India last. We also note that the most critical period in terms of volatility lasted longer in the U.S. than other BRIC countries, although it first hit BRIC stock markets almost simultaneously to the U.S.

[16] This is a combination of Hong Kong's and Shanghai's stock market indexes.

[17] India is a country where the English language is well spoken given the British colonial period. Dhir (2005) shows how language plays a role in the creation of intellectual and organizational capital.

We see that the Chinese stock market shows variability, but not extreme events. One reason may be that in January 2007, before 2008, an episode known as the 'Chinese Correction' triggered high volatility in Chinese markets. This episode was characterized by an abrupt fall on China's stock prices — the Shanghai index fell by 8.8% in one day. Even though financial companies dominate the Shanghai Stock Index, and they could be the ones that had been hit the hardest at the beginning of the crisis, the market was already volatile before 2008 and remained as such.

4.1.2. Bond markets (EMBI)

This index is used as a reference to measure the outcome of the return of the emerging markets' sovereign debt bonds. Fig. 5a shows the log levels and volatility of the EMBI rates of the BRIC nations in the sample. The vertical dark vertical line is the failure of the Lehman Brothers on September 18, 2008. Note that for bonds, the levels in Brazil, Russia, China and India were rising before the September 18 date. Afterwards, Brazil, Russia and China start a declining trend while India shows an initial drop and increasing trend afterwards. Volatility in China increases while in Brazil and Russia it remains roughly similar. Volatility in the India EMBI is much lower relative to the other nations and increases only slightly after the Lehman event.

Fig. 5b shows the spreads of the EMBI returns for the BRIC nations and the U.S. federal funds rate and the UK Libor rate. The spreads of all BRIC countries decline after the September 18 date. For the U.S. federal funds rate spreads, Brazil and Russia's volatility is moderate, but Russia is slightly more volatile than Brazil. China has the largest and increasing volatility, while India has the smallest volatility of the group. The spreads relative to the UK Libor rate have a similar pattern. The EMBI rate encompasses both the country yield curve and country risk. For China, a mixture of those two factors is making the spread much more volatile than the other countries.

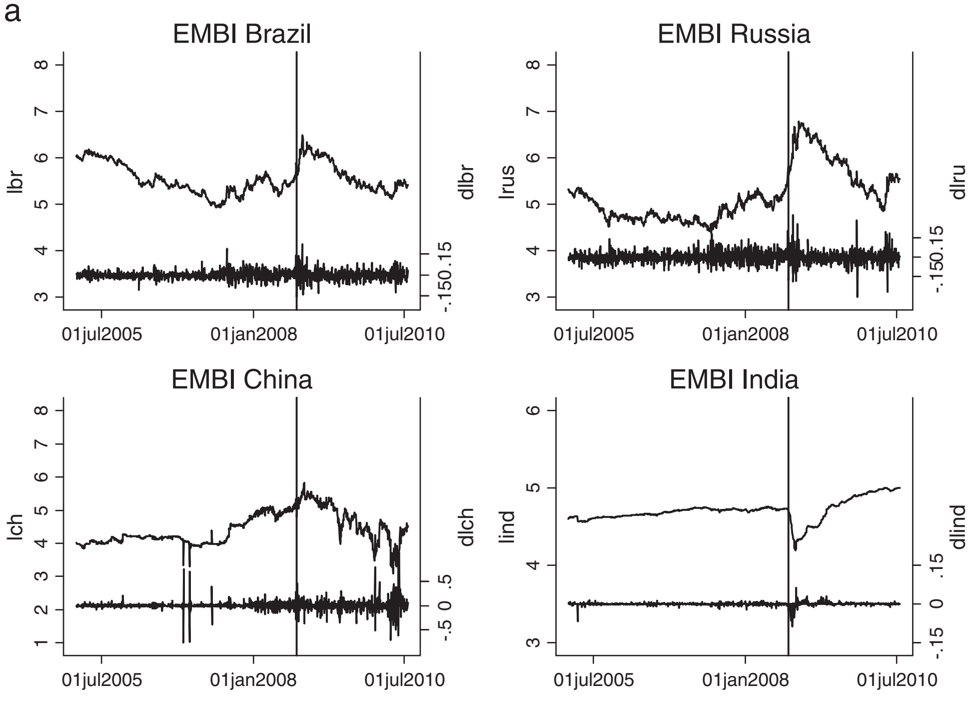


Fig. 5. a: BRIC EMBI — (log) levels and volatility. b: spreads federal funds rate over EMBI returns; Libor rate over EMBI returns.

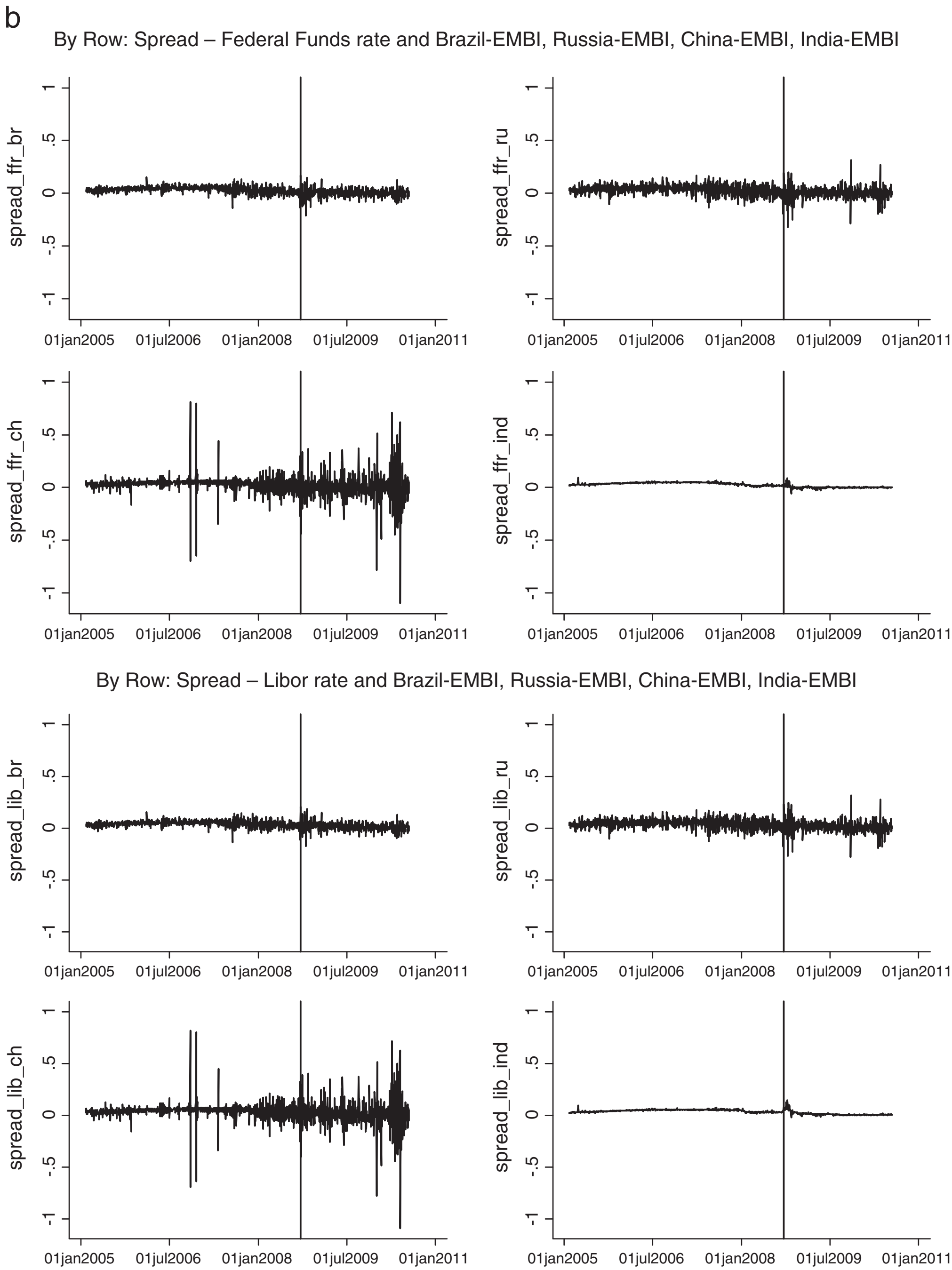


Fig. 5 (*continued*).

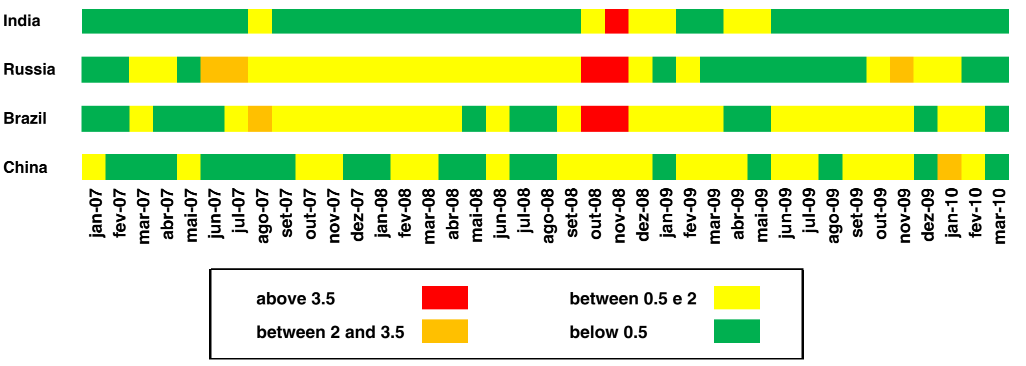


Fig. 6. Heat map EMBI.

The heat map for EMBI in Fig. 6 also shows a critical period between September and December 2008. The shocks spread more predominantly in Brazil, Russia and India, but less in China which follows a pattern of increasing volatility on its own.[18]

4.2. VIX and TED as measures of U.S. financial stress

We construct a financial stress measure for the U.S. based upon the linear sum of the z-scores of the implied volatility index VIX of the Chicago Exchange market and the TED spread, the difference between the Libor and the U.S. federal funds rate. This variable will be used to measure the sources of risks from the U.S. market to the BRIC countries. This follows the guidelines of Balakrishnan et al. (2009), however on a minimalist dimension that captures the basic event of the U.S. financial crisis without any specifics regarding sectoral sources.[19]

Fig. 7 shows the plot of the measure of financial stress (z-score of VIX plus z-score of TED) where the dark vertical line is the failure of the Lehman Brothers in September 18, 2008.

4.3. Short Term VARs

In this section we estimate simple short term VARs by using the order of transmission depicted in the heat maps above. The data are in first differences and the lag length is chosen according to the usual information criteria.

