Not all emerging markets are the same: A classification approach with correlation based networks

Ahmet Şensoy
Borsa İstanbul

Kevser Ozturk
Borsa İstanbul

Erk Hacıhasanoğlu
Borsa İstanbul

Benjamin M. Tabak
CNPq Foundation
Universidade Catolica de Brasilia
Not all emerging markets are the same: A classification approach with correlation based networks

Ahmet Sensoy\textsuperscript{a,*}, Kevser Ozturk\textsuperscript{a}, Erk Hacihasanoglu\textsuperscript{a,b}, Benjamin M. Tabak\textsuperscript{c,d}

\textsuperscript{a}Borsa Istanbul, Research Department, 34467 Emirgan, Istanbul, Turkey
\textsuperscript{b}Borsa Istanbul, Business & Product Development Department, 34467 Emirgan, Istanbul, Turkey
\textsuperscript{c}CNPq Foundation, Brasilia, DF, Brazil
\textsuperscript{d}Department of Economics, Universidade Catolica de Brasilia, SGAN 916, Modulo B Avenida W5, CEP 70790-160 Brasilia, DF, Brazil

Abstract

Using dynamic conditional correlations and networks, we bring a novel framework to define the integration and segmentation of emerging countries. The individual EMBI+ spreads of 13 emerging countries from 01/2003 to 12/2013 are used to compare their interaction structure before (phase 1) and after (phase 2) the global financial crisis. Accordingly, the average of dynamic correlations between cross country spreads significantly increases in phase 2. At first, the increased co-movement degree suggests an integration of the sample countries after the crisis. However, correlation based stable networks show that the increase is more likely to be caused by clusters of countries that exhibit high within-cluster co-movement but not between-cluster co-movement. Important implications for international investors and policymakers are discussed.

\textsuperscript{*}The views expressed in this work are those of the authors and do not necessarily reflect those of the Borsa Istanbul or their members.

\textsuperscript{**}Benjamin M. Tabak gratefully acknowledges financial support from CNPq Foundation.

Email address: ahmet.sensoy@borsaistanbul.com (Ahmet Sensoy)
Not all emerging markets are the same: A classification approach with correlation based networks

Abstract

Using dynamic conditional correlations and networks, we bring a novel framework to define the integration and segmentation of emerging countries. The individual EMBI+ spreads of 13 emerging countries from 01/2003 to 12/2013 are used to compare their interaction structure before (phase 1) and after (phase 2) the global financial crisis. Accordingly, the average of dynamic correlations between cross country spreads significantly increases in phase 2. At first, the increased co-movement degree suggests an integration of the sample countries after the crisis. However, correlation based stable networks show that the increase is more likely to be caused by clusters of countries that exhibit high within-cluster co-movement but not between-cluster co-movement. Important implications for international investors and policymakers are discussed.

Keywords: emerging markets, financial crisis, integration, segmentation, dynamic conditional correlation, financial networks

JEL: C58, D85, E44, F30, F62, G01
1. Introduction

The integration of financial markets lies at the heart of the asset and risk management, especially for the investors who are looking to diversify their portfolios internationally and policymakers trying to maintain financial stability. Unfortunately, analysis of the market integration is a challenging process; though they are structurally different, contagion can be confused with globalization as both have a tendency to raise correlations among assets. On top of this, the ongoing structural changes in the world economy and financial architecture, including technological improvements, raise this complexity further. Although it is a complex process, the effects on investment and policy decisions are crucial, thus necessary attention should be devoted while making analysis.

One of the problem faced in academic studies is that there is no consensus on the definition of contagion among economists. An accepted view in literature belongs to Forbes and Rigobon (2002) where they defined contagion as significant increase in correlation during the periods of turmoil. Therefore according to their study, if the correlation does not increase significantly, then any continued high level market co-movement suggests strong real linkages that can be called interdependence. In this study, we also use a similar definition i.e. while we call markets are interdependent when they have permanent (long-term) high correlations, contagion is defined as high however temporary (short-term) correlations.1

On application side, increased financial and economic integration amplified the correlations between developed markets which diminished the benefit of diversification and led investors to seek alternative investment opportunities. With the help technological innovations, in a more globalized financial system, emerging markets (EMs) attract the attention of investors who would like to diversify their portfolios. Consecutively, EMs sovereign debt securities, one of the main instruments of funding, have become an important instrument as an asset class for investors. Before 2000s, attributable to high volatility in shallow markets, international investors were reluctant to invest in EM bonds. Once Erb et al. (2000) described EM bonds as assets with small relative market capitalization and limited liquidity, and that are highly volatile and negatively skewed, however the credit quality of EMs has enhanced as many emerging countries have made improvements to their fiscal positions and banking systems since then. The investment grade percentage in J.P. Morgan’s Emerging Markets Bond Index (EMBI) was only about 40% in 2007 and became roughly 73% at the end of 2013. After 2008 financial crisis, there has been abundance in liquidity in markets and nominal short-term rates were close to zero in developed markets, with real rates stuck in negative territory while longer dated instruments were offering very little return, as a

---

1We use time-varying correlations to analyze market dependence structure. Thus, the concepts of long and short term high correlations make sense and they will be introduced in Section 2 later.
result more and more investors were looking for fixed income alternatives like EM sovereign bonds. While emerging market yields have also fallen in this period, yields offered were still well above the developed markets and risk appetite of investors has increased parallel to liquidity provided by quantitative easing operations.

