Journal of Financial Stability 33 (2017) 163–186

Contents lists available at ScienceDirect

Journal of Financial Stability

journal homepage: www.elsevier.com/locate/jfstabil

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

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ARTICLE INFO

Article history:
Received 29 June 2015
Received in revised form 14 May 2016
Accepted 29 June 2016
Available online 30 June 2016

JEL classification:
C58
D85
E44
F30
F62
G01

Keywords:
Emerging markets
Financial crisis
Segmentation
Dynamic conditional correlation
Financial networks

ABSTRACT

Using dynamic conditional correlations and network theory, this study brings a novel interdisciplinary framework to define the integration and segmentation of emerging countries. The individual EMBI+ spreads of 13 emerging countries from January 2003 to December 2013 are used to compare their interaction structure before (phase 1) and after (phase 2) the global financial crisis. Accordingly, the unweighted average of dynamic conditional correlations between cross country bond returns significantly increases in phase 2. At first glance, the increased co-movement degree suggests an integration of the sample countries after the crisis. However, using correlation based stable networks, we show that this is not enough to make such a strong conclusion. In particular, we reveal that the increased average correlation is more likely to be caused by clusters of countries that exhibit high within-cluster co-movement but not between-cluster co-movement. Potential reasons for the post-crisis segmentation and important implications for international investors and policymakers are discussed.

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 market integration is a challenging process; though they are structurally different, contagion at a global scale can be confused with financial 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 and innovative financial products, raise this complexity even further. Although it is a complex process, the effects of integration on investment choices and policy actions are crucial, thus necessary attention should be devoted while performing analysis and making decisions.

One of the problem faced in many academic studies is that the terms integration and contagion cannot be strictly differentiated in technical terms. At a fundamental basis, an accepted view in the literature belongs to Forbes and Rigobon (2002) where authors define contagion as a significant increase in correlation during the periods of turmoil. Accordingly, if the correlation does not increase significantly in turbulent times, then any continued high level market co-movement suggests strong real linkages that can be called

☆ The views expressed in this work are those of the authors and do not necessarily reflect those of the Borsa Istanbul or their members. Benjamin M. Tabak gratefully acknowledges financial support from CNPq Foundation.

☆☆ Earlier versions of this paper was presented at the conference on Assessing the Macroeconomic Implications of Financial and Production Networks organized by European Central Bank and Central Bank of Turkey, September 12–13, 2014; International Conference on the New Normal in the Post-Crisis Era co-organized by the City University of Hong Kong and Central Bank of Netherlands, May 21–22, 2015; 13th INFINITI Conference on International Finance co-organized by Trinity College Dublin, Monash University, and the University of Ljubljana, June 8–9, 2015; and 2nd Borsa Istanbul Finance and Economics Conference organized by Borsa Istanbul, October 1–2, 2015. We thank participants for insightful suggestions. We also thank the editor Iftekhar Hasan and anonymous reviewers for their comments which significantly improved this paper.

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http://dx.doi.org/10.1016/j.jfs.2016.06.009
1572-3089/

interdependence. In this study, we also have a similar approach, i.e. while we call markets are *interdependent* when they have long-term high correlations, *contagion* is defined as high however, short lived correlations.[1]

During the last two decades, 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) have attracted 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. Indeed, 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 the recent global 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 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 examined the integration of bond markets, sovereign bond markets in particular. For example, 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 the global 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) found that the same explanatory variables had quite different effects on different types of borrowers. They suggested that shifts in market sentiment (rather than shifts in macroeconomic fundamentals) truly explains the changes in spreads over time. 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. Baldacci et al. (2008) found that political risk factors and fiscal position of emerging countries played a significant role in EM bond pricing. Hilscher and Nosbusch (2010) added volatility of fundamentals into consideration 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) disentangled 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 segmentation[2] 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 and 2013, letting financial crisis in 2008 stays at the middle. So that equal weight has been given to the pre- and post-crisis periods 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 is relatively new, and to the best of our knowledge, only a simpler version has been used in the work of Sensoy et al. (2015) 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. Moreover, their currencies may be heavily manipulated due to their exchange rate regimes. EMBI+ spread data is more robust since the sovereign debt instruments used in this data fulfill very strict requirements

[1] However, the technical approach to differentiate integration and contagion is completely different than that of Forbes and Rigobon (2002) and will be introduced in Section 2 later.

[2] In 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.

in terms of liquidity and maturity, and attract more institutional investors.

Our analysis shows that the EMBI+ spreads of the emerging 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.

Although the results depend critically on the sample period used, i.e., might have been different if the sample extended until a more recent date; they indicate that different subgroups of emerging countries have appeared after the global financial crisis. Our analysis shows that geographical factors and budget balance to GDP ratio play important roles in this segmentation, rather than monetary policy rates, net government debt to GDP and current account deficit to GDP ratios.

Accordingly, one should expect that economic policies that are put in action by the biggest policy makers, the Federal Reserve (Fed) and the European Central Bank (ECB), might have different impacts on these countries. Furthermore, since these countries have become more segmented after the crisis, spillover effects is expected to be reduced and limited to specific subgroups. From an international investor's point of view, emerging markets should not be considered as a single asset class as they differ substantially, thus diversification opportunities may still exist and these fact should be taken into account in portfolio strategies.

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 main data used in this study is J.P. Morgan's EMBI+ index which is a debt index of emerging markets. It is constructed as a composite of the debt instruments such as bradies, eurobonds, and traded loans issued by sovereigns in U.S. dollars. At first, a daily total return for each single instrument is computed, then for each instrument type, a market-capitalization weighted average of the daily total returns is constructed. Finally, 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 sub-indices of the overall EMBI+ index. Such choice makes sure that the portfolios we study are priced more correctly, liquid enough and easily be traded. These sub-indices 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 this index. Since the case of Argentina is exceptional (due to its default in 2001) and causes computational problems in our estimations, it is omitted. Accordingly, sub-indices belonging to the remaining thirteen countries are subject to our analysis and their historic values are displayed in Fig. 1.

In this study, the methodology we follow will be mainly based on the time-varying contemporaneous relationship between the country individual sub-indices. 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.

$$r_{i,t} = \mu_i + \varepsilon_{i,t} + \sum_{p=1}^{P} \varphi_{i,p} r_{i,t-p} + \sum_{q=1}^{Q} \theta_{i,q} \varepsilon_{i,t-q} \quad (1)$$

where AR and/or MA parts are optional and used when necessary.

Let $\varepsilon_t = [\varepsilon_{1,t}, \ldots, \varepsilon_{n,t}]'$ 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

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

where γ 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).[4] 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 $\varepsilon_t, \varepsilon_{t-1}, \ldots$. The asset conditional covariance matrix H_t can be written as

$$H_t = D_t^{1/2} R_t D_t^{1/2} \quad (3)$$

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

$$\begin{aligned} R_t &= \{Q_t^*\}^{-1/2} Q_t \{Q_t^*\}^{-1/2}, \\ Q_t &= (1-a-b)S + a u_{t-1} u_{t-1}' + b Q_{t-1}, \end{aligned} \quad (4)$$

where $Q_t \equiv [q_{ij,t}]$, $u_t = [u_{1,t}, \ldots, u_{n,t}]'$ 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

[3] In theory, this spread seeks to compensate investors for assuming a greater risk premium and expected losses from default. It is a measure of financial fragility and vulnerability and how investors price those risks.

[4] A common alternative way of obtaining the time-varying correlations is using rolling window Pearson correlations. However, we do not prefer this methodology for several reasons: Resulting dynamic correlations are heavily autocorrelated due to the overlapping windows, and the choice of the window length and the rolling step can be controversial. More importantly, there is a heteroskedasticity problem when measuring correlations caused by volatility increases during turbulent times. These problems are overcomed with the cDCC methodology.