4.3.1. Stock markets

We define the order

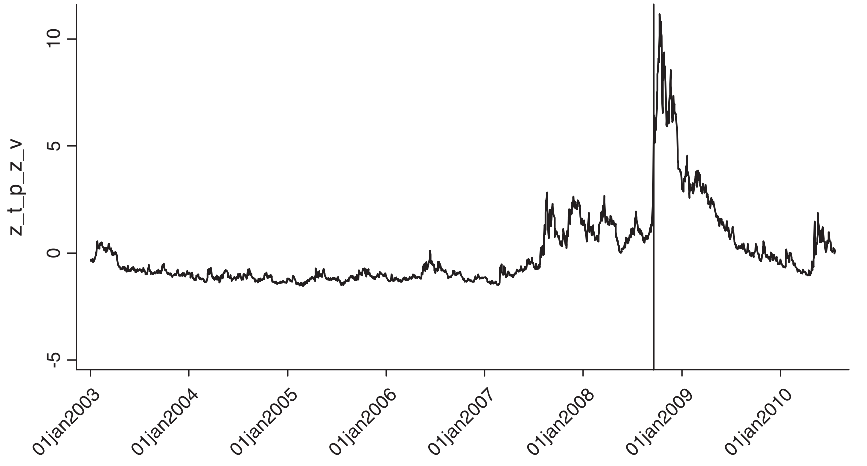
$$\text{Financial Stress (change)} \Rightarrow \text{Return Brazil} \Rightarrow \text{Return Russia} \Rightarrow \text{Return China} \Rightarrow \text{Return India}$$

based on the information of the heat map for the stocks of Fig. 4 above. In this order, the largest commodity exporters are hit first by the U.S. financial stress measure and China, the importer comes third with India as fourth.[20] The lag length criteria give one period (day) lag. The resulting five step

[18] Andrade (2009) presents a model and empirical evidence that sovereign yield spreads carry information about the likelihood of a negative regime change in an emerging market, i.e., pure country risk, thus assuming that the regime change is associated with a hostile renegotiation of the country's foreign debt.

[19] Demircug-Kunt et al. (2006) present an early analysis of financial distress in banking systems. Balakrishnan et al (2009) show how financial stress is transmitted from advanced to emerging economies by using a financial stress index for emerging economies which consist of a linear sum of z-scores of several market measures. They find that previous financial crises in advanced economies passed through strongly and rapidly to emerging economies. Aizenman and Pasricha (2011) use an alternative measure of own country stress based on relative net capital and portfolio inflows.

[20] Note that other orderings could be possible, say the U.S. crisis could affect China and India to some extent first due to their reliance on commodities.



Note: The index is the z-score of the VIX index plus the z-score of the TED spread.

Fig. 7. The Financial Stress Index.

orthogonalized impulse response functions (OIRF) of a one standard deviation shock in the change in the U.S. financial distress variable are shown in Fig. 8. The effects are short lived, up to two days only. All initial responses are negative. Brazil and Russia have the largest initial impact, with India following. The effect in

By Row: Shocks in change in Financial Stress variable. Response of stock returns in Brazil, China, India, Russia.

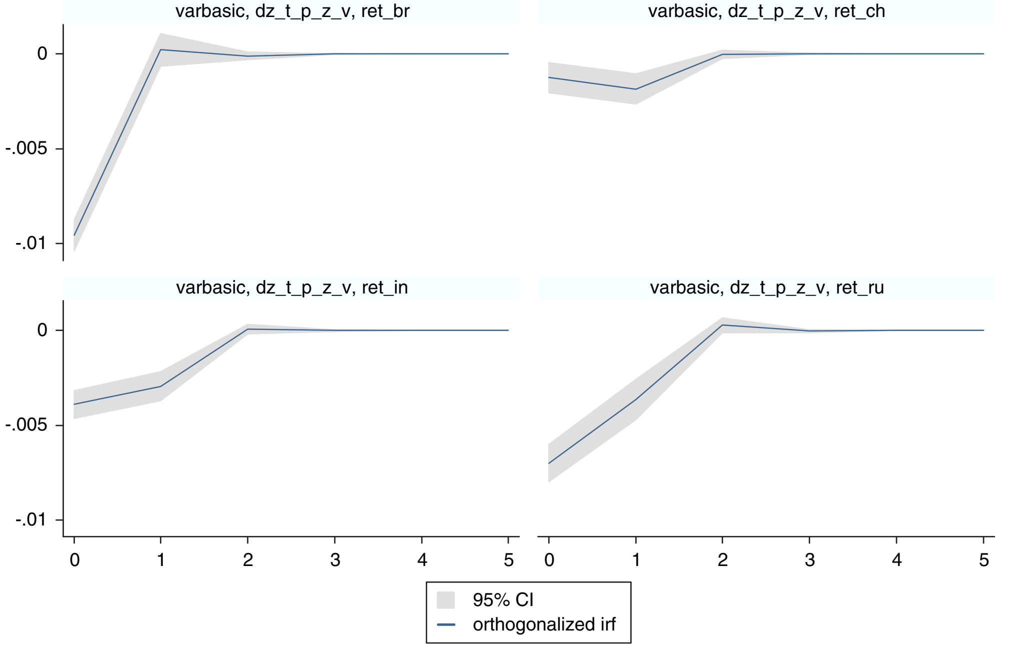


Fig. 8. Orthogonalized impulse response function — short term VAR–stock returns.

Brazil is one day, while in Russia and India is two days. China's initial impact is much smaller relative to the other three nations.

4.3.2. Bonds markets (EMBI)

In this case, based on the heat map in Fig. 6, we use the order

$$\text{Financial Stress (change)} \Rightarrow \text{Return Brazil} \Rightarrow \text{Return Russia} \Rightarrow \text{Return India} \Rightarrow \text{Return China}$$

The lag length criteria give two periods (days). The resulting five step orthogonalized impulse response functions (OIRF) of a one standard deviation shock in the change in the U.S. financial distress variable are given in Fig. 9.

The effect on bonds is null for India. The initial impact for the other countries is positive with similar magnitudes. Brazil and Russia have one day impacts while China has a two day impact with more volatility.

4.3.3. Joint behavior of stocks and bonds (EMBI)

We estimate a VAR with stocks and bonds included. We use the order

$$\begin{gathered}\text{Financial Stress (change)} \Rightarrow \text{Stock Return Brazil} \Rightarrow \text{EMBI Return Brazil} \Rightarrow \text{Stock Return Russia} \Rightarrow \\ \text{EMBI Return Russia} \Rightarrow \text{Stock Return China} \Rightarrow \text{EMBI Return China} \Rightarrow \\ \text{Stock Return India} \Rightarrow \text{EMBI Return India}\end{gathered}$$

based on the information of Figs. 4–6 above. The lag length criteria in this case give two periods (days). The resulting five step OIRF of a one standard deviation shock in the change in the U.S. financial distress variable are given in Fig. 10.

The first row shows the responses of the bonds in Brazil and Russia. Both effects are initially positive and short-lived. The second row shows the effects on the stocks in Brazil and Russia where they are

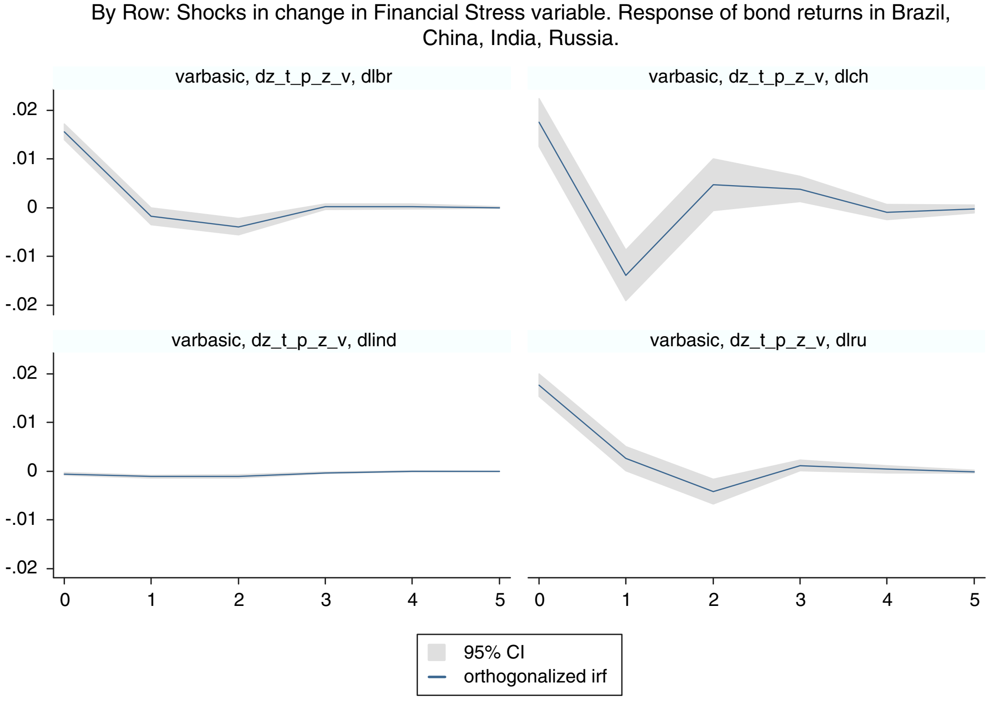
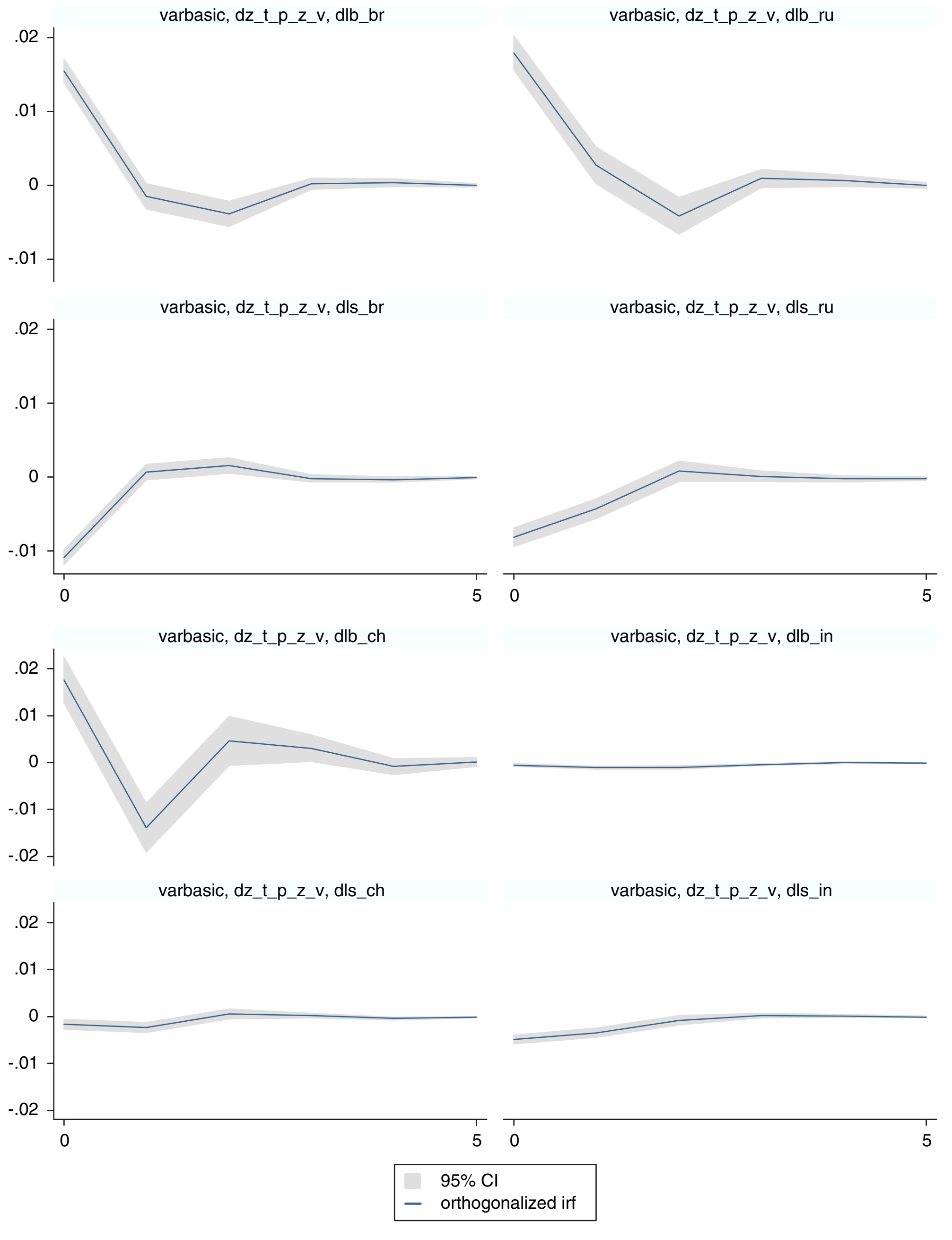