In line with the shift in investors’ perception of emerging markets as a viable investment opportunity, small, albeit increasing, number of papers examines the integration of bond markets, sovereign bond markets in particular. Cifarelli and Paladino (2006) analyzed the dynamic relationship between sovereign bond spreads of 10 EM countries located in Asia and Latin America from October 1999 to April 2002 and found out that conditional co-variations increase in periods of turbulence and subsequently subside and describe this as a kind of temporary contagion. Bunda et al. (2009) analyzed roles of external factors on co-movements in EMs and tried to find evidence of contagion and common external shocks by using the data of 18 countries bond spreads over the period of March 1997 to end of October 2008. They showed that before 2008 financial crisis, average correlations were low and decreasing, though some pairwise correlations were high. Based on this results, they suggested that bond markets were not unimodal but there were subgroups characterized by high within-group movements. They also analyzed the period after September 2008 and observed increase in correlations which they interpreted as diminish of investors’ discrimination across EMs. Jaramillo and Weber (2013) investigated the global spillovers into EM bond markets for 26 emerging economies between years 2007 and 2013. According to their results, domestic bond yields were influenced mainly by global risk appetite and liquidity conditions and vulnerability of EMs to these two factors is not uniform but rather depends on country specific factors.

In contrast to the number of studies analyzing integration of EM bond markets; there are quite many studies that investigate the determinants of EM bond pricing. As a pioneer study, Eichengreen and Mody (1998) claimed that their results support the view that the market discriminates among issuers according to risk. However they also found that the same explanatory variables had quite different effects on different types of borrowers and regarding the changes in spreads over time, they suggested that they were explained mainly by shifts in market sentiment rather than by shifts in macroeconomic fundamentals. McGuire and Schrijvers (2003) concluded that common forces account for the one third of the total variation in spreads and a single common factor explains approximately 80% of the common variation. Uribe and Yue (2006); Juttner et al. (2006); Ozatay et al. (2009); Kennedy and Palerm (2014) analyzed the influences of external/global versus domestic variables on EMBI spreads and suggested that much of the movements were explained by external conditions, whereas differences in spreads were related to the dissimilarity in country specific fundamentals. While Dailami et al. (2008) distinguished crisis period from non-crisis period and added external factors to model non-linearly, Weigel and Gemmill (2006) stressed the
role of regional factors by studying Latin American countries. Baldacci et al. (2008) found that political risk factors and fiscal position of countries played a significant role. Hilscher and Nosbusch (2010) added volatility of fundamentals and found that variation in country fundamentals explain a large share of variation in EM sovereign debt prices. Hartelius et al. (2008) showed that the Fed can play a role in reducing the risk in EMs and asserted that a clear communication strategy by Fed may guide investor expectations. Bellas et al. (2010) and Csonto and Ivaschenko (2013) disentangle spreads into short and long term effects and found that in the long-run fundamentals were more significant while global factors were the main determinants of spreads in the short-run. Comelli (2012) emphasized that the contribution of the explanatory variables might change across time and regions by giving the reasoning of over-time and across different emerging economies, investors did not always assign the same weight to domestic and external factors when selecting bonds to hold in their portfolio.

The above literature shows that there is a vast amount of studies on determinants of EM bond pricing, however, the studies on EM bond market integration stay relatively limited. This paper tries to fulfill this gap by investigating the integration and segmentation² of EM bond markets using individual EMBI+ spreads of 13 emerging countries from January 2003 to December 2013. Our study contributes to the literature in at least three ways. Firstly, the data used in this study cover the period between 2003-2013, letting financial crisis in 2008 stays at the middle. So that while using most up-to-date data, equal weight has been given to the pre and post crisis period in comparison. Secondly, the literature that analyzed the determinants of bond spreads or financial contagion used a range of different methodologies such as principle component analysis, panel data analysis, co-integration and vector error correction models, however the correlation based network analysis employed in the paper, to the best of our knowledge, has not been used before. Third the co-movements in EMs mostly examined by using stock markets or exchange rates, however sovereign bond markets constitutes a topic of little empirical investigation. With this paper, we would like to broaden the topics analyzed under EM bond market integration. Besides, while EM stock markets may differ by their market capitalization, liquidity and investor base, and their currencies may be heavily manipulated due to their exchange rate regimes, EMBI+ spread data are more robust since the sovereign debt instruments used in this data fulfill very strict requirements in terms of liquidity and maturity, and attract more institutional

²In finance literature, market integration occurs when prices among different markets follow similar patterns over a long period of time. Group of prices often move proportionally to each other and when this relation is very clear among different markets it is said that the markets are integrated. Market segmentation refers to the aggregating of markets into sub-groups (segments) that have common properties and will respond similarly to positive/negative external shocks.
investors. Our analysis shows that the EMBI+ spreads of the countries in our study has a higher collective co-movement degree after the global financial crisis. However, the increased co-movement degree is not due to the group integration of the sample countries but most likely caused by sub-groups of countries that exhibit high within sub-group co-movement but not between sub-group co-movement. This result with our additional analyses provide important information for investors and policymakers which will be discussed in the rest of the paper.

The reminder of the paper is organized as follows. In Section 2, the data used for empirical analysis and the methodology employed for model construction are presented. Section 3 reports the results and discussion. Finally, concluding remarks are stated in Section 4.
2. Data and Model Construction

The data used in our study is directly related to J.P. Morgan’s EMBI+ index which is a debt index of emerging markets. It started in January 1994 with five countries and is constructed as a composite of the following debt instruments of emerging countries: Bradies, eurobonds, and traded loans issued by sovereigns (issued in something other than local currency. Although, after 1998 only those instruments denominated in U.S. dollars are considered for inclusion). A daily total return for each single instrument is computed; for each instrument type, a market-capitalization weighted average of the daily total returns is constructed; and the same is done for the three instrument types. The result is a composite return for the overall EMBI+ market, measured in basis points over U.S. Treasuries.\(^3\) A strict liquidity requirement rule is used to determine inclusion. Only issues with a current amount outstanding of $500 million or more and a remaining life of greater than 2.5 years are eligible for inclusion in the index and at least 1 year to maturity is required to maintain in the inclusion.