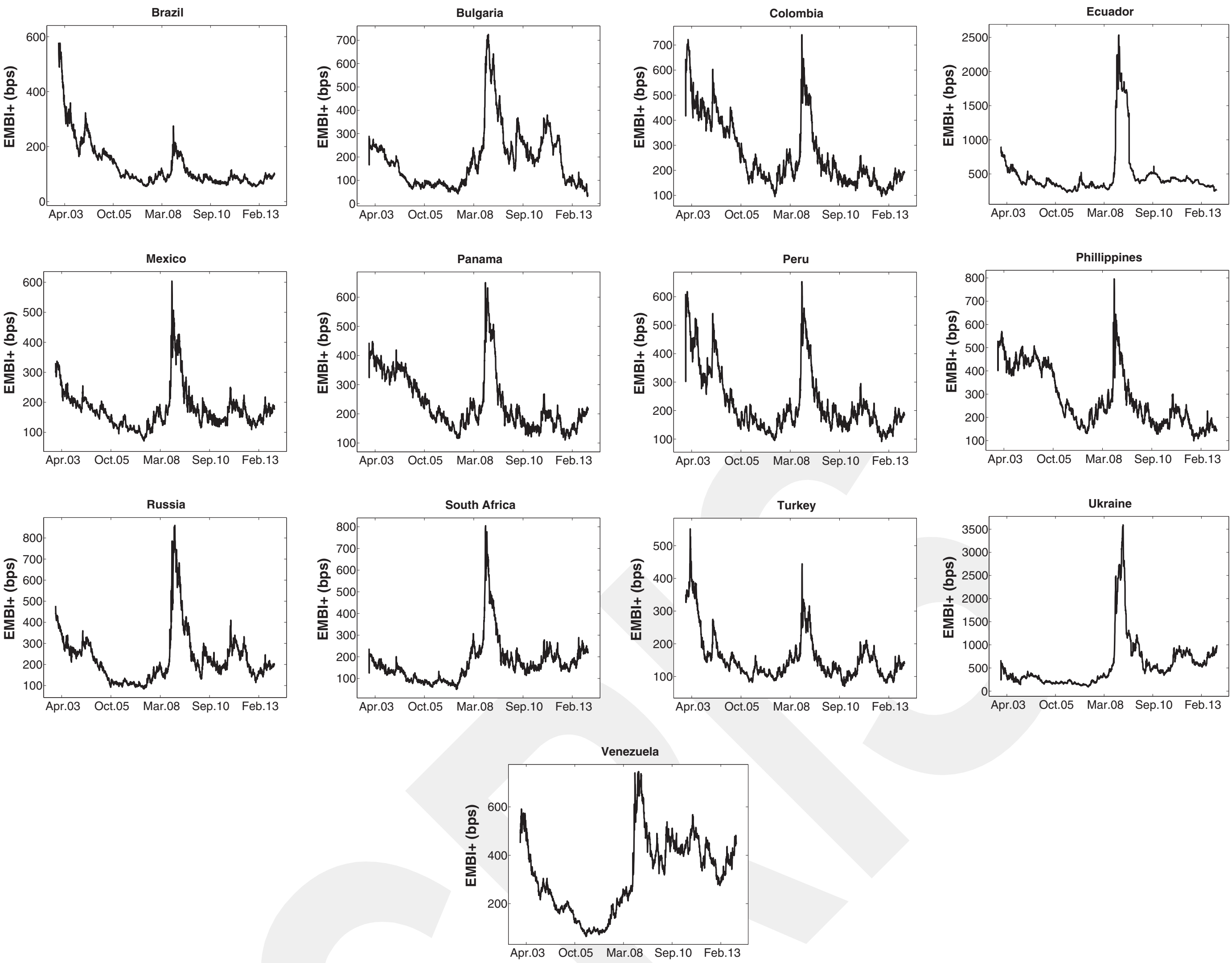

Fig. 1. EMBI+ series for individual countries.

way is inconsistent since $E[R_t] \neq E[Q_t]$. He proposes the following consistent model with the correlation driving process

$$Q_t = (1-a-b)S + a\{Q_{t-1}^{*1/2} u_{t-1} u'_{t-1} Q_{t-1}^{*1/2}\} + bQ_{t-1} \qquad (5)$$

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 is relatively new in the relevant literature, and we expect it to provide noteworthy implications regarding the subject. To be able to follow our approach, we first 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 be connected to each other according to some t-dependent criterion. As it can be easily understood, in this construction, the nodes included in the network and the edges connecting these nodes need not to be stable and are subject to change in time. Now, we introduce the following 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 the 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 $1 \geq s/m \geq p > 0$, 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 $\overline{\rho}(t)$ be the mean of the lower triangular part of R_t, and

[5] For example, see Iori et al. (2008), Tola et al. (2008), Tumminello et al. (2010), Minoiu and Reyes (2013), Tabak et al. (2014), Peltonen et al. (2014), Tonzer (2015), Poledna et al. (2015), Kanno (2015) 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 $p_2 \leq p_1 \leq 1$.

Table 1
Descriptive statistics of the daily changes from 02/01/2003 to 10/12/2013 (2727 observations).

	Brazil	Bulgaria	Columbia	Ecuador	Mexico	Panama	Peru
Mean	−0.0006	−0.0008	−0.0005	−0.0004	−0.0002	−0.0003	−0.0004
Max	0.2359	0.5228	0.3869	0.3311	0.2160	0.2379	0.6317
Min	−0.1739	−0.5613	−0.4362	−0.7433	−0.1920	−0.3151	−0.703
Std. dev.	0.0301	0.0533	0.0375	0.0273	0.0362	0.0332	0.0413
Kurtosis	7.56	17.27	15.84	220.04	6.24	9.08	54.41
Skewness	0.51	0.52	0.12	−6.20	0.17	0.01	−0.22
Jarque–Bera	2485.8	23268.0	18749.0	5.3×10^6	1207.9	4200.5	0.3×10^6
ADF	−29.7	−35.3	−29.3	−27.2	−29.8	−29.6	−29.6
KPSS	0.27	0.21	0.07	0.14	0.07	0.07	0.09

	Philippines	Russia	S. Africa	Turkey	Ukraine	Venezuela
Mean	−0.0005	−0.0003	0.0000	−0.0003	0.0001	0.0000
Max	0.2570	0.3875	0.5330	0.2586	0.9440	0.1537
Min	−0.3296	−0.3153	−0.6440	−0.1972	−1.0198	−0.1927
Std. dev.	0.0357	0.0382	0.0490	0.0340	0.0478	0.0245
Kurtosis	12.61	11.59	19.86	7.24	143.82	9.14
Skewness	0.13	0.36	−0.25	0.27	−0.06	0.33
Jarque–Bera	10508.0	8445.8	32327.0	2075.7	2.2×10^6	4339.7
ADF	−30.7	−30.9	−33.4	−29.7	−29.0	−28.1
KPSS	0.03	0.12	0.08	0.09	0.18	0.31

$\sigma(t)$ be its standard deviation. A correlation level $\rho_{ij}(t) \in R_t$ is called c-**strong** if $\rho_{ij}(t) \geq \overline{\rho}(t) + c \cdot \sigma(t)$ where the constant $c \geq 0$.[7, 8]

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 integrated. As c-level is chosen higher, this integration degree gets stronger.

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

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 all except one 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 return series.

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 cannot 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 φ_1 and θ_1 parameters for these series. Table 2 also shows that the tail parameter β 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 (γ) 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 this region.

3.2. Network analysis

Fig. 2 displays the time-varying mean correlation $\overline{\rho}(t)$ 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 duration bias.

Fig. 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.[9] The naive approach would lead us to

[7] 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 this approach, the threshold level is determined endogenously and updated everyday. Thus, possible bias arising due to changing global conditions is minimized.

[8] When $c < 0$, c-strong correlation levels become below the average. In order to consider a reasonable strength concept for correlations, minimum c should be taken as 0.

[9] Same 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.

Table 2
Parameter estimates for the mean-variance equations and the driving parameters of the cDCC process.