Fig. 9. Orthogonalized impulse response function — short term VAR–bond returns.



Shocks in change in Financial Stress variable.
Row 1: Response of bond returns in Brazil, Russia.
Row 2: Response of stock returns in Brazil, Russia.
Row 3: Response of bond returns in China, India.
Row 4: Response of stock returns in China, India.

Fig. 10. Orthogonalized impulse response function — short term VAR joint dynamics stocks and bonds returns.

Table 1
Johansen tests for cointegration — stocks.

Trend: trend Sample: 3 — 1884					Number of obs = 1882 Lags = 2
Maximum rank	Parms	LL	Eigenvalue	Trace statistic	5% critical value
1	44	19910.916	0.02136	37.9587*	54.64

* $p<0.05$.

Table 2
Cointegrating vector — stocks.

Beta	Coef	Std. err.	Z	P>|z|	[95% conf. interval]	
_ce1	1					
Fin. Stress						
Lbrazil	−13.20242	3.458942	−3.82	0.000	−19.98182	−6.423014
Lrussia	−.0297672	1.437839	−0.02	0.983	−2.847881	2.788346
Lchina	−.4092626	1.046911	−0.39	0.696	−2.461171	1.642646
Lindia	12.3761	3.791875	3.26	0.001	4.944158	19.80803
_cons	39.72194					

initially negative and short-lived as well. The third row gives responses for the bonds in China and India respectively where India shows no effect and China shows a volatile pattern in the two day period after the shock. The last row shows the effects on the stocks in China and India which in this case are almost inexistent.

4.3.4. Summary

Overall, the results for the short term VARs show that while the stocks react initially negatively, the bonds go in the opposite direction at least for Brazil, Russia and China. The effects are very short lived and temporary with Brazil and Russia showing more similar dynamic patterns. The bond index measure EMBI contains information of the domestic yield curve and the country risk. Our negative correlation between the stock return and EMBI could be due partly to domestic interest rate effects and/or country risk effects.[21] We continue with an analysis of long versus short term dynamics and conditional volatilities.

5. Cointegration, ARCH and dynamic conditional correlations

In this section, we extend the empirical analysis by using Johansen's (1988) cointegration method and Engle's (2002) conditional volatility and conditional correlation method.

5.1. Stock markets

First, we test for the unit roots in the log-levels of the stock market indexes of the four countries and the financial stress measure. The levels do have unit roots and are robust to structural breaks.[22] We test for potential cointegrating relationships by using Johansen's trace and eigenvalue tests and find that there is evidence of one cointegrating relationship in this case, e.g., Table 1.

Thus, we estimate a vector error correction model with one cointegrating relationship. The selection order criteria indicate a lag length of two (days). The results are in Tables 2–3. The cointegrating relationship is given by

$$\mathrm{FinStress}_t - 13.20\ \ \mathrm{Stock\_Brazil}_t + 12.38\ \ \mathrm{Stock\_India}_t + \mathrm{Const} = 0 \tag{1}$$

[21] The economic measures among the BRIC countries in response to the crisis were different and this may explain the negative correlation between the stocks and bonds. See Aizenman and Pasricha (2011) and Aizenman and Sengupta (2011).

[22] All the unit root tests are not presented for space reasons. The results are available from the authors upon request.

Table 3
Speed of adjustments to cointegrating relationship — stocks.

D_lbrazil	0.000144 (0.000256)
L._ce1	
D_lrussia	−0.000725* (0.000305)
L._ce1	
D_lchina	0.0000127** (0.000235)
L._ce1	
D_lindia	−0.000874*** (0.000225)
L._ce1	
N	1881

Standard errors in parentheses.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

where the terms for Russia and China are omitted for lack of statistical significance. In the long term, a shock in the financial stress measure impacts the stocks in Brazil positively and negatively in India while the effects in Russia and China are insignificant.

The speeds of adjustment are significant for India, and marginally for Russia, but not significant for Brazil and China. The information from the long term relationship indicates that under the U.S. financial stress, in this sample period between 2003 and 2010, the (log) level of the stock market in Brazil has provided some hedge against U.S. losses while India does not provide a hedge. The predicted cointegrating relationship, Eq. (1) is shown in Fig. 11 where we note a relatively calm period between 2003 and 2007 and more relevant deviations from mid-2007 to mid-2009. A peak occurs at the height on the crisis in September–December 2008.

Fig. 12 shows the orthogonalized impulse response functions of the vector error correction model. The first graph refers to the response of the log-level of the Brazilian stock market to a one standard deviation shock on the financial stress index, and respectively for Russia, China and India. All level effects are negative and persistent for the 14 day horizon, but China has a relatively smaller effect consistent with the results of the short term VARs in Fig. 8.

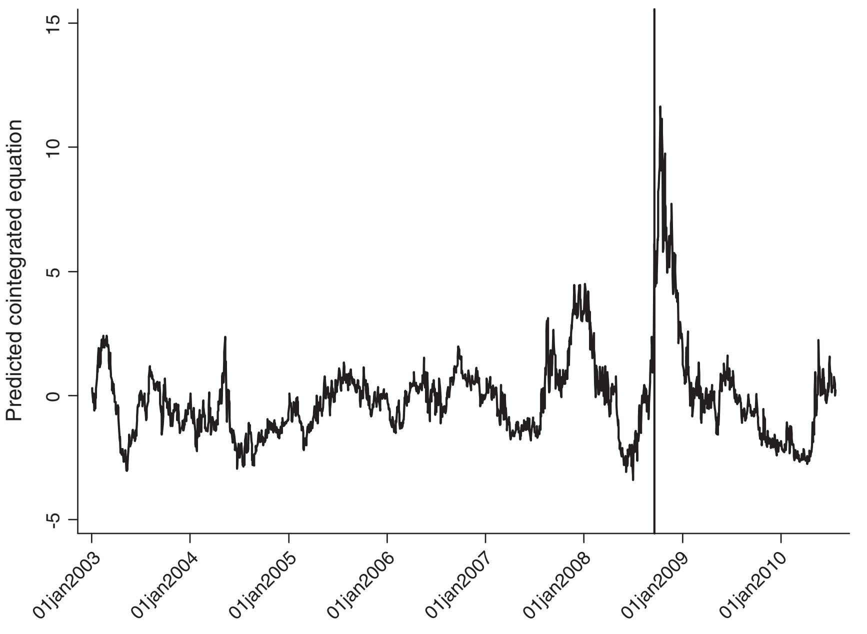


Fig. 11. Vector error correction model: cointegrating relationship — stock returns.

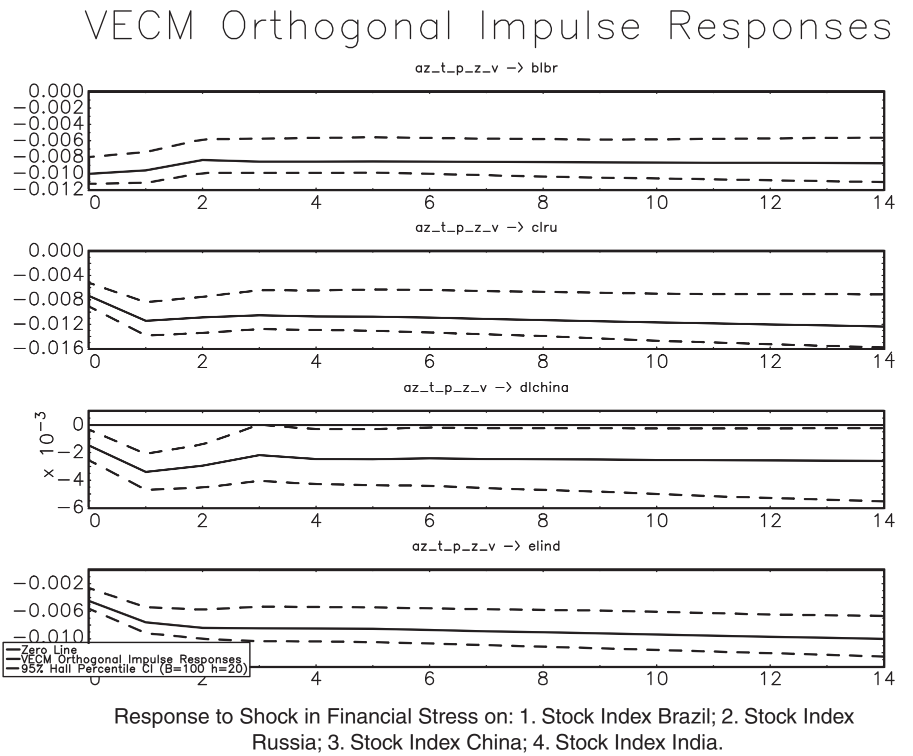


Fig. 12. Vector error correction model (VECM) — stocks.