In our analysis, we use the daily country individual subindices of the overall EMBI+ index. Such choice makes sure the portfolios we study can actually and easily be traded. These subindices are obtained from Bloomberg database and cover a time period from January 2, 2003 to December 10, 2013 (dataset covering the largest number of countries starts in late 2002. Therefore, initial point is chosen as the beginning of 2003). Over this period, fourteen countries; namely Argentina, Brazil, Bulgaria, Columbia, Ecuador, Mexico, Panama, Peru, Philippines, Russia, South Africa, Turkey, Ukraine and Venezuela are continuously included in the index. Since the case of Argentina is exceptional (due to its default in 2001) and causes convergence problems in our estimations, it is omitted. Accordingly, subindices belonging to the remaining thirteen countries are subject to our analysis and their historic values are displayed in Figure 1.

In this study, the methodology we follow will be mainly based on the time-varying contemporaneous relationship between the country individual subindices. In particular, a dynamic correlation analysis will be employed as the first step of our main approach. The following subsections describe the details.

2.1. Preparation of the data

For each subindex \(i\), we use log-returns \(r_{i,t} = \ln(P_{i,t}/P_{i,t-1})\) to obtain the daily changes. Furthermore, we apply an ARMA\((P,Q)\) filtering for individual returns to account for the serial correlation and lingering effects of random shocks i.e.

\(^3\)In theory, this spread seeks to compensate investors for assuming a greater risk premium and expected losses from default; that is it is a measure of financial fragility and vulnerability and how investors price those risks.
Figure 1: EMBI+ series for individual countries.
where AR and/or MA parts are optional and used when necessary.

Let \( \varepsilon_t = [\varepsilon_{1,t}, ..., \varepsilon_{n,t}]' \) be the vector of residuals. In the next step, we obtain the conditional volatilities \( h_{i,t} \) from univariate GJR-GARCH(1,1) process. In particular, we estimate the following

\[
h_{i,t}^2 = \omega + (\alpha + \gamma I_{\varepsilon_{i,t-1} < 0})\varepsilon_{i,t-1}^2 + \beta h_{i,t-1}^2
\]

where \( \gamma \) is the leverage coefficient.

### 2.2. Consistent dynamic conditional correlation

The dynamic correlations between the analyzed variables will be obtained by the cDCC model of Aielli (2013). To consider cDCC modeling, we start by reviewing the DCC model of Engle (2002). Assume that \( E_{t-1}[\varepsilon_t] = 0 \) and \( E_{t-1}[\varepsilon_t \varepsilon_t'] = H_t \), where \( E_t[\cdot] \) is the conditional expectation on \( \varepsilon_t, \varepsilon_{t-1}, ... \). The asset conditional covariance matrix \( H_t \) can be written as

\[
H_t = D_t^{1/2} R_t D_t^{1/2}
\]

where \( R_t = [\rho_{ij,t}] \) is the asset conditional correlation matrix and the diagonal matrix of the asset conditional variances is given by \( D_t = diag(h_{1,t}, ..., h_{n,t}) \). Engle (2002) models the right hand side of Eq.(3) rather than \( H_t \) directly and proposes the dynamic correlation structure

\[
R_t = \{Q_t^*\}^{-1/2} Q_t \{Q_t^*\}^{-1/2},
Q_t = (1 - a - b) S + a u_{t-1} u_t' + b Q_{t-1},
\]

where \( Q_t \equiv [q_{ij,t}], u_t = [u_{1,t}, ..., u_{n,t}]' \) and \( u_{i,t} \) is the transformed residuals i.e. \( u_{i,t} = \varepsilon_{i,t}/h_{i,t} \), \( S \equiv [s_{ij}] = E[u_t u_t'] \) is the \( n \times n \) unconditional covariance matrix of \( u_t \), \( Q_t^* = diag(Q_t) \) and \( a, b \) are non-negative scalars satisfying \( a + b < 1 \). The resulting model is called DCC.

However, Aielli (2013) demonstrates that such model specification produces quite a high bias and the estimation of \( Q \) by this way is inconsistent since \( E[R_t] \neq E[Q_t] \). He proposes
the following consistent model with the correlation driving process

\[ Q_t = (1 - a - b)S + a\{Q_{t-1}^{1/2} u_{t-1} u_{t-1}^T Q_{t-1}^{1/2}\} + bQ_{t-1} \]  \hspace{1cm} (5)

where \( S \) is the unconditional covariance matrix of \( Q_t^{1/2} u_t \).

2.3. Passing from correlations to networks

If we consider our framework as consisting of two main parts, the first one would be obtaining the dynamic conditional correlation matrix \( R_t \). Following that, the second part is the analysis of networks constructed by the time-varying correlations. During recent years, networks have proven to be an efficient way to characterize and investigate a wide range of complex financial systems including stock, bond, commodity, foreign exchange and interbank lending markets.\(^5\) Similarly, a correlation based network could be very useful in understanding the integration and segmentation structure of emerging markets in our case. Such an approach has not been used in the relevant literature before and we expect it to provide noteworthy implications regarding the subject. To be able to follow our approach, we first need to give some introductory context:

Suppose that an undirected and unweighted network \( N_t \) evolves in time and includes at most \( k \) nodes from the set \( \{n_1, n_2, \ldots, n_k\} \) on any given time step \( t \). At that time \( t \), let some (or all) of the nodes in the network are connected to each other according to some \( t \)-dependent criterion. As easily understood, in this construction, the nodes included in the network and the edges connecting these nodes need not to be stable and subject to change in time. Now, we introduce the following genuine definitions.