	μ	φ_1	θ_1	$\omega \times 10^4$	α	β	γ
Brazil	−0.0006	–	–	0.2955***	0.1283***	0.8830***	−0.0941***
	(0.262)	–	–	(0.003)	(0.000)	(0.000)	−0.002
Bulgaria	−0.0007	–	−0.2755***	0.3701***	0.1305***	0.8599***	0.0136
	(0.300)	–	(0.000)	(0.007)	(0.000)	(0.000)	−0.66
Columbia	−0.0005	–	–	0.4988***	0.1772***	0.8147***	−0.0486
	(0.531)	–	–	(0.000)	(0.000)	(0.000)	−0.146
Ecuador	−0.0005	0.9724***	−0.9476***	0.6133	1.0542	0.7071***	−1.055
	(0.616)	(0.000)	(0.000)	(0.140)	(0.449)	(0.000)	−0.449
Mexico	−0.0002	–	–	0.2397***	0.1345***	0.8799***	−0.0588**
	(0.745)	–	–	(0.008)	(0.000)	(0.000)	−0.033
Panama	−0.0003	–	–	0.2717**	0.1031***	0.8771***	−0.0108
	(0.688)	–	–	(0.010)	(0.001)	(0.000)	−0.673
Peru	−0.0004	−0.0775***	–	1.3902***	0.1798***	0.7588***	−0.0647*
	(0.569)	(0.000)	–	(0.000)	(0.000)	(0.000)	−0.058
Philippines	−0.0005	−0.0335*	–	0.1613**	0.1426***	0.8533***	−0.0019
	(0.484)	(0.083)	–	(0.011)	(0.000)	(0.000)	−0.944
Russia	−0.0003	−0.0497***	–	0.4941***	0.1381***	0.8554***	−0.0521*
	(0.637)	(0.009)	–	(0.006)	(0.000)	(0.000)	−0.059
S. Africa	0.0000	–	−0.2168***	2.5720*	0.1469***	0.7656***	−0.0687**
	(0.980)	–	(0.000)	(0.058)	(0.000)	(0.000)	−0.03
Turkey	−0.0003	–	–	0.4873***	0.1444***	0.8545***	−0.0855***
	(0.605)	–	–	(0.000)	(0.000)	(0.000)	−0.001
Ukraine	0.0002	−0.1655***	–	1.2515***	0.2239***	0.7045***	0.013
	(0.807)	(0.000)	–	(0.003)	(0.000)	(0.000)	−0.802
Venezuela	0.0000	0.1303***	–	0.3257***	0.1507***	0.8259***	−0.0700**
	(0.999)	(0.000)	–	(0.001)	(0.000)	(0.000)	−0.038

cDCC

a	b
0.0168***	0.9766***
(0.003)	(0.000)

1. For the mean and variance equations, refer to Eqs. (1) and (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.
* Significance level at 10%.
** Significance level at 5%.
*** Significance level at 1%.

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 for the network construction process. As a rough and practical approach, we use 0.2 as increment size for this construction. We know 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 fashion, 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 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, c-strong correlation levels exceed 1 from time to time for $c \geq 1.2$, which is theoretically unachievable). And as stated before, when $c < 0$, c-strong correlation levels become below the average. Considering the concept of integration, minimum c should be taken as 0 in order to have a reasonable definition of strength for correlations. Eventually, we have $5 \times 6 = 30$ different (p, c) combinations in total, yielding to 30 different network structures.

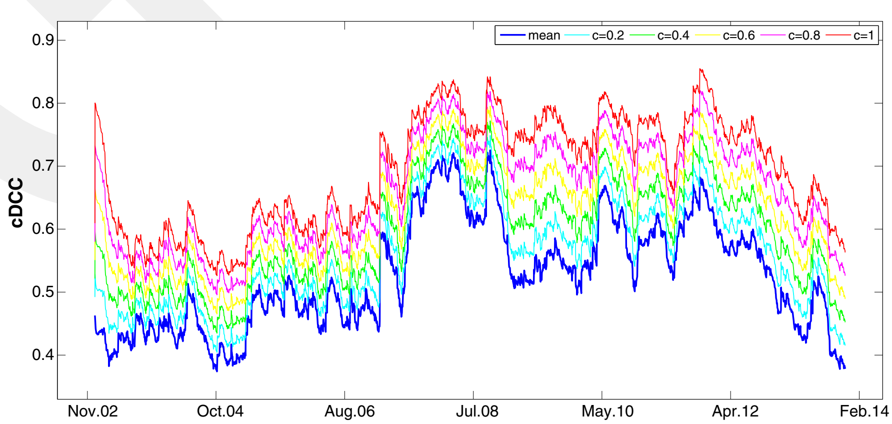

Fig. 2. Time-varying mean correlation $\overline{\rho}(t)$ and c-strong correlation levels.

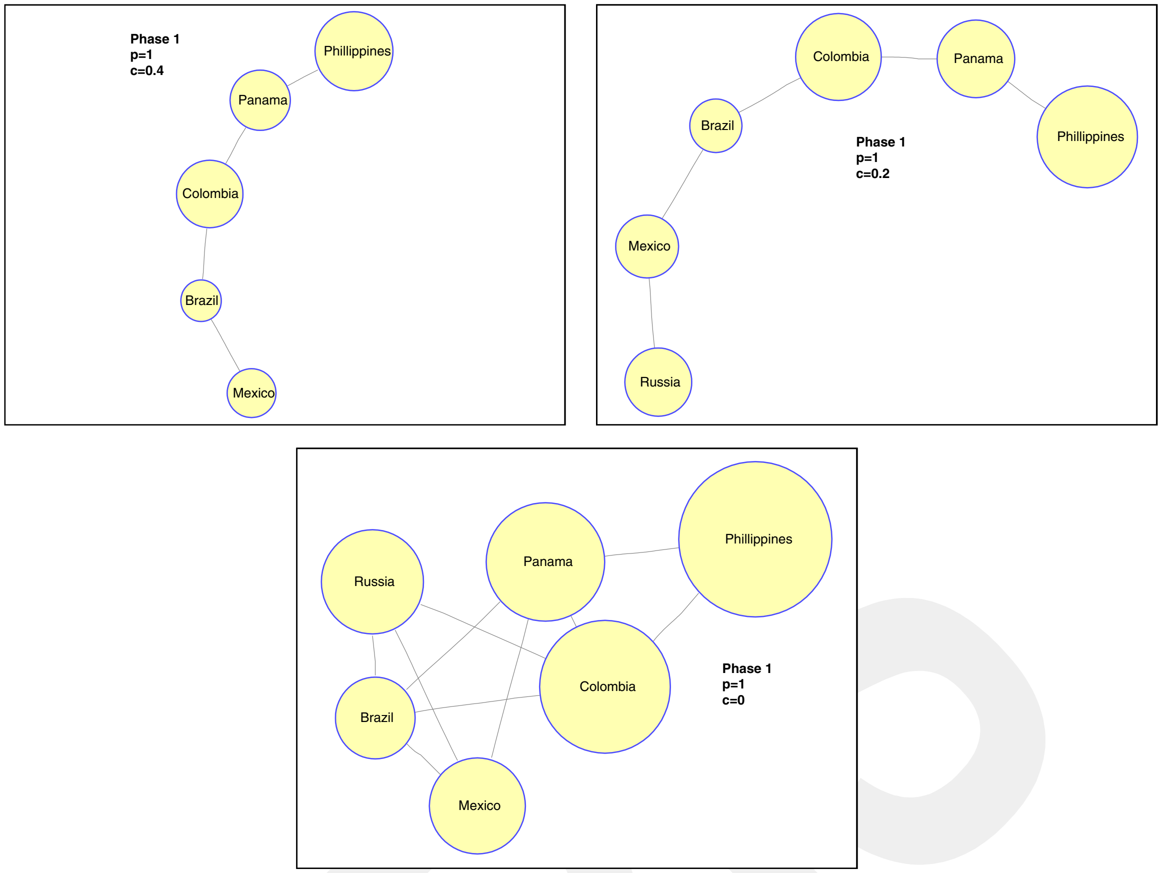

Fig. 3. *p*-Stable networks for $p = 1$ and different *c*-levels in phase 1 (there does not exist a *p*-stable network for $c = 1$, 0.8 and 0.6 when $p = 1$).

In the following, Figs. 3–7 display the *p*-stable networks for selected (p, c) combinations in phase 1. For the same combinations, Figs. 8–12 show the *p*-stable networks in phase 2.[10]

3.2.1. General view

Figs. 3–12 display the detailed results of our analysis and they will be mentioned in a while. However at first, we will try to provide a bigger picture of what's going on in phase 1 and phase 2 for ease of understanding.

In Figs. 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. Naturally, having more than one circle in a box is a representative of segmentation. The numbers in each circle represent the number of countries belonging to that cluster. Finally, the sum of the numbers in a box gives the number of stable connections for that specific (p, c) combination.