Finally, we report results of multivariate GARCH models. The volatilities in Figs. 3–5 call for models that accommodate for time varying conditional heteroskedaticity. The potential for conditional correlations is also of interest since we are examining the interrelationships among a small group of countries deemed to be on a same path of growth.

Table 4
ARCH effects — stock returns.

ARCH_ret_brazil	
L.arch	0.0761*** (3.30)
_cons	0.000360*** (17.43)
ARCH_ret_russia	
L.arch	0.285*** (5.37)
_cons	0.000346*** (14.14)
ARCH_ret_china	
L.arch	0.157** (2.89)
_cons	0.000296*** (14.22)
ARCH_ret_india	
L.arch	0.224*** (5.03)
_cons	0.000212*** (14.56)
N	1882

t Statistics in parentheses.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

Table 5
Unconditional correlations — stock returns.

corr(FinStress, Ret_Brazil)	
_cons	−0.462*** (−21.49)
corr(FinStress, Ret_Russia)	
_cons	−0.197*** (−7.89)
corr(FinStress, Ret_China)	
_cons	0.0000571 (0.00)
corr(FinStress, Ret_India)	
_cons	−0.129*** (−4.88)
corr(Ret_Brazil, Ret_Russia)	
_cons	0.279*** (11.72)
corr(Ret_Brazil, Ret_China)	
_cons	0.108*** (4.65)
corr(Ret_Brazil, Ret_India)	
_cons	0.211*** (8.30)
corr(Ret_Russia, Ret_China)	
_cons	0.0918*** (3.86)
corr(Ret_Russia, Ret_India)	
_cons	0.260*** (11.05)
corr(Ret_China, Ret_India)	
_cons	0.146*** (6.26)
Adjustment	
lambda1	0.0191* (1.24)
lambda2	0.365 (0.79)
df	
_cons	4.083*** (20.13)
N	1882
[Adjustment]lambda1 − [Adjustment]lambda2 = 0	
[Adjustment]lambda1 = 0	
chi2(2) = 11.28	
Prob > chi2 = 0.0036	

t Statistics in parentheses.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

Tables 4–5 report autoregressive conditional heteroskedastic effects and unconditional correlations for a multivariate GARCH model of returns on the stocks with one lag memory including the estimated long term relationship in Table 2. The multivariate GARCH models are estimated by using the Student's *t* distribution to account for potential heavy tails.

In Table 4, the conditional heteroskedasticity effects are all statistically significant with Russia followed by India having the largest autoregressive parameter while Brazil has the smallest. Thus, in terms of stock return volatility, Russia is the most responsive country to news, while China does not respond to news.

The dynamic conditional correlation model of Engle (2002) is given by

$$q_{i,j,t} = \overline{\rho_{I,J}} + \lambda_1\left(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \overline{\rho_{I,J}}\right) + \lambda_2\left(q_{i,j,t-1} - \overline{\rho_{I,J}}\right); \quad i = 1, 2, \ldots; j = 1, 2, \tag{2}$$

where $q_{i,j,t}$ is the time varying conditional correlation of the endogenous variables, $\overline{\rho_{I,J}}$ is the constant unconditional correlation of the bond and stock returns, $(\varepsilon_{i,t-1}\varepsilon_{j,t-1})$ are the standardized residuals of the

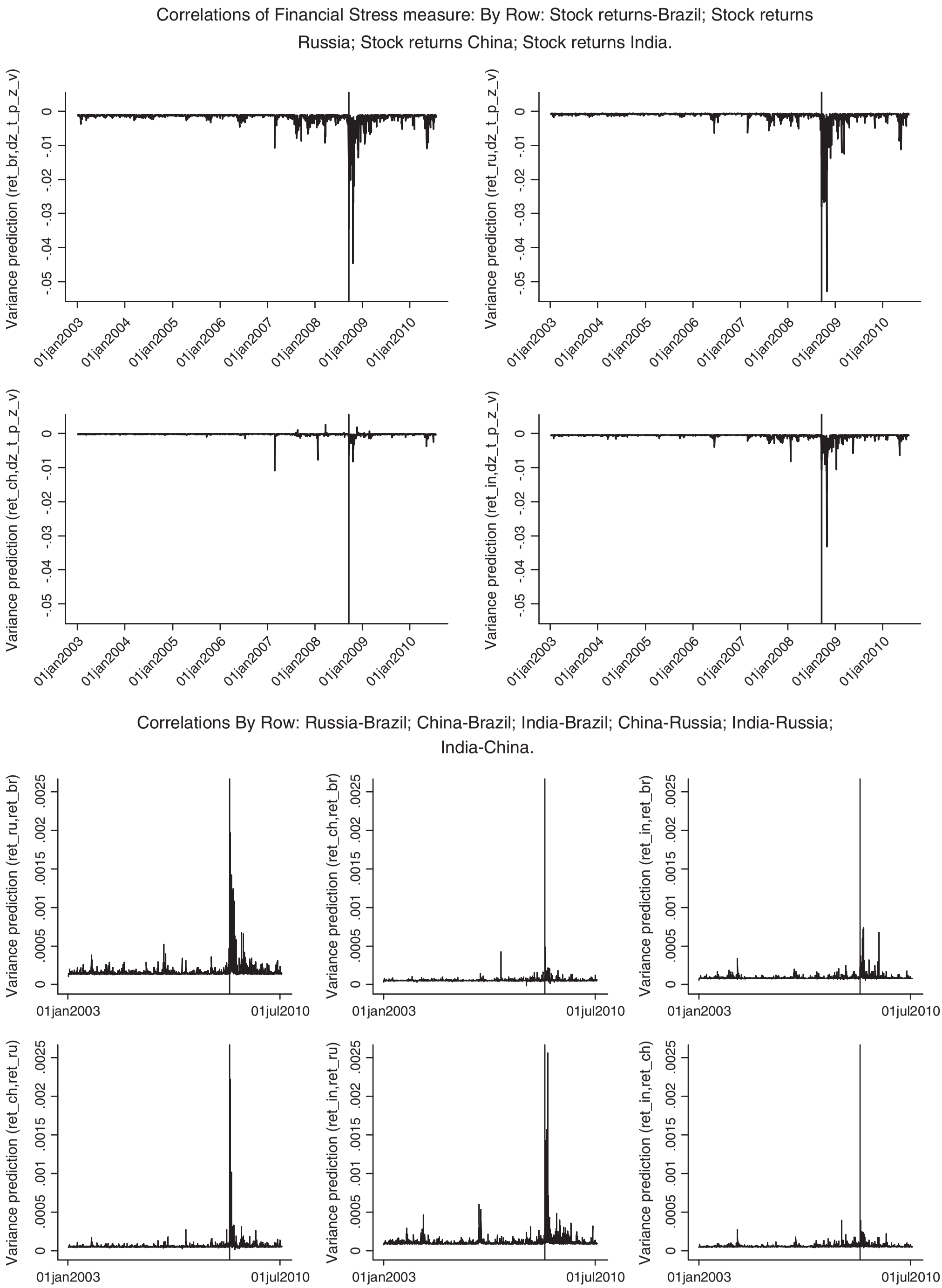


Fig. 13. Predicted dynamic conditional correlations — stock returns.

Table 6
Johansen tests for cointegration — bonds.

Trend: constant Sample: 3 − 1366					Number of obs = 1364 Lags = 2
Maximum rank	Parms	LL	Eigenvalue	Trace statistic	5% critical value
1	39	12233.801	0.09798	42.2813*	47.21

* $p<0.05$.

Table 7
Cointegrating relationship — bonds.

Beta	Coef.	Std. err.	Z	P>|z|	[95% conf. interval]	
_ce1	1					
Fin. Stress						
Lbrazil	1.971387	.4493078	4.39	0.000	1.09076	2.852014
Lrussia	−2.007209	.263539	−7.62	0.000	−2.523736	−1.490683
Lindia	4.107216	.9120391	4.50	0.000	2.319652	5.894779
Lchina	−1.505091	.2699617	−5.58	0.000	−2.034207	−.9759761
_cons	−13.31114					

bond and stock returns, and λ_1, λ_2 are the adjustment parameters in the correction mechanism (2) for the dynamic conditional correlations, assumed to be common to all endogenous variables. In particular, λ_1 is the news parameter which captures the deviations of the standardized residuals from the unconditional correlation, while λ_1 is the decay adjustment parameter that captures the autocorrelation of the correlations themselves. In effect, the process (2) is such that correlations rise when returns move together and fall when they move in opposite directions, see Engle (2002).[23]

The unconditional correlations are reported in Table 5. The correlations reported refer to $\overline{\rho_{I,J}}$ in Eq. (2) above. The correlations between the change in financial stress and the returns in Brazil, Russia and India are negative and statistically significant, with Brazil showing the largest magnitude in absolute value. The correlation of the change in financial stress and China's stock market is not significant. All correlations between the stock markets in the BRIC nations are positive and statistically significant. The largest magnitudes are between Russia and Brazil and Russia and India. The last rows of Table 5 show the estimated adjustment parameters λ_1, λ_2 for the dynamic conditional correlation process (2). They are not individually statistically significant, but the joint F-test reported shows that they are jointly significant. This shows that, surprisingly, neither news nor autocorrelation in the correlations play a predominant role in the case of the stock returns, but they jointly have a significant effect.

Fig. 13 shows the dynamic conditional correlations estimated in the multivariate GARCH model. The top row reports the dynamic correlations between the change in financial stress and the returns in Brazil and Russia respectively. The evolution and magnitudes of the negative correlations are similar and after the Lehman event in September 2008, the correlations increase robustly. The next row reports the dynamic correlations between the change in financial stress and the returns in China and India respectively. The evolution and magnitudes of the negative correlations are similar, but much smaller than the row above for Brazil and Russia. After the Lehman event in September 2008, the correlations increase for all nations, but not for India. The last two rows show the dynamic conditional correlations of the stock returns among the BRIC countries. They are all positive. Russia and Brazil and Russia and India show the largest in magnitude. More importantly, they increase in most cases after the Lehman event in September 2008.

Overall, the evidence suggests that Brazil and Russia respond more to the U.S. financial stress measure and are more correlated among each other relative to India and China at least in the short term. The long term

[23] The quantities $q_{i,j,t}$ are rescaled by using the formula $\rho_t = q_{i,j,t}/\sqrt{q_{ii,t}q_{jj,t}}$ so that the correlation is between −1 and 1; e.g., Engle (2002).

Table 8
Speed of adjustment to cointegrating relationship — bonds.