**Definition 1:** Let \( N_t \) be a dynamic network described as above. Let \( e_{ij} \) be an edge connecting specific nodes \( n_i \) and \( n_j \) and time variable \( t \) spans the set \( \{t_1, t_2, \ldots, t_m\} \). Suppose \( e_{ij} \) appears in the network \( s \) out of \( m \) times. Then if \( 1 \geq \frac{s}{m} \geq p > 0 \), \( e_{ij} \) is called a \( p \)-stable edge or \( p \)-stable connection.\(^6\) A network \( M \) consisting of only \( p \)-stable connections of \( N_t \) is called \( p \)-stable network of \( N_t \).

**Definition 2:** Let \( R_t \) be the cDCC matrix defined in Section 2.2. At time \( t \), let \( \rho(t) \) be the mean of the lower triangular part of \( R_t \), and \( \sigma(t) \) be its standard deviation. A correlation

\(^5\)For example, see Iori et al. (2008); Tola et al. (2008); Tumminello et al. (2010); Minoiu and Reyes (2013); Tabak et al. (2014) for some of the noteworthy studies in recent years.

\(^6\)It is clear that every \( p_1 \)-stable connection is also \( p_2 \)-stable for any \( p_2 \leq p_1 \leq 1 \).
level $\rho_{ij}(t) \in \mathbb{R}$ is called $c$-strong if $\rho_{ij}(t) \geq \bar{\rho}(t) + c \cdot \sigma(t)$ where the constant $c \geq 0$.\footnote{It would be naive to choose a fixed threshold level to determine if a correlation value is strong or not. Several studies in the literature have shown that correlations are time-varying and tend to increase in turbulent times. Therefore, a fixed choice would most likely introduce a bias depending on the global conditions. With our model, the threshold level is determined endogenously and updated everyday. Thus, possible bias arising due to changing global conditions is minimized.}

Then our approach is as follows: For a pre-determined strength level $c$, we construct a dynamic network $N_t$ consisting of nodes connected by only $c$-strong correlations at time $t$, where nodes represent the sample countries. Next, for the considered time period, we construct $M$; the $p$-stable network of $N_t$. For relatively high $p$ values, we can intuitively state that members connected in $M$ are interdependent or integrated. As $c$-level is chosen higher, this integration degree gets stronger.

In the following section, we will study the integration structure between the selected countries by analyzing the $p$-stable connections for several $(p, c)$ values.

\footnote{When $c < 0$, $c$-strong correlation levels become below the average. In order to consider a reasonable strength concept for correlations, minimum $c$ is taken to be 0.}
3. Results and Discussion

3.1. Descriptive statistics and model estimations

Table 1 presents the statistical properties of the returns. We can see that only Ukraine’s spread has positive daily average change over the study period. Thus, the spread measured in basis points over U.S. Treasuries tend to decrease with various degrees for majority of the emerging markets in the last decade.

The unconditional volatilities, measured by standard deviations, seem relatively smaller than others for Latin American countries. Distributions of the daily changes are skewed to the right in general, and also all of them exhibit excess kurtosis (fat tails). Skewness and kurtosis coefficients indicate that daily changes are far from normally distributed. This departure from normality is formally confirmed by the Jarque-Bera test statistics that rejects normality at the 1% level for all series.

The Table 1 also presents the results of the conventional stationarity test for our return series (unit root tests contain a constant). Augmented Dickey-Fuller (ADF) test rejects the null hypothesis of unit root for all the return series at the 1% significance level. Similarly, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test can not reject the stationarity of the returns at the 1% significance level. All daily changes are therefore stationary.

The estimation results for the mean equation and the GJR-GARCH model are presented in Table 2. As mentioned before, some of the series suffer from serial correlation and the lingering effects of the random shocks. This situation is validated by the significant $\phi_1$ and $\theta_1$ parameters for these series. Table 2 also shows that the tail parameter $\beta$ is statistically significant for each series, which confirms the existence of the leptokurtic behavior of the daily changes. In 7 out of the 14 countries, strong evidence of volatility asymmetry is observed as the parameter ($\gamma$) is statistically significant. Out of these 7 countries, 4 of them belong to Latin America which emphasizes the asymmetric reaction of the volatility of the spread series in the region.
Table 1: Descriptive statistics of the daily changes from 02/01/2003 to 10/12/2013 (2727 observations)