A natural analysis of these structures involves the division of the (p, c) combinations into 4 main parts. These parts can be designated and interpreted intuitively as follows:

1. *Zone 1 (Integration Zone):* This part 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 joining together in Zone 1 can be thought of permanently (or long-term) and strongly integrated.
2. *Zone 2 (Contagion Zone):* This part 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 and connection in Zone 1 will also exist in Zone 2, countries joining together only in Zone 2 can be thought to be strongly, however temporary (or short-term) connected to each other. This type of connection shall be considered as contagion instead of integration.
3. *Zone 3 (Weak-interdependence Zone):* This part 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 and connection in Zone 1 will also exist in Zone 3, countries joining together only in Zone 3 can be thought to be weakly interdependent to each other. Therefore, this type of connection shall be considered as weak interdependence.
4. *Zone 4 (Dis-integration Zone):* This part 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 joining to the whole system only in Zone 4 can be thought of outliers. They may be considered to be dis-integrated from the others.

Comparing Figs. 13 and 14 yields to some crucial observations: First of all, 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 $c = 1$. This shows that the global financial crisis results with strong integration of some emerging countries. A direct measure of this phenomenon is the number of countries in a stable network per box in Zone 1. The higher this number is, the more emerging countries get integrated to each other. Accordingly, this value is 5.33 in phase 1, whereas it is 7.33 in phase 2.

[10] The size of the circles in the figures do not have any economic interpretation and are chosen for optimal allocation purposes when constructing networks.

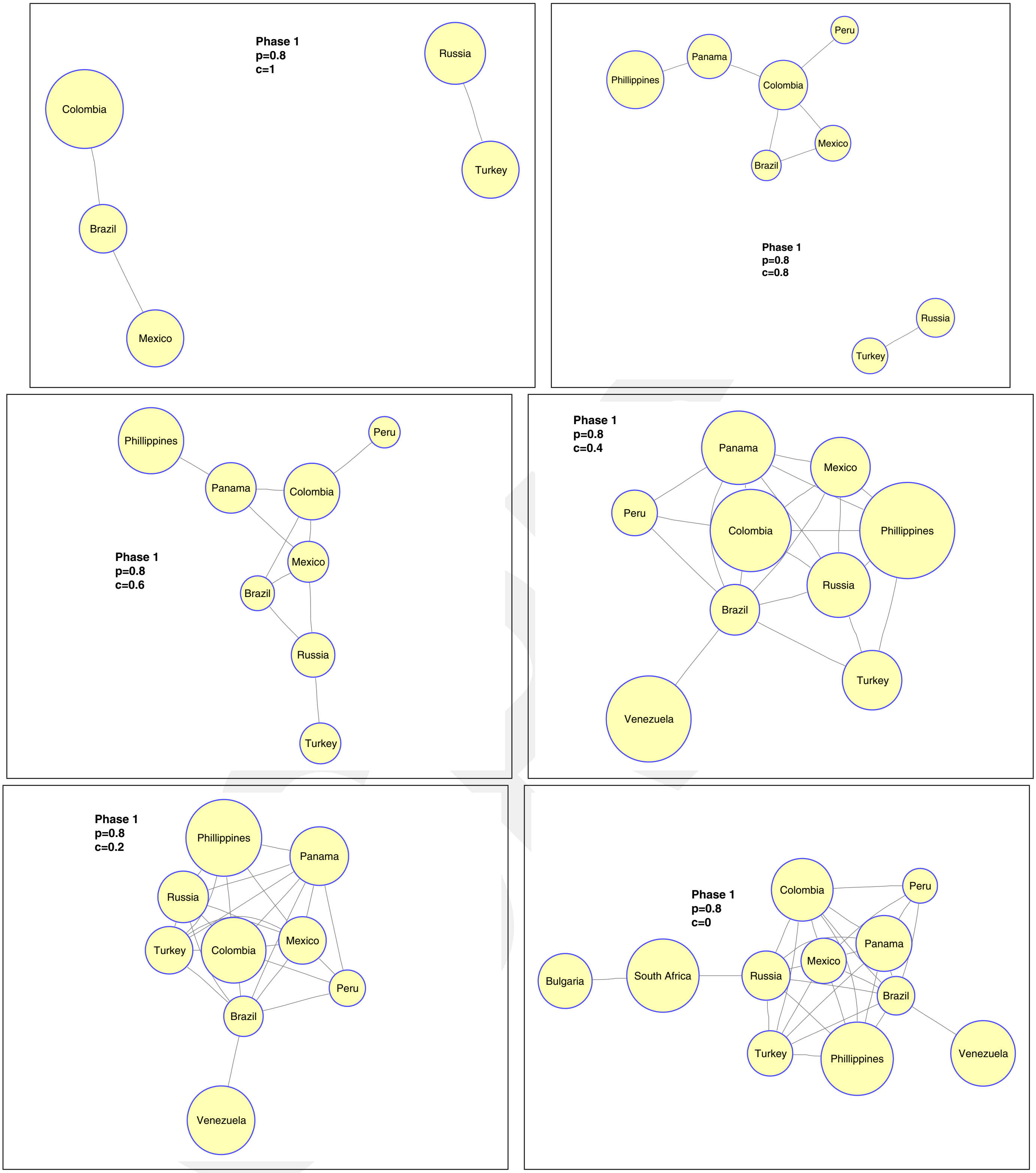

Fig. 4. *p*-Stable networks for $p = 0.8$ and different *c*-levels in phase 1.

Secondly, the same crisis also results with some specific segmentations among emerging markets. A direct way to see this phenomenon is to observe the number of clusters in a stable network in Zone 1. The higher this number is, the more segmentation occurs among emerging markets. In phase 1, the number of such clusters per box is 1. This values increases up to 1.67 in phase 2. Therefore, emerging countries tend to have sub-group integrations after the global financial crisis.

Finally, an interesting point arises in 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, which means that there is enough amount of dependency among emerging markets to connect at least one of

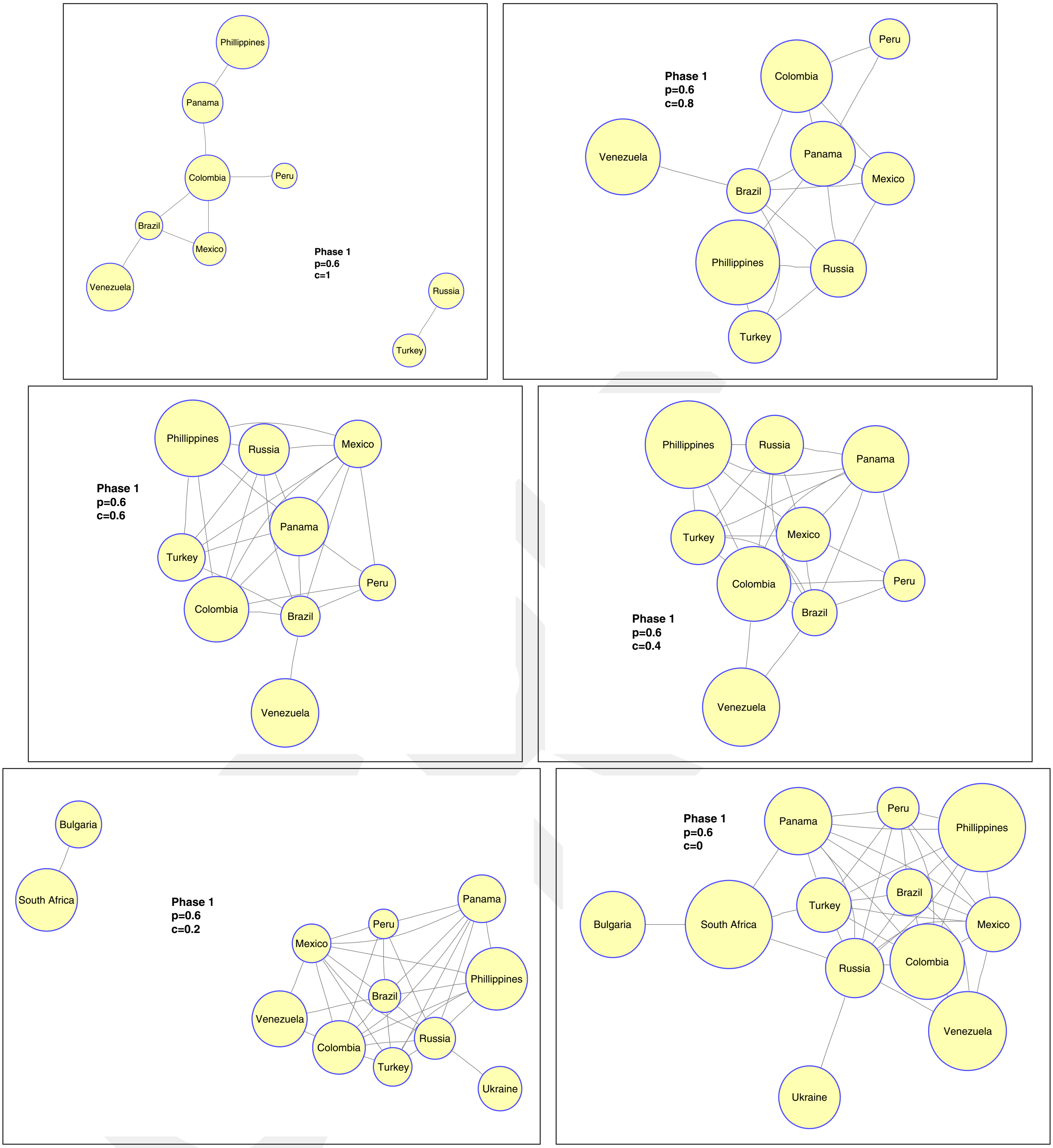

Fig. 5. *p*-Stable networks for $p = 0.6$ and different *c*-levels in phase 1.