D_lbrazil	
L._ce1	0.00303** (2.85)
D_lrussia	
L._ce1	0.00471** (3.12)
D_lindia	
L._ce1	−0.00160*** (−8.77)
D_lchina	
L._ce1	0.00877** (2.82)
N	1363

t Statistics in parentheses.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

relationship between the stock market returns in Brazil, India and the U.S. measure of financial stress is significant, but only India is approaching the longer term in a significant rate of speed in this period. Russia responds more to conditional volatility news, but neither news nor the autocorrelation of correlations play a predominant role in the case of the dynamic conditional correlations of stock returns. The correlations among all parties have increased since the beginning of the financial crisis in this case.

5.2. Bond markets (EMBI)

We also find the unit roots for the (log) levels of EMBI's in the sample. The cointegration tests show the presence of one cointegrating vector as reported in Table 6. We proceed and estimate a vector error correction model with one cointegrating relationship. The selection order criteria indicate a lag length of

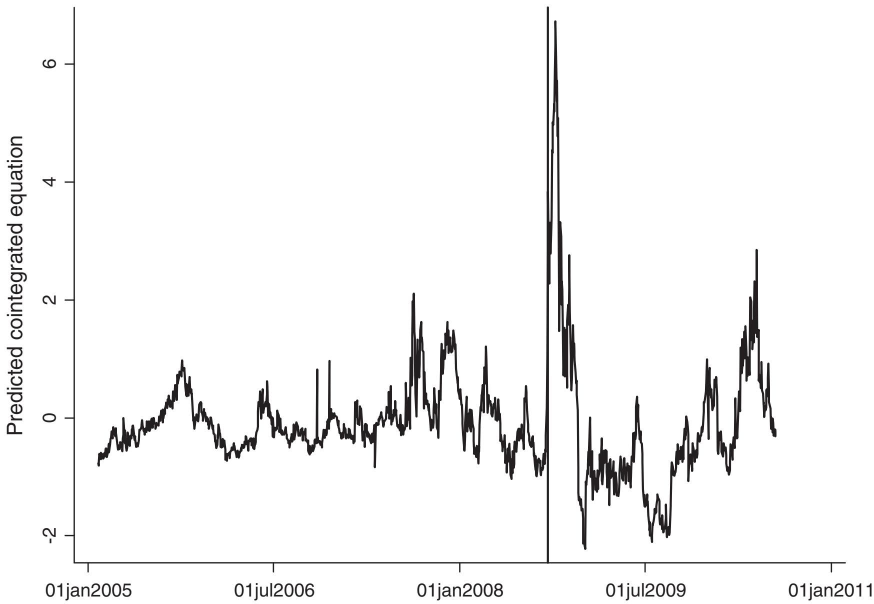


Fig. 14. Vector error correction model: cointegrating relationship — bonds.

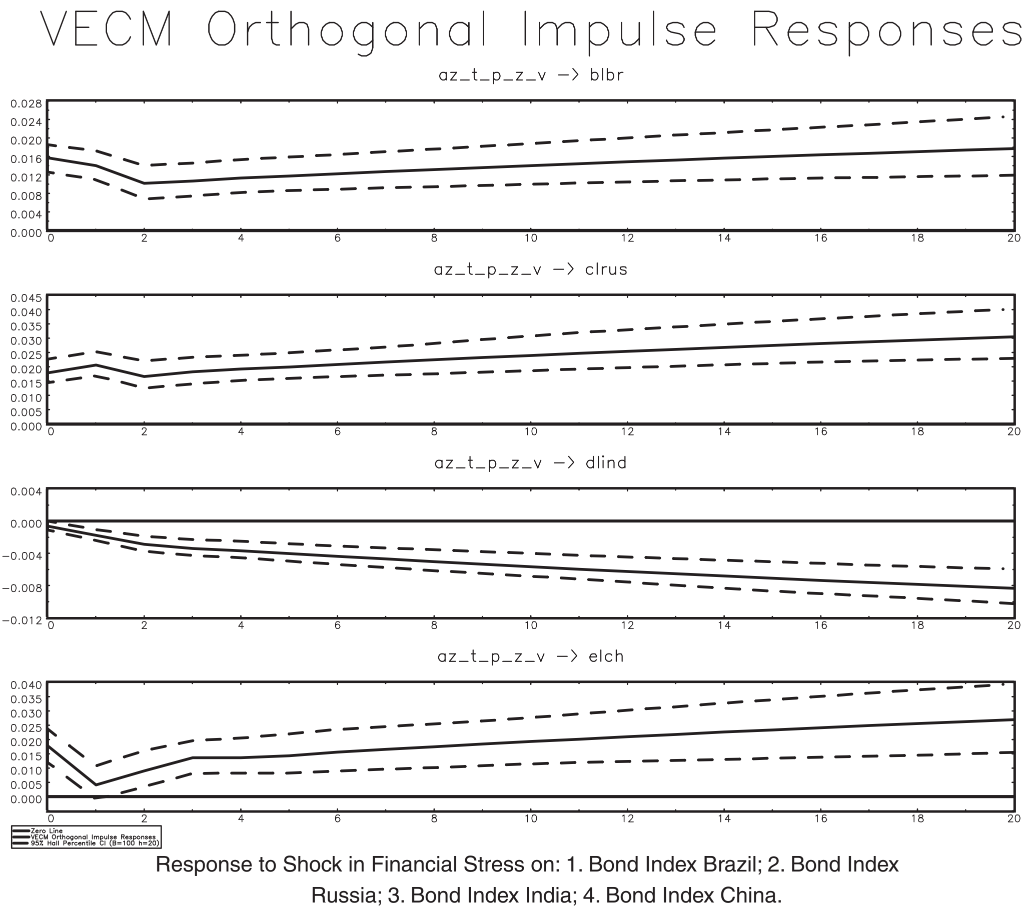


Fig. 15. Vector error correction model (VECM): bonds.

two (days). The results are in Tables 7–8. The cointegrating relationship with statistically significant terms is given by

$$\begin{aligned} &\mathrm{FinStress}_t + 1.97\ \mathrm{Embi\_Brazil}_t - 2.01\ \mathrm{Embi\_Russia}_t + 4.11\ \mathrm{Embi\_India}_t \\ &\quad - 1.51\ \mathrm{Embi\_China}_t + \mathrm{Const} = 0. \end{aligned} \tag{3}$$

In the long term, a shock in the financial stress measure impacts the level of the bond index in Brazil negatively, in Russia positively, in India negatively and in China positively. The speeds of adjustment are significant for all the BRIC countries. The predicted cointegrating relationship is shown in Fig. 14 where we also note a relatively calm period between 2005 and early 2008 and more relevant deviations from September 2008 and on. A peak also occurs at the height on the crisis in September–December 2008.

Fig. 15 shows the orthogonalized impulse response functions of the vector error correction model. The first graph refers to the response of the log-level of the Brazilian EMBI to a one standard deviation shock on the financial stress index, and respectively for Russia, India and China. The effects on Brazil, Russia and China are positive and persistently consistent with the short term VARs of Fig. 9. The effect in India is negative and persistent as well, all for the 20 day horizon.

Table 9
Multivariate GARCH–ARCH effects — bond returns.

ARCH_dlbrazil	
L.arch	0.295*** (3.50)
_cons	0.00177*** (6.23)
ARCH_dlrussia	
L.arch	0.394*** (3.62)
_cons	0.00343*** (6.16)
ARCH_dlchina	
L.arch	1.705*** (4.69)
_cons	0.00296*** (5.13)
ARCH_dlindia	
L.arch	0.245* (1.86)
_cons	0.0000224*** (5.73)
N	1364

t Statistics in parentheses.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

Finally, we report the results of the multivariate GARCH models. Tables 9–10 report the autoregressive conditional heteroskedastic effects and dynamic conditional correlations for a multivariate GARCH model of returns on the stocks with one lag memory including the estimated long term relationships in Table 7. The multivariate GARCH models are estimated by using the Student's *t* distribution to account for potential heavy tails.

In Table 9, the conditional heteroskedasticity effects are all statistically significant with China followed by Russia having the largest autoregressive parameter. The parameter for China shows that the conditional variance is not stable. In terms of bond return volatility, China is the most responsive to news and the effects of news on volatility are not stable. Russian bond returns also respond to news, but Brazil and India bond returns do not.

The unconditional correlations are reported in Table 10. The correlations reported refer to $\overline{\rho_{I,J}}$ in Eq. (2). The correlations between the change in financial stress and EMBI in Brazil, Russia and China are positive and statistically significant, with Brazil showing the largest magnitude. The correlation of the change in financial stress and India's EMBI is not significant. The correlations between the EMBI in Brazil–Russia, Brazil–China, and Russia–China are positive and significant, while Russia–India is also positive but marginally significant. The largest magnitude is between Russia and Brazil since both are more intensive commodity exporters.

The last rows of Table 10 show the estimated adjustment parameters λ_1, λ_2 for the dynamic conditional correlation process (2). They are individually significant and the joint test reported shows that they are jointly significant. In this case the news parameter is statistically significant, but of several orders of magnitude smaller than the decay parameter reflecting the autocorrelation in the correlations. This indicates that the own correlations are more important in determining the evolution of the conditional correlations of bond returns relative to the unexpected news.

Fig. 16 shows the dynamic conditional correlations. The top row reports the dynamic correlations between the change in financial stress and the EMBI in Brazil and Russia respectively. The evolution and magnitudes of the positive correlations are similar and after the Lehman event in September 2008, the correlations increase. The next row reports the dynamic correlations between the change in financial stress and the EMBI in China and India respectively. In this case, China shows a very high correlation throughout with a dramatic increase after the September 2008 mark. On the other hand, India is flat showing a minor negative correlation in the days after the September 2008 mark. The last two rows show the dynamic

Table 10
Unconditional correlations — bond returns.

corr(Fin Stress, ret_brazil)	
_cons	0.455*** (14.97)
corr(Fin Stress, ret_russia)	
_cons	0.352*** (10.71)
corr(Fin Stress, ret_china)	
_cons	0.196*** (5.73)
corr(Fin Stress, ret_india)	
_cons	0.0123 (0.35)
corr(dlbrazil_ret_russia)	
_cons	0.695*** (33.65)
corr(dlbrazil_ret_china)	
_cons	0.343*** (10.30)
corr(dlbrazil_ret_india)	
_cons	0.0622 (1.73)
corr(dlrussia_ret_china)	
_cons	0.345*** (11.32)
corr(dlrussia_ret_india)	
_cons	0.0865* (2.45)
corr(dlchina_ret_india)	
_cons	−0.0546 (−1.66)
Adjustment	
lambda1	0.0209** (3.13)
lambda2	0.914*** (52.58)
df	
_cons	2.564*** (20.75)
N	1364
[Adjustment]lambda1 − [Adjustment]lambda2 = 0	
[Adjustment]lambda1 = 0	
chi2(2) = 2996.88	
Prob > chi2 = 0.0000	

t Statistics in parentheses.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

conditional correlations of EMBI among the BRIC countries. They are positive and increasing for Russia–Brazil, China–Brazil, and China–Russia. However, the correlations with India are almost non-existent.