<table>
<thead>
<tr>
<th></th>
<th>Brazil</th>
<th>Bulgaria</th>
<th>Columbia</th>
<th>Ecuador</th>
<th>Mexico</th>
<th>Panama</th>
<th>Peru</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-0.0006</td>
<td>-0.0008</td>
<td>-0.0005</td>
<td>-0.0004</td>
<td>-0.0002</td>
<td>-0.0003</td>
<td>-0.0004</td>
</tr>
<tr>
<td>Max</td>
<td>0.2359</td>
<td>0.5228</td>
<td>0.3869</td>
<td>0.3311</td>
<td>0.2160</td>
<td>0.2379</td>
<td>0.6317</td>
</tr>
<tr>
<td>Min</td>
<td>-0.1739</td>
<td>-0.5613</td>
<td>-0.4362</td>
<td>-0.7433</td>
<td>-0.1920</td>
<td>-0.3151</td>
<td>-0.7030</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.0301</td>
<td>0.0533</td>
<td>0.0375</td>
<td>0.0273</td>
<td>0.0362</td>
<td>0.0332</td>
<td>0.0413</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>7.56</td>
<td>17.27</td>
<td>15.84</td>
<td>220.04</td>
<td>6.24</td>
<td>9.08</td>
<td>54.41</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.51</td>
<td>0.52</td>
<td>0.12</td>
<td>-6.20</td>
<td>0.17</td>
<td>0.01</td>
<td>-0.22</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>2485.8</td>
<td>23268.0</td>
<td>18749.0</td>
<td>5.3×10^6</td>
<td>1207.9</td>
<td>4200.5</td>
<td>0.3×10^6</td>
</tr>
<tr>
<td>ADF</td>
<td>-29.7</td>
<td>-35.3</td>
<td>-29.3</td>
<td>-27.2</td>
<td>-29.8</td>
<td>-29.6</td>
<td>-29.6</td>
</tr>
<tr>
<td>KPSS</td>
<td>0.27</td>
<td>0.21</td>
<td>0.07</td>
<td>0.14</td>
<td>0.07</td>
<td>0.07</td>
<td>0.09</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Philippines</th>
<th>Russia</th>
<th>S. Africa</th>
<th>Turkey</th>
<th>Ukraine</th>
<th>Venezuela</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-0.0005</td>
<td>-0.0003</td>
<td>0.0000</td>
<td>-0.0003</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Max</td>
<td>0.2570</td>
<td>0.3875</td>
<td>0.5330</td>
<td>0.2586</td>
<td>0.9440</td>
<td>0.1537</td>
</tr>
<tr>
<td>Min</td>
<td>-0.3296</td>
<td>-0.3153</td>
<td>-0.6440</td>
<td>-0.1972</td>
<td>-1.0198</td>
<td>-0.1927</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.0357</td>
<td>0.0382</td>
<td>0.0490</td>
<td>0.0340</td>
<td>0.0478</td>
<td>0.0245</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>12.61</td>
<td>11.59</td>
<td>19.86</td>
<td>7.24</td>
<td>143.82</td>
<td>9.14</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.13</td>
<td>0.36</td>
<td>-0.25</td>
<td>0.27</td>
<td>-0.06</td>
<td>0.33</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>10508.0</td>
<td>8445.8</td>
<td>32327.0</td>
<td>2075.7</td>
<td>2.2×10^6</td>
<td>4339.7</td>
</tr>
<tr>
<td>ADF</td>
<td>-30.7</td>
<td>-30.9</td>
<td>-33.4</td>
<td>-29.7</td>
<td>-29.0</td>
<td>-28.1</td>
</tr>
<tr>
<td>KPSS</td>
<td>0.03</td>
<td>0.12</td>
<td>0.08</td>
<td>0.09</td>
<td>0.18</td>
<td>0.31</td>
</tr>
</tbody>
</table>
Table 2: Parameter estimates for the mean-variance equations and the driving parameters of the cDCC process

<table>
<thead>
<tr>
<th>Country</th>
<th>$\mu$</th>
<th>$\varphi_1$</th>
<th>$\theta_1$</th>
<th>$\omega \times 10^4$</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\gamma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brazil</td>
<td>-0.0006</td>
<td>-</td>
<td>-0.2955***</td>
<td>0.000003</td>
<td>0.1283***</td>
<td>0.8830***</td>
<td>-0.0941***</td>
</tr>
<tr>
<td></td>
<td>(0.262)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Bulgaria</td>
<td>-0.0007</td>
<td>-</td>
<td>-0.2755***</td>
<td>0.3701***</td>
<td>0.1305***</td>
<td>0.8599***</td>
<td>0.0136</td>
</tr>
<tr>
<td></td>
<td>(0.300)</td>
<td>(0.000)</td>
<td>(0.007)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.660)</td>
</tr>
<tr>
<td>Columbia</td>
<td>-0.0005</td>
<td>-</td>
<td>-0.4988***</td>
<td>0.1772***</td>
<td>0.8147***</td>
<td>-0.0486</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.531)</td>
<td>-</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.146)</td>
<td>(0.146)</td>
</tr>
<tr>
<td>Ecuador</td>
<td>0.0005</td>
<td>0.9724***</td>
<td>-0.9476***</td>
<td>0.6133</td>
<td>1.6542</td>
<td>0.7071***</td>
<td>-1.0550</td>
</tr>
<tr>
<td></td>
<td>(0.616)</td>
<td>(0.000)</td>
<td>(0.140)</td>
<td>(0.449)</td>
<td>(0.000)</td>
<td>(0.449)</td>
<td>(0.449)</td>
</tr>
<tr>
<td>Mexico</td>
<td>-0.0002</td>
<td>-</td>
<td>-0.2397***</td>
<td>0.1345***</td>
<td>0.8799***</td>
<td>-0.0588***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.745)</td>
<td>-</td>
<td>(0.008)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.033)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Panama</td>
<td>-0.0003</td>
<td>-</td>
<td>-0.2717***</td>
<td>0.1031***</td>
<td>0.8771***</td>
<td>-0.0108</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.688)</td>
<td>-</td>
<td>(0.010)</td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.673)</td>
<td>(0.673)</td>
</tr>
<tr>
<td>Peru</td>
<td>-0.0004</td>
<td>-0.0775***</td>
<td>-1.3902***</td>
<td>0.1798***</td>
<td>0.7588***</td>
<td>-0.0647**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.569)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.058)</td>
<td>(0.058)</td>
</tr>
<tr>
<td>Philippines</td>
<td>-0.0005</td>
<td>-0.0335***</td>
<td>-0.1613**</td>
<td>0.1426***</td>
<td>0.8533***</td>
<td>-0.0019</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.484)</td>
<td>(0.083)</td>
<td>(0.11)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.944)</td>
<td>(0.944)</td>
</tr>
<tr>
<td>Russia</td>
<td>-0.0003</td>
<td>-0.0497***</td>
<td>-0.4941***</td>
<td>0.1381***</td>
<td>0.8554***</td>
<td>-0.0521**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.637)</td>
<td>(0.009)</td>
<td>(0.006)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.059)</td>
<td>(0.059)</td>
</tr>
<tr>
<td>S. Africa</td>
<td>0.0000</td>
<td>-2.1688***</td>
<td>2.5720***</td>
<td>0.1469***</td>
<td>0.7656***</td>
<td>-0.0878**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.980)</td>
<td>(0.000)</td>
<td>(0.058)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.030)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Turkey</td>
<td>-0.0003</td>
<td>-</td>
<td>0.4873***</td>
<td>0.1444***</td>
<td>0.8545***</td>
<td>-0.0855***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.605)</td>
<td>-</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Ukraine</td>
<td>0.0002</td>
<td>-0.1655***</td>
<td>1.2515***</td>
<td>0.2239***</td>
<td>0.7045***</td>
<td>0.0130</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.807)</td>
<td>(0.000)</td>
<td>(0.003)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.802)</td>
<td>(0.802)</td>
</tr>
<tr>
<td>Venezuela</td>
<td>0.0000</td>
<td>0.1303***</td>
<td>-0.3257***</td>
<td>0.1507***</td>
<td>0.8259***</td>
<td>-0.0700***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.999)</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.038)</td>
<td>(0.038)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>cDCC</th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.0168***</td>
<td>0.9766***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