them to some other. However, this is not the case in phase 2: as it can be easily observed, maximum number of countries included in a stable network is twelve in this period; meaning that no matter the choice of (p, c) combination, one country will always be missing in the stable network structure. This event is also supported by the observation that the number of countries per box in Zone 4 is 12.67 in phase 1, whereas this number is 10.5 in phase 2. Therefore, with the weakest satisfactory conditions to have a stable connection, phase 2 tends to miss such connections on the average. These cases shall indicate the dis-integration of some members from others after the global financial crisis.

As stated previously, mean of the dynamic conditional correlations between bond returns is found to be significantly higher in phase 2 than in 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

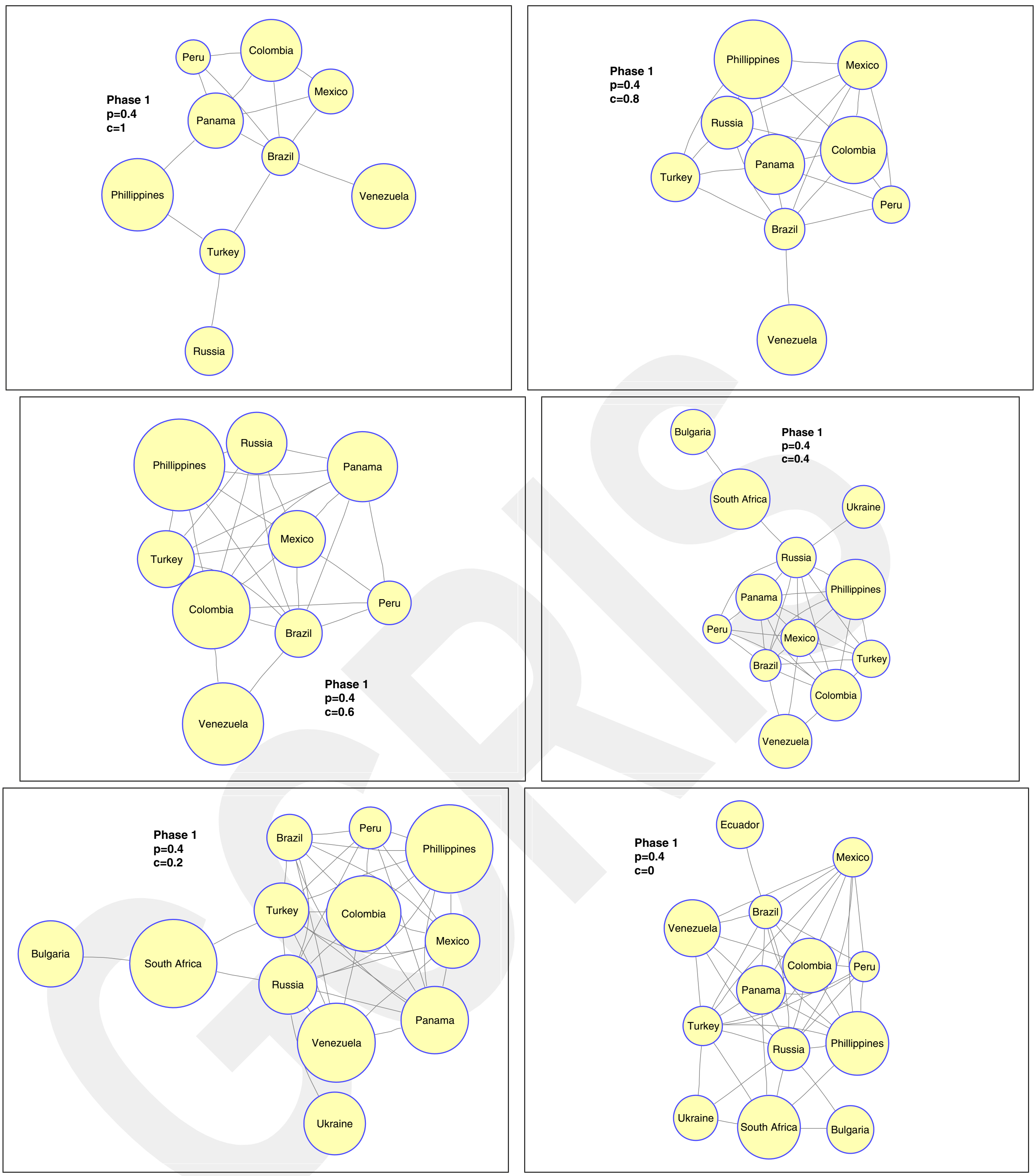

Fig. 6. *p*-Stable networks for $p=0.4$ and different *c*-levels in phase 1.

exhibit high within-cluster co-movement but not between-cluster co-movement. The summary statistics used in our network comparisons are given in Table 3.

3.2.2. *Micro details*

Fig. 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.