Overall, the evidence for bonds is very different than for stocks both qualitatively and quantitatively. The bond market shows that in the long term all EMBI indexes for Brazil, Russia, India and China are related to the U.S. financial stress measure. All the BRIC countries display significant conditional heteroskedasticity with Russia as the most responsive country to conditional volatility news, while China does respond and shows signs of volatility instability in its bond return index. The own correlations are more important in determining the evolution of the conditional correlations of the bond returns relative to the unexpected news. The dynamic conditional correlations among the bond returns of all the BRIC nations have increased after the September 2008 event, but not for India-EMBI which is seen to be insulated and uncorrelated to other BRIC countries.

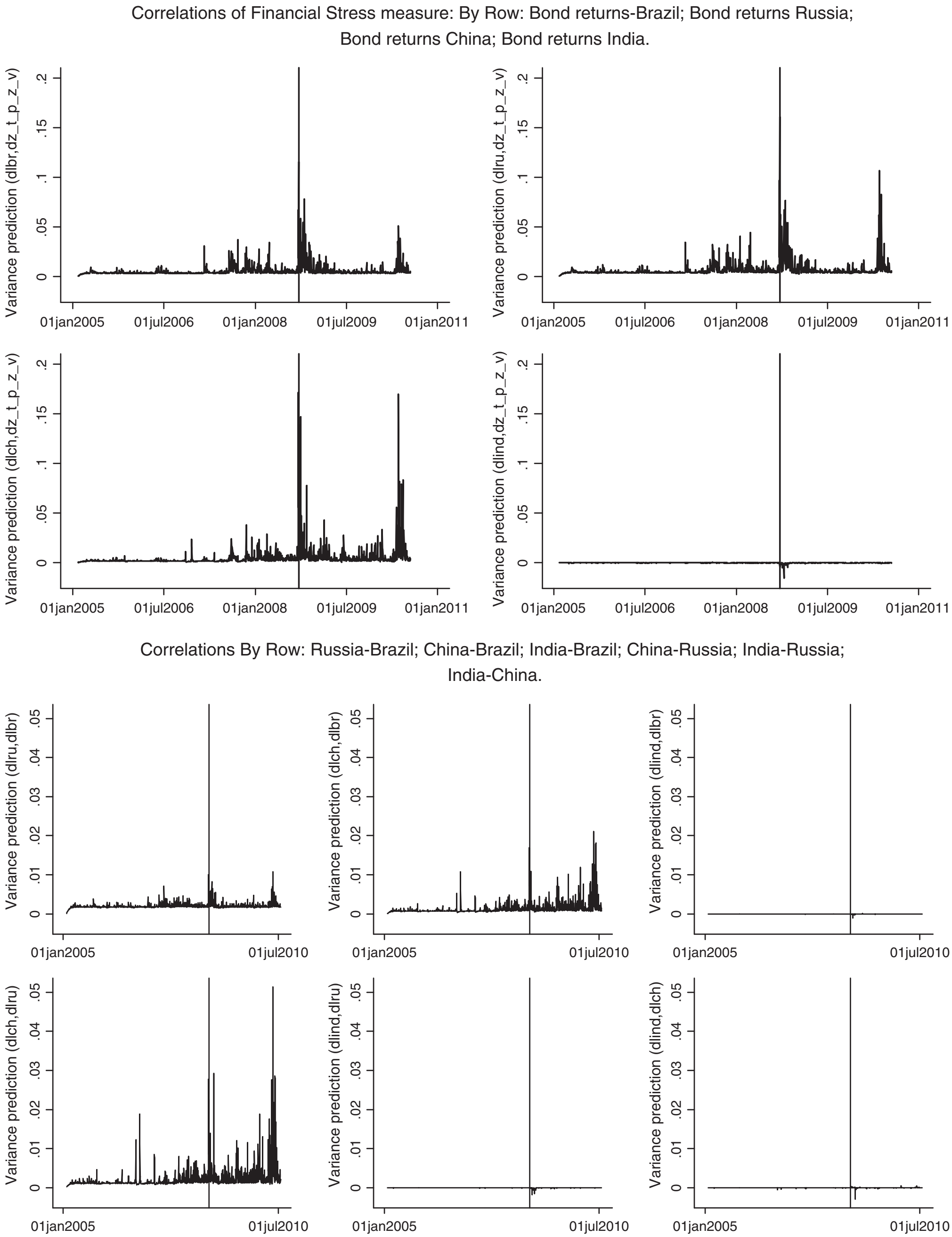


Fig. 16. Predicted dynamic conditional correlations — bond returns.

5.3. Joint behavior of stocks and bonds

We consider all data for the stocks and bonds jointly. In this case, the cointegration tests show the presence of two cointegrating vectors as reported in Table 11.

Table 11
Johansen tests for cointegration — stocks–bonds.

Trend: constant				Number of obs = 1364	
Sample: 3 — 1366				Lags = 2	
Maximum rank	Parms	LL	Eigenvalue	Trace statistic	5% critical value
2	122	26541.359	0.05025	118.1825*	124.24

* $p<0.05$.

We proceed and estimate a vector error correction model with two cointegrating relationships. The selection order criteria indicate a lag length of two (days). The results are in Tables 12–13. The cointegrating relationships are given by

$$\begin{aligned} &\text{FinSress}_t + 1.63\ \text{Embi\_Brazil}_t - 1.33\ \text{Embi\_Russia}_t + 3.08\ \text{Embi\_India}_t \\ &\quad - 1.95\ \text{Embi\_China}_t + \text{Const} = 0 \end{aligned} \tag{4a}$$

$$\begin{aligned} &\text{Stocks\_Brazil}_t + 0.61\ \text{Stocks\_Russia}_t - 0.31\ \text{Embi\_Russia}_t - 1.72\ \text{Embi\_India}_t \\ &\quad - 0.16\ \text{Stocks\_China}_t - 0.66\ \text{Embi\_China} + \text{Const} = 0 \end{aligned} \tag{4b}$$

where only statistically significant terms are included. The first relationship (4a) shows a long term relationship among bond returns and the U.S. financial stress measure qualitatively comparable to the relationship obtained in expression (2) above. The second relationship (4b) is among the BRIC nations only. It shows a long term relationship between the bond returns in Russia, India and China and the stock returns in Brazil, Russia and China. The speeds of adjustment in Table 13 show that for the long term relationship of bonds and the U.S. measure of stress, Brazil bonds, Russia bonds and India bonds have significant speeds of adjustment. For the long term relationship among the BRIC nations, Brazil stocks, India stocks and bonds and China bonds have significant convergence parameters.

The predicted cointegrating relationships are shown in Fig. 17. It shows a rather striking result that bond markets deviate much more from the U.S. financial stress measure [cointegrating relationship (4a)] than the bonds and stocks of the BRIC nations that deviate among themselves [cointegrating relationship

Table 12
Cointegrating relationships — stocks–bonds.

Beta	Coef.	Std. err.	Z	P>|z|	[95% conf. interval]	
_ce1	1					
Fin. Stress						
lstocks_brazil	0	(omitted)				
lbonds_brazil	1.63288	.7821285	2.09	0.037	.0999366	3.165824
lstocks_russia	.6138576	.9094743	0.67	0.500	−1.168679	2.396395
lbonds_russia	−1.329604	.5037811	−2.64	0.008	−2.316997	−.3422109
lstocks_india	−.1625172	1.126383	−0.14	0.885	−2.370188	2.045153
lbonds_india	3.075735	1.408213	2.18	0.029	.3156893	5.835781
lstocks_china	−.2745978	.4210314	−0.65	0.514	−1.099804	.5506085
lbonds_china	−1.946538	.4193028	−4.64	0.000	−2.768357	−1.12472
_cons	−9.055833					
_ce2	0	(omitted)				
Fin. Stress						
lstocks_brazil	1					
lbonds_brazil	.7540704	.1580703	4.77	0.000	.4442584	1.063882
lstocks_russia	.607236	.1838072	3.30	0.001	.2469805	.9674915
lbonds_russia	.3106149	.1018155	3.05	0.002	.1110601	.5101696
lstocks_india	−.0243861	.2276451	−0.11	0.915	−.4705622	.42179
lbonds_india	−1.718489	.2846035	−6.04	0.000	−2.276302	−1.160677
lstocks_china	−.1585688	.0850916	−1.86	0.062	−.3253453	.0082076
lbonds_china	−.6602796	.0847422	−7.79	0.000	−.8263713	−.4941879
_cons	−8.42973					

Table 13
Adjustments to cointegrating relationship — stocks–bonds.

D_lstocks_brazil	
L._ce1	−0.0000341 (0.000749)
L._ce2	−0.0121** (0.00454)
D_lbonds_brazil	
L._ce1	0.00324** (0.00119)
L._ce2	−0.00444 (0.00720)
D_lstocks_russia	
L._ce1	−0.000481 (0.000911)
L._ce2	−0.00558 (0.00552)
D_lbonds_russia	
L._ce1	0.00414* (0.00168)
L._ce2	0.00575 (0.0102)
D_lstocks_india	
L._ce1	−0.000211 (0.000658)
L._ce2	−0.0101* (0.00399)
D_lbonds_india	
L._ce1	−0.00193*** (0.000203)
L._ce2	0.00606*** (0.00123)
D_lstocks_china	
L._ce1	0.000912 (0.000726)
L._ce2	−0.00854 (0.00440)
D_lbonds_china	
L._ce1	0.00327 (0.00345)
L._ce2	0.0959*** (0.0209)
N	1363

Standard errors in parentheses.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

(4b)]. In fact the peak of the crisis had a small effect on the long term behavior of the stocks and bonds in the BRIC nations relative to the effect on the deviations of the bond markets to the financial stress measure.

Fig. 18 shows the orthogonalized impulse response functions of the vector error correction model. The first two graphs show the response of the log-level of the Brazilian stock market and EMBI to a one standard deviation shock on the financial stress index, and the following two graphs for the stocks and bonds in Russia. The bottom graphs show analogous effects for China and India. The results confirm the negative correlation of the level effects of the stock and bond indexes in the sample.

Finally, we report the results of the multivariate GARCH models. Tables 14–15 report autoregressive conditional heteroskedastic effects and dynamic conditional correlations for a multivariate GARCH model of returns on the stocks with one lag memory including the estimated long term relationships in Table 12. The multivariate GARCH models are estimated by using the Student's *t* distribution to account for potential heavy tails.