1. For the mean and variance equations, refer to Eq. (1) and Eq. (2) respectively.
2. For the cDCC process, refer to Eq. (5).
3. The values in the parentheses are the $p$-values obtained from robust standard errors.
4. *, ** and *** denote significance levels at 10%, 5% and 1% respectively.
3.2. Network analysis

Figure 2 displays the time-varying mean correlation $\rho(t)$ obtained from $R_t$ and the $c$-strong correlation levels for different $c$ values. To see the effects of the global financial crisis on the integration structure of emerging markets, we need to split our time interval as before (phase 1) and after (phase 2) the crisis. The National Bureau of Economic Research (NBER) identifies December 2007 as the start of the global recession caused by the financial crisis, and the end of this recession as June 2009 (http://www.nber.org/cycles.html). Therefore, we take phase 1 as the time interval between January 2, 2003 and November 30, 2007 (4.9 years). Naturally, phase 2 covers from July 1, 2009 to December 10, 2013 (4.5 years). Since the duration of the two phases are close, data is not exposed to a serious duration bias.

![Figure 2: Time-varying mean correlation $\rho(t)$ and $c$-strong correlation levels.](image)

Figure 2 shows that mean correlation fluctuates around higher levels in phase 2 compared to phase 1: Arithmetic averages of the mean correlations in phase 1 and phase 2 are 0.47 and 0.55 respectively, and after employing several statistical mean comparison tests, we confirm that the second average is significantly higher than the first one. The naive approach would lead us to think that emerging markets in our sample tend to integrate in phase 2, however in this case we should not jump to immediate conclusions. In particular, the increased average in phase 2 may be caused by the strong integration between some particular emerging countries, although some others may be dis-integrated from the group. Indeed, this scenario is very similar to our situation and the following analysis draws us a picture of this case.

To continue with further analysis, we need to determine several $(p,c)$ combinations. As a rough and practical approach, we use 0.2 as increment size for this construction. We know

---

9Similar conclusion is still valid when we compare medians. For the time-varying descriptive statistics of the dynamic conditional correlation matrix $R_t$, refer to Appendix A.
by definition $0 < p \leq 1$, therefore, $p$ values are taken as 0.2, 0.4, 0.6, 0.8 and 1. In a similar way, $c$ values are taken as 0, 0.2, 0.4, 0.6, 0.8 and 1. The reasons for the choice of upper and lower $c$ limits are explained as follows: For $c \geq 1.2$ and our choices of $p$, there is no $p$-stable connections in both phases, therefore maximum value of $c$ is taken to be 1 (besides for $c \geq 1.2$, $c$-strong correlation levels exceed 1 from time to time). And as stated before, when $c < 0$, $c$-strong correlation levels become below the average. Considering integration/segmentation concepts, in order to have a reasonable strength definition for correlations, minimum $c$ is taken to be 0. Eventually, we have $5 \times 6 = 30$ different $(p, c)$ combinations in total.

In the following, Figures 3 - 7 display the $p$-stable networks for selected $(p, c)$ combinations in phase 1. For the same combinations, Figures 8 - 12 show the $p$-stable networks in phase $2$.\footnote{The size of the circles in the figures do not have any economic interpretation and are chosen for optimal allocation purposes when constructing networks.}
Figure 3: $p$-stable networks for $p=1$ and different $c$-levels in phase 1 (there does not exist a $p$-stable network for $c=1, 0.8$ and $0.6$ when $p=1$).
Figure 4: $p$-stable networks for $p = 0.8$ and different $c$-levels in phase 1.
Figure 5: $p$-stable networks for $p = 0.6$ and different $c$-levels in phase 1.
Figure 6: $p$-stable networks for $p = 0.4$ and different $c$-levels in phase 1.
Figure 7: p-stable networks for $p = 0.2$ and different $c$-levels in phase 1.
Figure 8: p-stable networks for $p = 1$ and different $c$-levels in phase 2.
Figure 9: $p$-stable networks for $p = 0.8$ and different $c$-levels in phase 2.
Figure 10: $p$-stable networks for $p = 0.6$ and different $c$-levels in phase 2.
Figure 11: P-stable networks for \( p = 0.4 \) and different \( c \)-levels in phase 2.
Figure 12: $p$-stable networks for $p = 0.2$ and different $c$-levels in phase 2.
3.2.1. General view

Figures 3 - 12 display the detailed results of our analysis and they will be mentioned in a while. However at first, for ease of digestion, we will try to provide a bigger picture of what’s going on in phase 1 and phase 2 in terms of integration and segmentation: In Figures 13 and 14, every box corresponds to a stable network for different \((p,c)\) combination. A circle in a box denotes a *cluster* (in our context, the term “cluster” is used to denote a connected group) of countries and having more than one circle in a box is a representative of segmentation. The numbers in the circles represent the number of countries belonging to that cluster. Finally, the sum of the numbers in the circles in a box gives the number of stable connections for that specific \((p,c)\) combination.