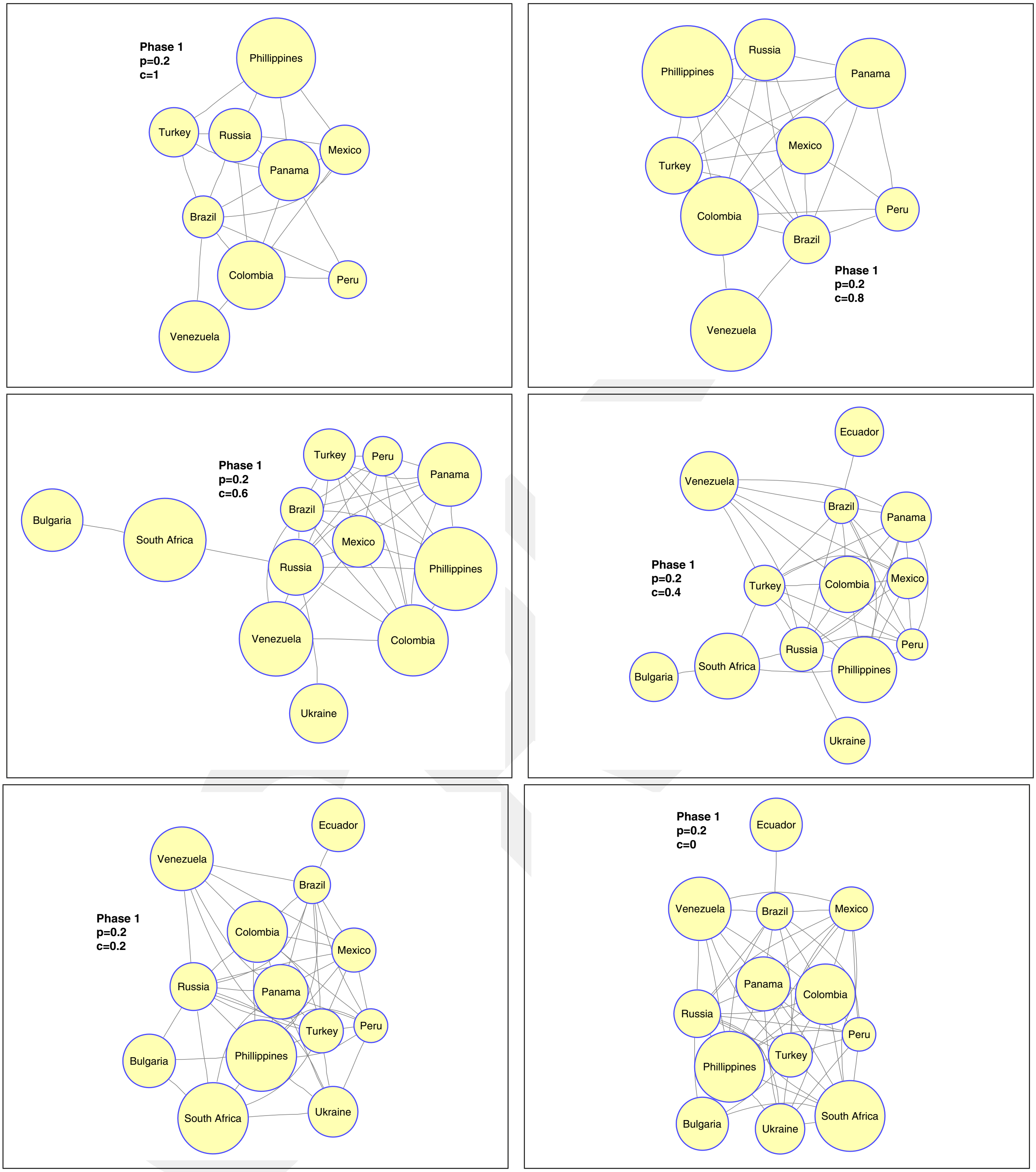

Fig. 7. *p*-Stable networks for $p = 0.2$ and different *c*-levels in phase 1.

Fig. 4 presents the results for $p = 0.8$ in phase 1, which is still a high value as the network will 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 is very much likely to be one of the reasons that causes these links.

In Fig. 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

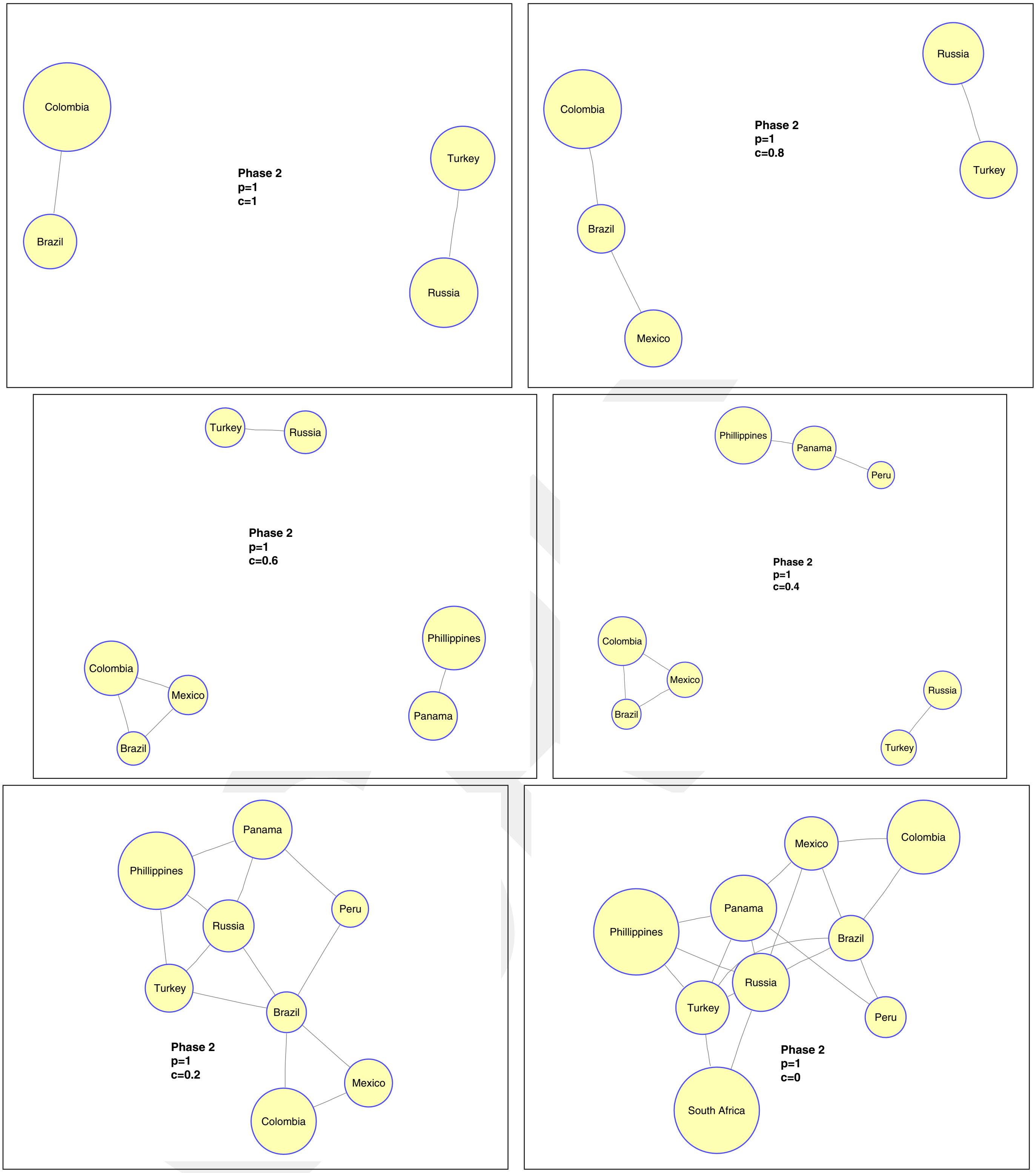

Fig. 8. p-Stable networks for $p = 1$ and different c-levels in phase 2.

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.

Figs. 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.

Fig. 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

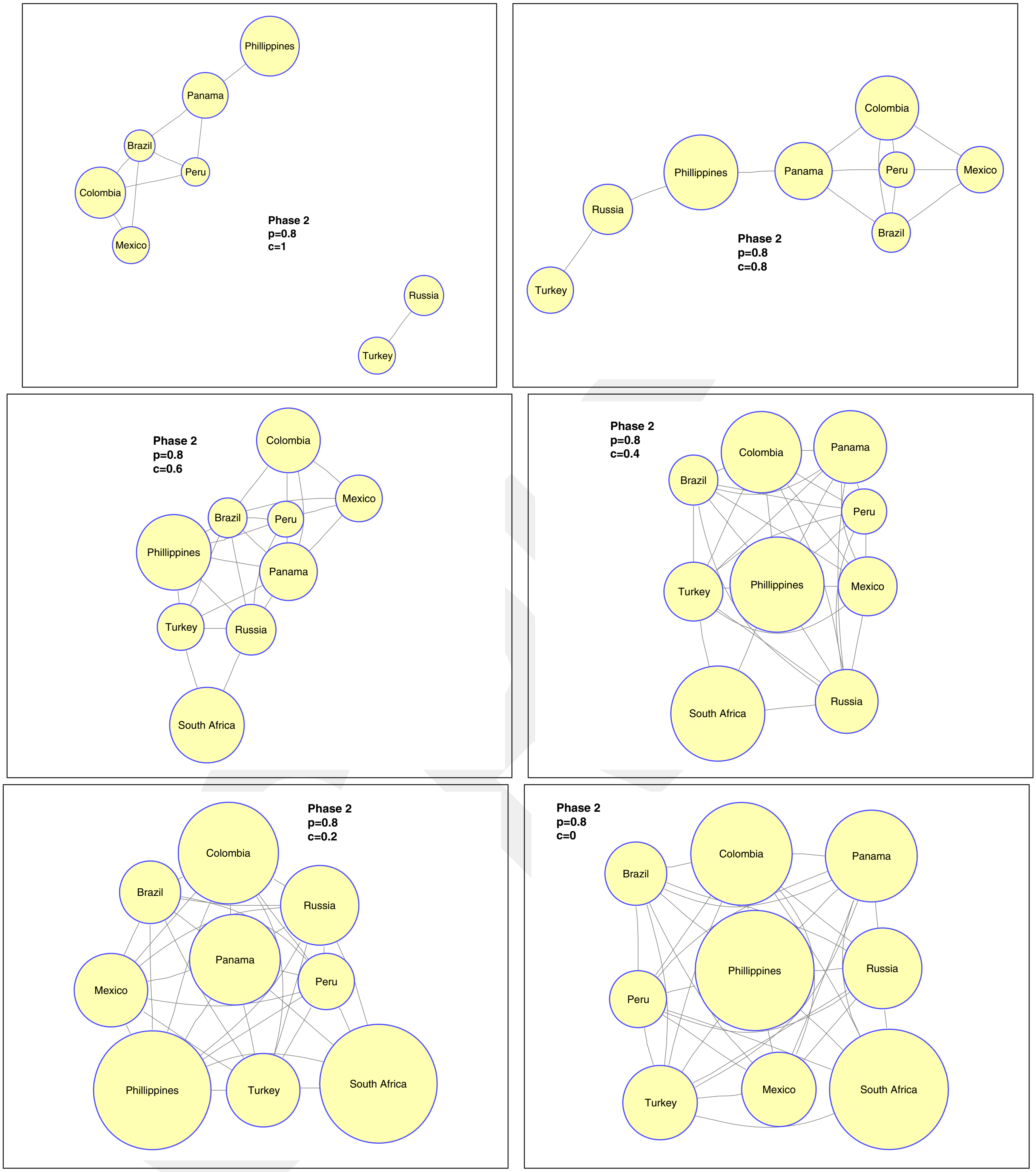

Fig. 9. p-Stable networks for $p = 0.8$ and different c-levels in phase 2.