In Table 14, the conditional heteroskedasticity effects are all statistically significant, except for the EMBI of India. The stocks and bonds in Russia respond robustly to news, followed by stocks in India. The stocks and bonds in Brazil respond more moderately. China bonds respond more aggressively and the conditional autoregressive heteroskedasticity parameter for China-EMBI continues to show that the conditional variance is not stable.

The unconditional correlations are reported in Table 15. Of interest are the correlations between the stock and bond returns among the BRIC nations. First, note that the stock and bond returns are significantly

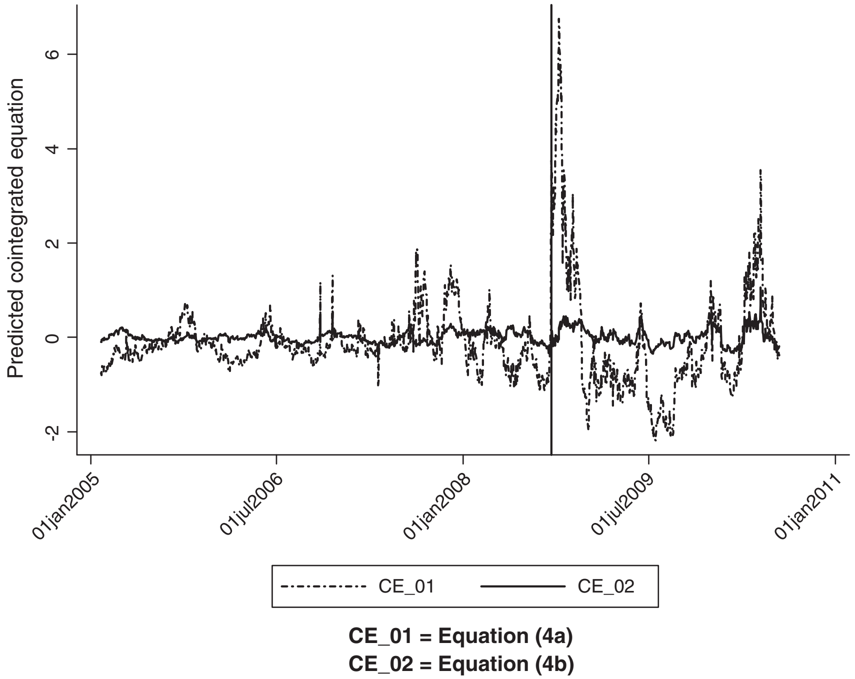


Fig. 17. Vector error correction model: cointegrating relationships. Joint behavior of the stocks–bonds.

negatively correlated for Brazil and Russia, but not significant for China and India. The returns of the stocks in Brazil are significantly negatively correlated with Russia and China and the bond returns in Brazil are negatively correlated with the stock returns in Russia and India. The bond returns in Russia are significantly negatively correlated with the stock returns in India. The largest correlations are between Brazil and Russia.

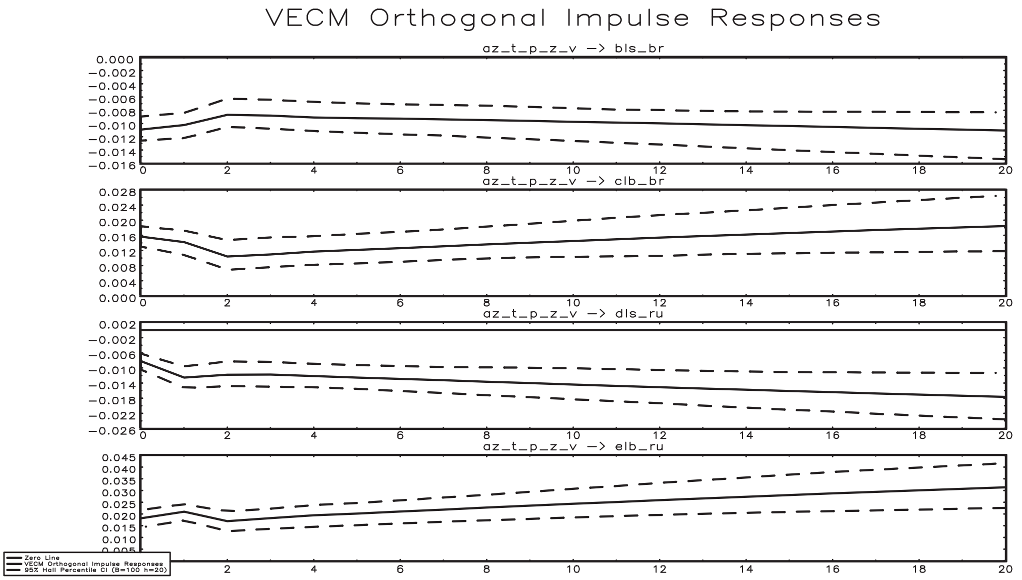
The last rows of Table 15 show the estimated adjustment parameters λ_1, λ_2. They are individually significant and the joint test reported shows that they are jointly significant. The news parameter continues to be significant and much smaller in magnitude than the decay parameter. In the stock–bond multivariate model, the own correlations are more important in determining the evolution of the conditional correlations relative to the unexpected news.

Fig. 16 shows the dynamic conditional correlations. The pattern is that the correlations between the stock and bond returns increase after the Lehman event in September 2008 except for some cases of the bond returns in India.

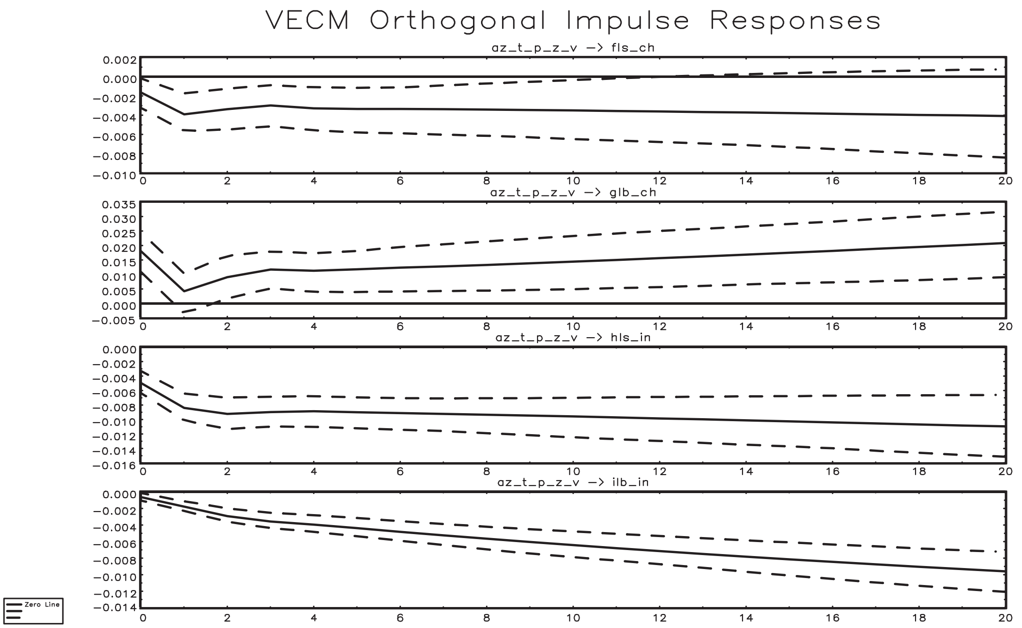
In summary, the joint dynamic behavior of the stocks and bonds displays one long run relationship between the U.S. financial stress and the BRIC bond returns and another for the stocks and bonds of the BRIC countries only, independent of the U.S. financial stress measure. The stock and bond returns are significantly negatively correlated for Brazil and Russia, but not significant for China and India. The bond returns in Russia are significantly negatively correlated with the stock returns in India. The largest correlations are between Brazil and Russia. In the stock–bond multivariate model, the own correlations are more important in determining the evolution of the conditional correlations relative to the unexpected news. The pattern of the dynamic conditional correlations is that the correlations between the stock and the bond returns increase after the Lehman event in September 2008, except for the bond returns in India.

6. Summary and conclusions

The main contribution of this paper is to provide empirical evidence of the behavior of the stock and bond index and return volatility and correlation among the BRIC countries conditional on a simple measure of the U.S. financial stress. In summary, Tables 16–18 present the main qualitative results of the



Plots are Shock in Financial Stress on: 1. Stocks-Brazil; 2. EMBI-Brazi; 3. Stocks-Russia; 4. EMBI-Russia.



Response to Shock in Financial Stress on: 1. Stocks-China; 2. EMBI-China; 3. Stocks-India; 4. EMBI-India.

Fig. 18. Vector error correction model (VECM): joint behavior of the stock returns and bond returns.

effects of the U.S. financial stress measure on the stock and bond markets of the BRIC countries, and own volatility and interactions of the stock and bond markets among the BRIC countries. In Table 16, we note that the effect of the U.S. financial stress on the Chinese stock market is negligible. The effect on the stock