Roughly, we partition the \((p,c)\) combinations into 4 main parts. The intuitive interpretations of these parts are explained below:

1. **Zone 1 (Integration Zone):** refers to the area where \(p \in (0.5, 1]\) and \(c \in (0.5, 1]\). In this region, we have relatively high \(p\) and \(c\) values. Accordingly, countries connected in the networks in Zone 1 can be thought of permanently (or long-term) and strongly integrated.

2. **Zone 2 (Contagion Zone):** refers to the area where \(p \in (0, 0.5)\) and \(c \in (0.5, 1]\). In this region, we have relatively high \(c\) but low \(p\) values. Since every country/connection in Zone 1 will also exist in Zone 2, connections appearing in the networks only in Zone 2 can be thought to be strong, however temporary (or short-term) connections. For countries having these type of connections, their relationship with the connected countries may be considered as contagion instead of integration.

3. **Zone 3 (Weak-interdependence Zone):** refers to the area where \(p \in (0.5, 1]\) and \(c \in [0, 0.5)\). In this region, we have relatively high \(p\) but low \(c\) values. Since every country/connection in Zone 1 will also exist in Zone 3, connections appearing in the networks only in Zone 3 can be thought to be stable but weak connections. For countries having these type of connections, their relationship with the connected countries may be considered as weak interdependence.

4. **Zone 4 (Dis-integration Zone):** refers to the area where \(p \in (0, 0.5)\) and \(c \in [0, 0.5)\). In this region, we have relatively low \(p\) and \(c\) values. Accordingly, countries/connections appearing in the network only in Zone 4 can be thought of outliers. Countries joining to the networks in this zone may be considered to be dis-integrated from the others.

Although several conclusions can be deducted by comparing Figures 13 and 14, we will focus on a few specific points: For the highest stability level i.e. \(p = 1\), there is not a single stable connection in phase 1 for any \(c\)-level. On the contrary, for the same \(p\)-level, we have stable connections in phase 2 even for the highest strength level. This shows that the global financial crisis results with strong integration for some specific emerging countries.
Statistically speaking, number of countries in a stable network per \((p, c)\) combination in Zone 1 is 5.33 in phase 1, whereas this value is 7.33 in phase 2.

Interestingly, the same crisis also result with some specific segmentations among emerging markets which can be denoted by the number of clusters in a stable network. In phase 1, the number of clusters in Zone 1 per \((p, c)\) combination is 1. This values increases up to 1.67 in phase 2. Therefore, emerging countries tend to have subgroup integrations after the financial crisis.

Another interesting point is regarding to Zone 4. In phase 1, for \((p, c)=(0.4, 0), (0.2, 0.4)\) and \((0.2, 0)\), all the countries are included in a stable network, however this is not the case in phase 2: Maximum number of countries included in a stable network is twelve, which is the minimum number per box in phase 1. Also the number of countries per \((p, c)\) combination in Zone 4 is 12.67 in phase 1, whereas this number is 10.5 in phase 2. These cases might indicate the dis-integration of some members from others after the financial crisis.

As previously stated, mean of dynamic conditional correlations between bond returns is found to be significantly higher in phase 2 compared to phase 1. And such an increase might suggest the integration of the sample countries after the crisis. However, combining the aforementioned results about the changes in different zone structures, we can state that the increased mean correlations is more likely to be caused by clusters of countries that exhibit high within-cluster co-movement but not between-cluster co-movement. The summary statistics used in our comparisons are given in Table 3.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Phase 1</th>
<th>Phase 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>clusters/(p, c)</td>
<td>countries/(p, c)</td>
</tr>
<tr>
<td>Zone 1</td>
<td>1.00</td>
<td>5.33</td>
</tr>
<tr>
<td>Zone 2</td>
<td>1.00</td>
<td>9.50</td>
</tr>
<tr>
<td>Zone 3</td>
<td>1.11</td>
<td>8.78</td>
</tr>
<tr>
<td>Zone 4</td>
<td>1.00</td>
<td>12.67</td>
</tr>
</tbody>
</table>

3.2.2. Micro details

Figure 3 shows the \(p\)-stable network for \(p = 1\) and phase 1 (pre-crisis). Therefore, it exhibits which countries are connected for the entire period. When \(c = 0\) we allow for the degree of integration to be at the lower bound and we find that these countries have a variety of direct relationships. Brazil, for example, is connected to Mexico, Colombia, Panama and Russia. However, when we increase correlation strength \(c\) we find that each country has at most two direct neighbors, whereas Philippines and Russia (for \(c = 0.2\)) and Philippines and Mexico (for \(c = 0.4\)) have only one.

Figure 4 presents the results for \(p = 0.8\), which is still a high value as the network will
Figure 13: Each box corresponds to a \( p \)-stable network for different \((p, c)\) combination in phase 1. Each circle in a box denotes a cluster and the number in the circles represent the amount of countries belonging to that cluster. Total number in a box corresponds to the amount of countries belonging to that \( p \)-stable network.
Figure 14: Each box corresponds to a $p$-stable network for different $(p, c)$ combination in phase 2. Each circle in a box denotes a cluster and the number in the circles represent the amount of countries belonging to that cluster. Total number in a box corresponds to the amount of countries belonging to that $p$-stable network.
be formed by countries that are connected most of the time. As we increase the value of $c$ to depict the network with large strength correlation, we obtain similar results and the network gets thinner and more sparse. We also find that geographic proximity may be one of the reasons that causes these links.