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

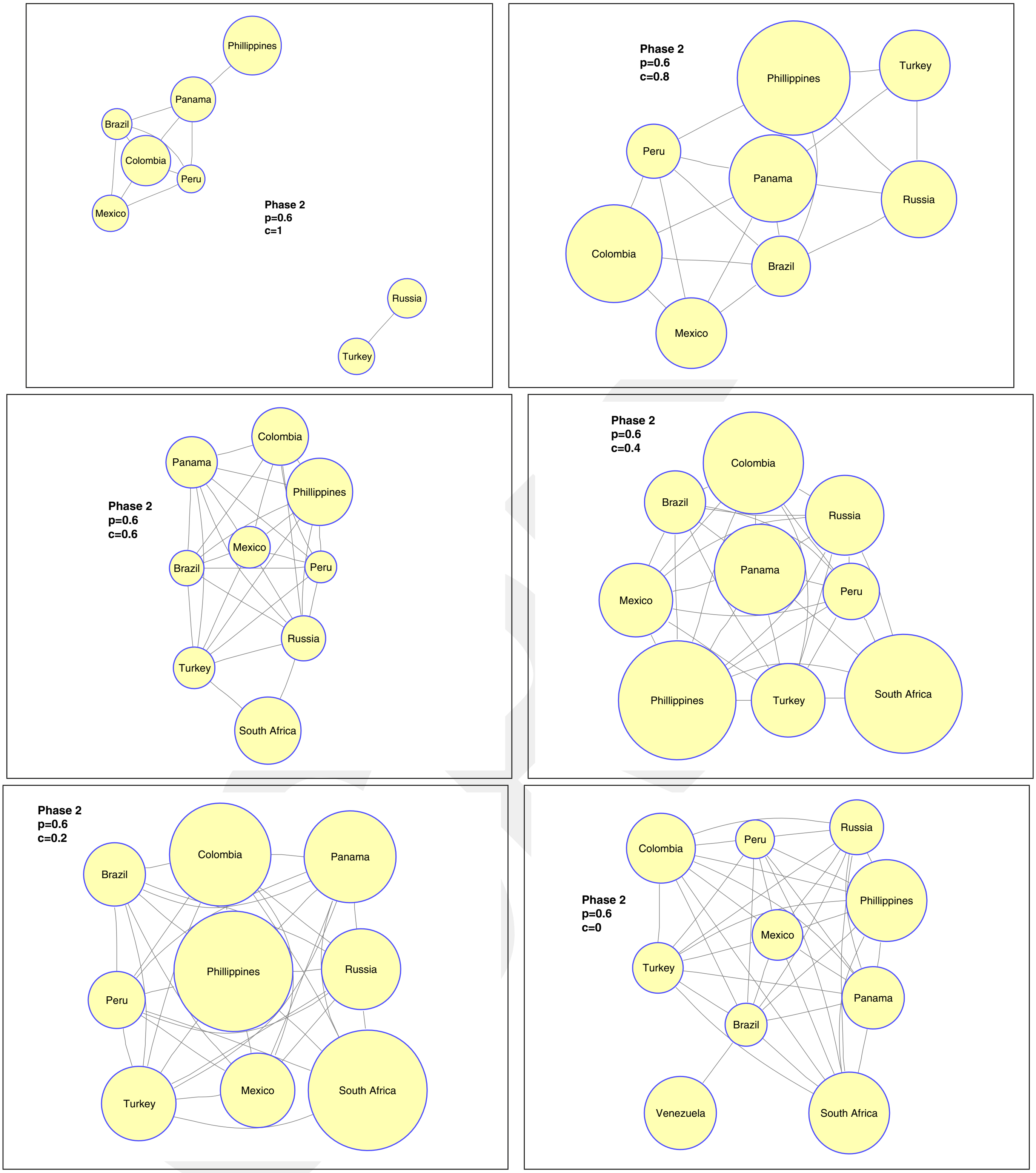

Fig. 10. *p*-Stable networks for $p = 0.6$ and different *c*-levels in phase 2.

structure after the crisis. Also, one can witness the dis-integration of Ecuador from the others as it cannot join the network for any (p, c) combination. Other than that, we find similar results as in the phase 1 case from Figs. 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 countries in our study. It is worth remembering that if some

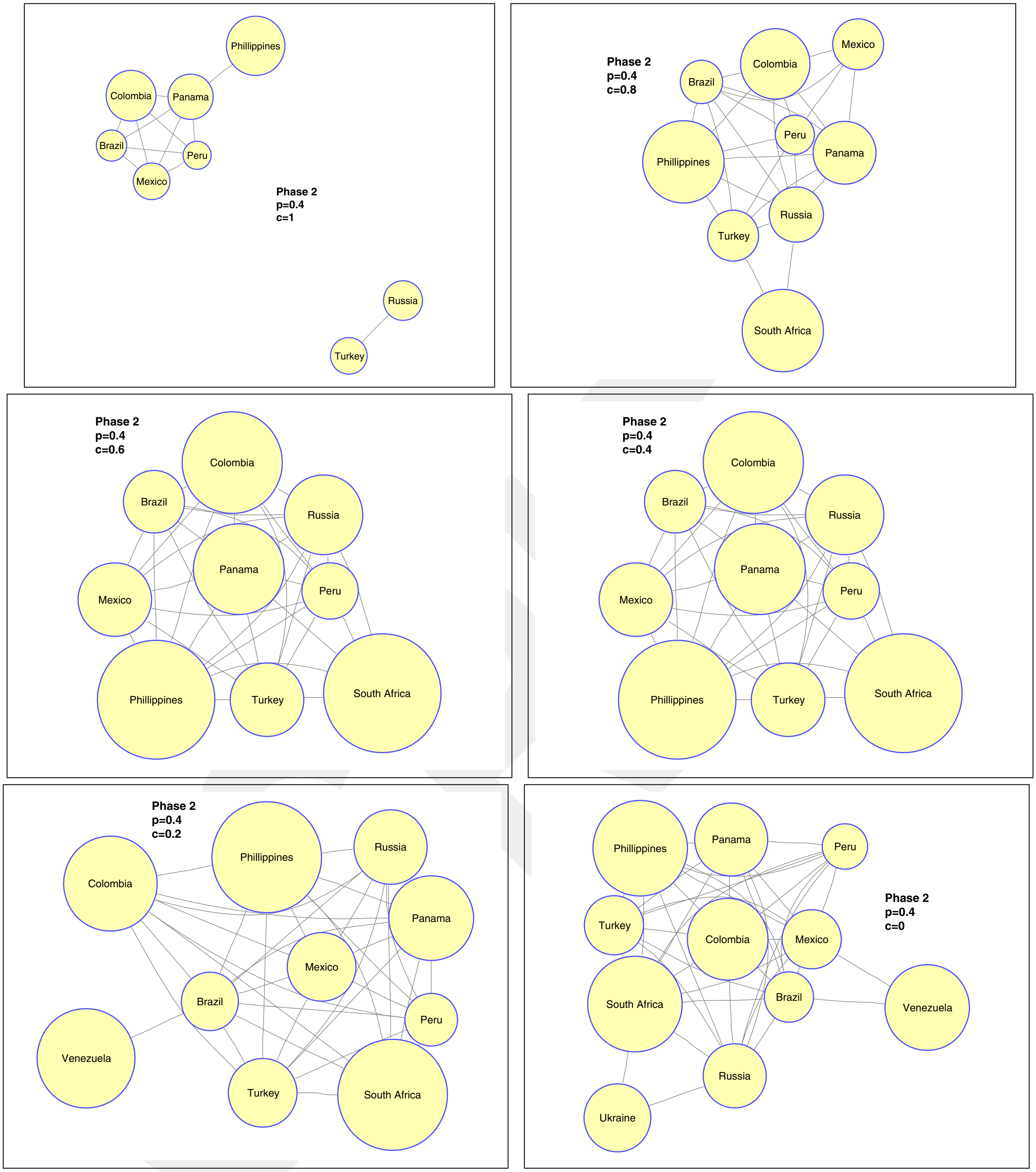

Fig. 11. *p*-Stable networks for $p = 0.4$ and different c-levels in phase 2.