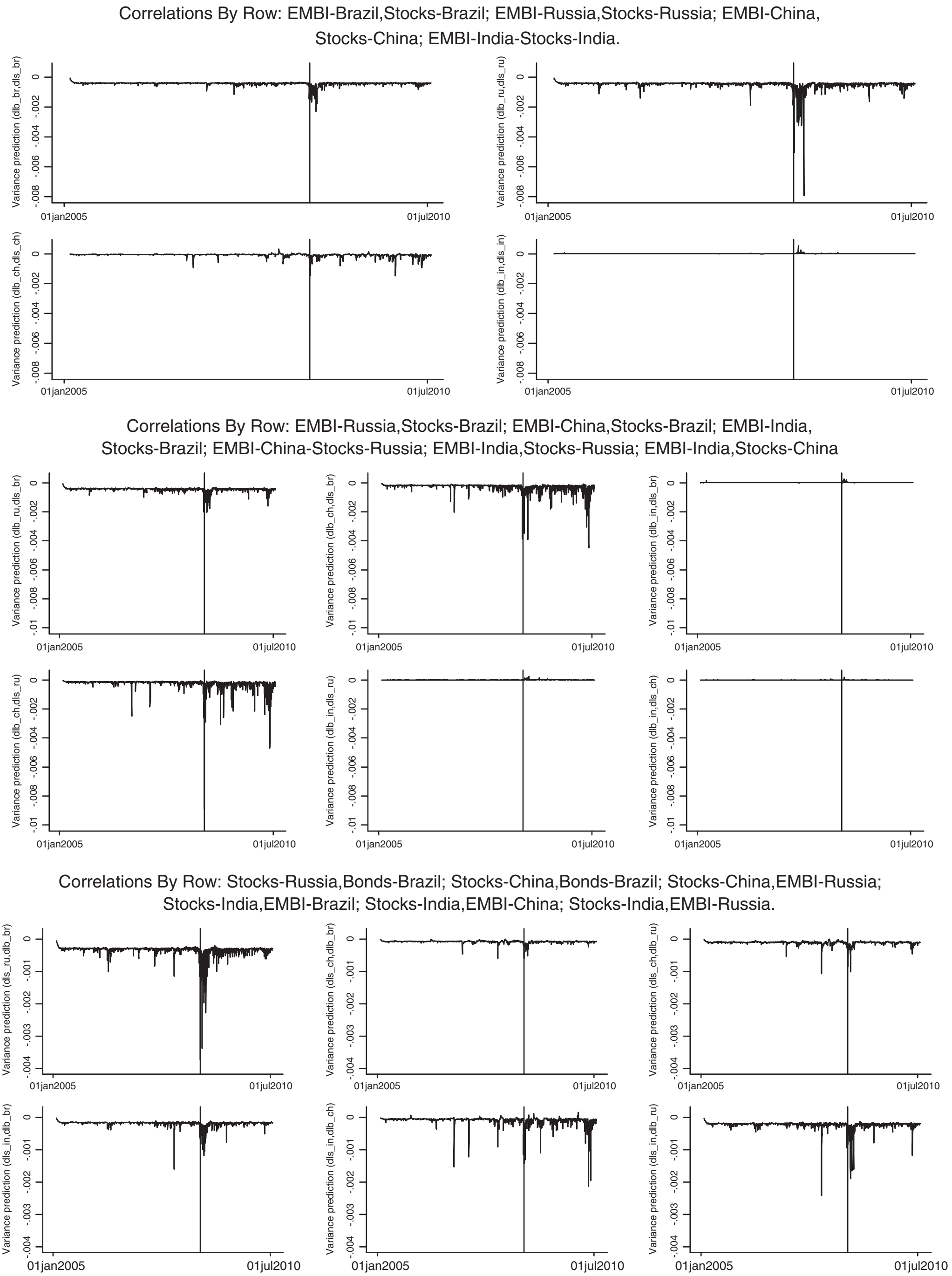


Fig. 19. Predicted dynamic conditional correlations — joint behavior of the stock–bond returns. Brazil and Russia were most affected by the U.S. financial stress measure.

Table 14
Multivariate GARCH–ARCH effects — stocks and bonds returns.

ARCH_dlstocks_brazil	
L.arch	0.102** (0.0345)
_cons	0.000450*** (0.0000345)
ARCH_dlbonds_brazil	
L.arch	0.163** (0.0504)
_cons	0.00107*** (0.0000830)
ARCH_dlstocks_russia	
L.arch	0.265*** (0.0771)
_cons	0.000489*** (0.0000441)
ARCH_dlbonds_russia	
L.arch	0.240*** (0.0623)
_cons	0.00209*** (0.000164)
ARCH_dlstocks_china	
L.arch	0.125* (0.0559)
_cons	0.000490*** (0.0000412)
ARCH_dlbonds_china	
L.arch	1.122*** (0.208)
_cons	0.00206*** (0.000301)
ARCH_dlstocks_india	
L.arch	0.233*** (0.0674)
_cons	0.000286*** (0.0000260)
ARCH_dlbonds_india	
L.arch	0.173 (0.0924)
_cons	0.0000151*** (0.00000165)
N	1364

Standard errors in parentheses.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

returns in Brazil and Russia is negative and relatively larger than the effect in the India stock market. Similar results are found for correlations between the U.S. financial stress and the stock markets in Brazil, Russia and India. Own conditional volatility news effects are all significant. Table 17 shows the results for the bond markets. The EMBI-India returns are insulated from the U.S. financial stress and show no conditional volatility news effect. The effects on the EMBI returns for Brazil, Russia and China are positive and the correlations are also positive and increase after the September 2008 events.

Table 18 presents unconditional and conditional correlations between the stock and the bond returns among the BRIC countries. The own country correlations are negative for Brazil and Russia in both cases. India shows no significant correlations between its bond and stock markets. The conditional correlation for China is negative and increases after September 2008, but the unconditional correlation is not significant. Across the BRIC countries, the stock and bond market correlations for Brazil and Russia are negative and robust; but much less significant with India and China and among India and China.

Quantitatively, our results show that in the short term VARs for stock returns the effects are mostly of two days with null response in Chinese stock returns; while for the bond returns, the short term VAR shows no response for EMBI-India. The joint dynamics of the stocks and bonds show short term negative correlations with the stocks responding negatively and bonds positively to the U.S. stress measure. For the long term, the joint behavior of the stocks and bonds displays one long run relationship between the U.S. financial stress and the BRIC bond returns only, and another for the stocks and bonds of the BRIC countries only, independent of the U.S. financial stress measure. The multivariate GARCH and dynamic conditional correlations show that in terms of the stock returns, all the BRIC countries display significant conditional

Table 15
Unconditional correlations — stocks and bonds returns.

corr(stocks_brazil,bonds_brazil)	−0.486*** (0.0259)
corr(stocks_brazil,bonds_russia)	−0.302*** (0.0301)
corr(stocks_brazil,bonds_china)	−0.139*** (0.0289)
corr(stocks_brazil,bonds_india)	0.00261 (0.0305)
corr(bonds_brazil,stocks_russia)	−0.298*** (0.0297)
corr(bonds_brazil,stocks_china)	−0.0336 (0.0301)
corr(bonds_brazil,stocks_india)	−0.163*** (0.0313)
corr(stocks_russia,bonds_russia)	−0.265*** (0.0292)
corr(stocks_russia,bonds_china)	−0.0581 (0.0314)
corr(stocks_russia,bonds_india)	0.000667* (0.0276)
corr(bonds_russia,stocks_china)	−0.0236** (0.0294)
corr(bonds_russia,stocks_india)	−0.144*** (0.0298)
corr(stocks_china,bonds_china)	−0.0235 (0.0302)
corr(stocks_china,bonds_india)	0.0219 (0.0302)
corr(bonds_china,stocks_india)	−0.00496 (0.0295)
corr(stocks_india,bonds_india)	0.000624 (0.0305)
Adjustment	
lambda1	0.0139*** (0.00370)
lambda2	0.861*** (0.0337)
df	3.472*** (0.162)
N	1364
(1) [Adjustment]lambda1 − [Adjustment]lambda2 = 0	
(2) [Adjustment]lambda1 = 0	
chi2(2) = 1057.23	
Prob > chi2 = 0.0000	

Standard errors in parentheses.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

heteroskedasticity with Russia as the most responsive country to conditional volatility news. However, neither news nor autocorrelation of correlations play a predominant role in the case of the dynamic conditional correlations. In terms of the bond returns, the evidence is different. In this case, the own correlations are more important in determining the evolution of the conditional correlations of the bond returns relative to the unexpected news. The dynamic conditional correlations among the bond returns of

Table 16
Qualitative effect of U.S. financial stress on BRIC stock markets.
Source: Tables 2–5; Figs. 8, 12, and 13.

Stock markets	Effect of U.S. financial stress to			
	Brazil	Russia	India	China
Short term VAR impulse response returns	Negative	Negative	Negative	Null
VECM long term cointegration levels	Positive	Null*	Negative	Null*
VECM impulse response levels	Negative permanent	Negative permanent; significant speed of adjustment	Negative permanent; significant speed of adjustment	Negative temporary
ARCH own conditional volatility news returns	Yes	Yes	Yes	Yes
MGARCH unconditional correlation returns	Negative	Negative	Negative	Null*
MGARCH dynamic conditional correlation returns	Negative > after September 2008	Negative > after September 2008	Negative, small > after September 2008	Negligible

* Not statistically significant.

Table 17
Qualitative effect of U.S. financial stress on BRIC bond markets.
Sources: Tables 6–10; Figs. 9, 15, and 16.

Bond markets	Effect of U.S. financial stress to			
	Brazil	Russia	India	China
Short term VAR impulse response returns	Positive	Positive	Null	Positive
VECM long term cointegration levels	Negative; significant speed of adjustment	Positive; significant speed of adjustment	Negative; significant speed of adjustment	Positive; significant speed of adjustment
VECM impulse response levels	Positive; permanent	Positive; permanent	Negative; permanent	Positive; permanent
ARCH own conditional volatility news returns	Yes	Yes	Null*	Yes not stable
MGARCH unconditional correlation returns	Positive	Positive	Null	Positive
MGARCH dynamic conditional correlation returns	Positive > after September 2008	Positive > after September 2008	Negligible	Positive > after September 2008

* Not statistically significant.

all the BRIC nations have increased after the September 2008 event, but not for India-EMBI which seems to be insulated and uncorrelated to other BRIC countries. The largest correlations of the stocks and bonds are between Brazil and Russia.

We were set to answer three basic questions. First it is to determine whether or not BRIC can be considered insulated from the financial stress of the U.S., and the answer seems to balance towards the negative. We found that Brazil and Russia are the most affected countries followed by China, and India much less so. We also found that the conditional correlations of the stock and bond returns with the U.S. financial stress increased after the 'official' start of the financial crisis in September 2008. Second, it is to determine whether or not BRIC can provide diversification opportunities. Our findings indicate that the BRIC bond markets respond positively in the very short term to the U.S. financial stress, but the bond market in India seems more detached from the other BRIC bond markets and respond quantitatively less to the U.S. financial stress measure overall. Also, the stock market of China responded much less to the U.S. financial stress relative to the other countries in this period. Third, it is to determine whether or not BRIC

Table 18
Joint behavior of stock and bond returns: BRIC correlations.
Sources: Table 15; Fig. 19.

BRIC correlations				
Bonds	Stocks			
	Brazil	Russia	India	China
Unconditional				
Brazil	Negative	Negative	Negative	Null*
Russia	Negative	Negative	Negative	Null*
India	Null*	Null*	Null*	Null*
China	Negative	Null*	Null*	Null*
Dynamic conditional				
Brazil	Negative	Negative > after September 2008	Negative > after September 2008	Negative, small
Russia	Negative > after September 2008	Negative > after September 2008	Negative > after September 2008	Negative, small
India	Null	Null	Null	Null
China	Negative > after September 2008	Negative > after September 2008	Negative > after September 2008	Negative > after September 2008

* Not statistically significant.

can perform the role of locomotive in sustaining world economic growth. It is less clear to us whether this is the case given by our evidence. We found that, in the long run, bond markets deviate much more from the U.S. financial stress measure than the bonds and stocks of the BRIC nations that deviate among themselves. However, we found evidence of a relative increase in volatility after the crisis thus pointing to potential interdependencies and contagion effects.

There are several potential avenues for future research. At a lower frequency, a larger set of variables for the BRIC countries including real factors such as GDP and unemployment would be useful to determine the potential locomotive role of BRIC. Also the sensitivity analysis to other measures of the U.S. economic influence on the BRIC nations could be of potential interest.

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