In Figure 5, we study the case of a more intermediate degree of integration ($p = 0.6$). A very similar figure is obtained with Latin American countries and Philippines in one group and, Russia and Turkey in another group (for $c = 1$). As we reduce the correlation strength $c$, we see that the network gets more dense and connections increase substantially.

Figures 6 and 7 present the case for $p = 0.4$ and 0.2, respectively. In this case, since we include low levels of integration with countries that are weakly connected over time, we have a more dense network. However, the number of connections is still inversely related to the correlation strength $c$.

Figure 8 presents that case of $p = 1$ for phase 2 (post-crisis). As we increase the correlation strength $c$, we find a more sparse network, which suggests that after the crisis some countries drifted apart. These results may reflect differences in investor perceptions regarding potential banking problems in these countries and different expectations about the impact of the crisis on these economies.

Countries with macroeconomic and financial similarities could respond similarly to the crisis, whereas more vulnerable countries would suffer a higher impact. Nonetheless, when we look at the case of $c = 1$, a very high correlation strength, we find a similar picture as we had in the case of phase 1, with only two groups. One comprises Brazil and Colombia (Latin American economies) and the other Russia and Turkey (Emerging European countries). However, letting $c$ to be 0.8 or 0.6 creates 3 clusters which differs from phase 1 and tells much about segmentation. Another interesting observation is joining of South Africa in the network: Compared to phase 1, this country can connect to Turkey and Russia for high $(p, c)$ values i.e. fulfills a much stronger connectivity requirement, displaying a new structure after the crisis. Also, one can witness the dis-integration of Ecuador from the others as it can not join the network for any $(p, c)$ combination. Other than that, we find similar results as in the phase 1 case from Figures 9-12, in general.

Overall, these results suggest that an increase in average collective correlation can be misleading as it could suggest that integration of these economies have increased after the crisis. But in our case, this is a local phenomena with a small subset of countries having their correlations increased and different groups with low correlation.

3.2.3. Relation with the monetary policy

We are analyzing debt international markets for all the emerging counties in our study. It is worth remembering that if some countries suffered similar impacts from the global crisis then they may have adopted similar economic policies to deal with it. For example, some countries may have reduced their interest rates (expansionary monetary policy) after the
crisis. If domestic interest rates are linked to EMBI+ rates due to absence of arbitrage then the interest rates in their international bonds should have behaved accordingly increasing their correlation. To see if this is the case here, we present the post-crisis monetary policy rates of the emerging countries that belong to 3 different clusters in Figure 10 when $c = 0.4$. If the above argument is true i.e. policy rates are the main drivers of the EMBI+ correlations, then we should expect these policy rates to strongly co-move for the countries belonging to the same clusters. Figure 15 displays these policy rates and we can see that the above argument is not valid as the policy rates do not present significant collective behavior within clusters.
4. Conclusion

The quantitative easing policy that has been launched by the Federal Reserve (Fed) after the global financial crisis has created excessive global liquidity. In addition, the expansionary monetary policies implemented in other major currency areas like EU and Japan affected all the markets around the world. Combined with the low yields in developed countries’ bond markets, this excessive liquidity has generated high capital inflows in emerging markets and appreciated their currencies, leading to new financial structures in these economies.

In this study, we show that the unweighted average of dynamic conditional correlations between cross emerging country bond returns has significantly increased after the global financial crisis. However, we reveal that the increased average correlation is due to the clusters of countries that exhibit high within-cluster co-movement but not between-cluster co-movement. We also observe (and intuitively infer) that excessive global liquidity and geographic proximity play important roles in high within-cluster co-movement, however monetary policy rates are shown to not, even though we use bond data in cross county correlation analysis.

Our results suggest that after the crisis, different subgroups of emerging countries have appeared. Therefore, one should expect that economic policies that are put in action by the Fed or even the European Central Bank (ECB) have different impacts on these countries. Since these countries have become more segmented after the crisis, spillover effects should be reduced and limited to specific subgroups.\textsuperscript{11} Recently, Fed has argued that “to a considerable extent, investors appear to have been differentiating among emerging market economies (EME) based on their economic vulnerabilities” (Board of Governors, 2014). Our results are in line with those provided by the Fed in which they rank emerging markets according to vulnerability. Accordingly, international investors should not consider emerging markets as a single asset class as they differ substantially and different clusters found in our network analysis corroborate this idea. From an investor’s point of view, potential benefits of international diversification is low for the economies that are in the same cluster, however cross cluster diversification opportunities may still exist and these fact should be taken into account in portfolio strategies.

There are several potential extensions for further research. Firstly; previous studies treated all emerging markets as a single block and investigated bond spread determinants accordingly, however analyzing spreads within subgroups may result more meaningful re-

\textsuperscript{11}Theoretically, we can expect these different impacts as emerging markets economies have very different levels of vulnerability after the financial crisis. For example, countries that are specialized in commodity exports such as Colombia and Brazil have suffered from deteriorating terms of trade and widening current account deficits. Therefore, they are likely to be prone to larger capital outflows than the rest as they can pose higher risks.
sults. Secondly, researchers can focus on the possible effects of Fed tapering or recovery of the developed European economies on the integration/segmentation structure of EM bond markets. Our analysis reveals that in pre-crisis period, the segmentation between EMs were not that strict compared to excessive liquidity environment after the crisis. Accordingly, the answer to the question of “is it possible to turn back to the old structure?” might be very beneficial in providing guidance for both policymakers and investors.
References


Appendix A.

Figure A.1: Time-varying descriptive statistics of the dynamic conditional correlation matrix $R_t$. Red vertical lines split the pre-crisis, crisis and post-crisis periods according to NBER. Red points in the J-B stat denote the rejection of normality at 5% significance level.