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 Fig. 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

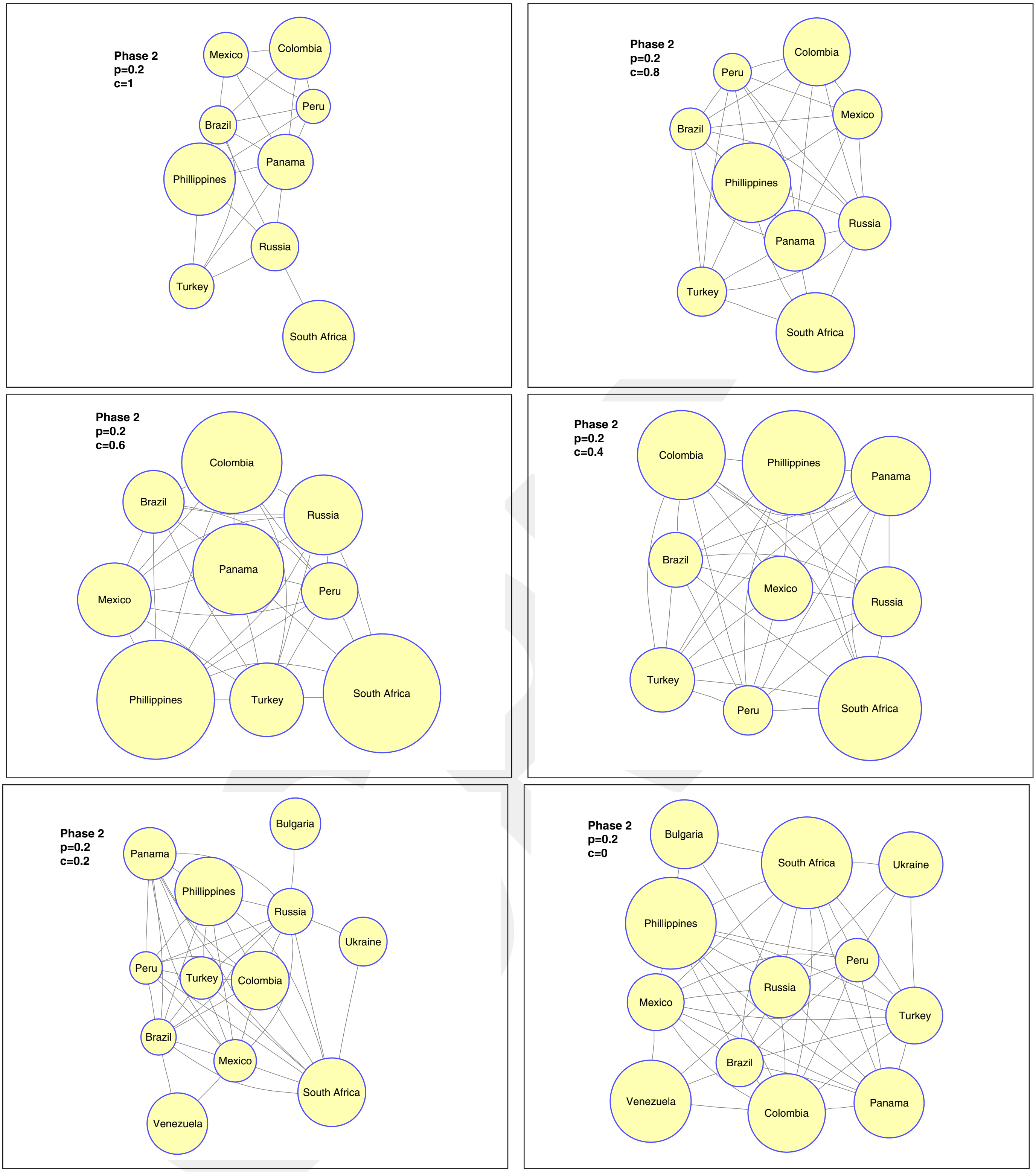

Fig. 12. *p*-Stable networks for $p = 0.2$ and different *c*-levels in phase 2.

same clusters. Fig. 15 displays these policy rates. We can see that the above argument is not valid as the policy rates do not present significant collective behavior within clusters.

3.2.4. Relation with the macro-vulnerabilities

In an attempt to search for the main factors that determine markets segmentation of EM sovereign bond markets, except from the geographical factor, we focus on the key indicators for macroeconomic vulnerability; namely net government debt to GDP, current account deficit to GDP, and budget balance to GDP ratios. The following Figs. 16–18 display annually how these ratios evolve through the beginning of phase 1 to the end of phase 2. Table 4 presents the simple correlations between the annual changes in these key indicators for the countries in the same clusters. Finally,

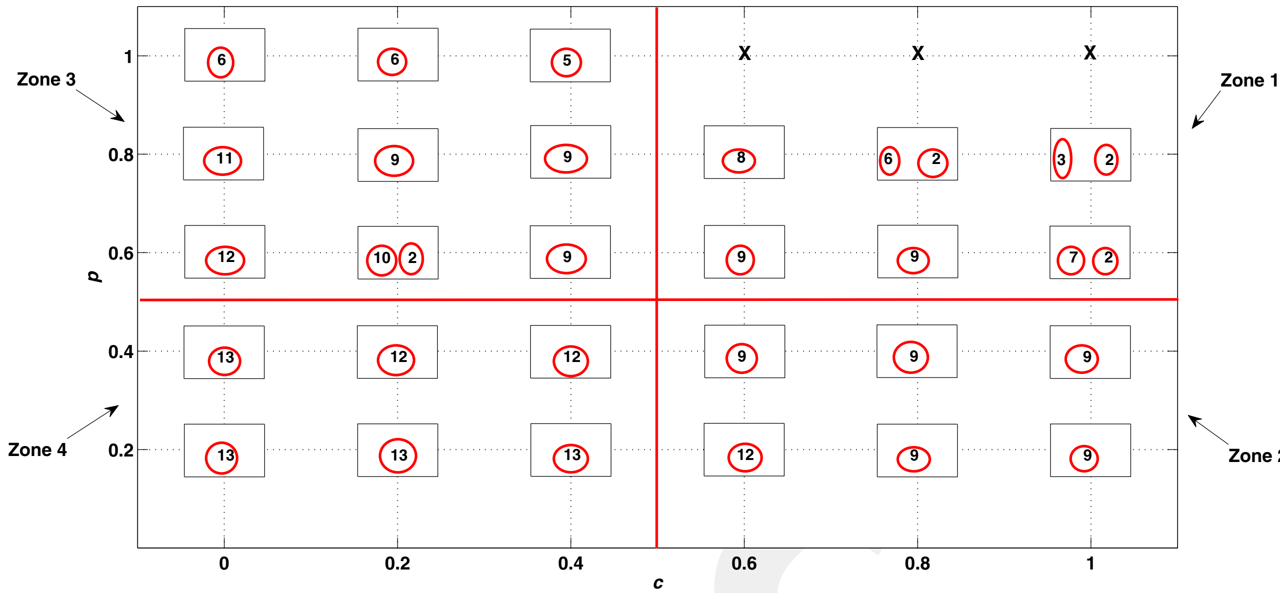

Fig. 13. Each box corresponds to a *p*-stable network for different (*p*, *c*) combination in phase 1. Each circle in a box denotes a cluster and the number in the circles represent the amount of countries belonging to that cluster. Total number in a box corresponds to the amount of countries belonging to that *p*-stable network.

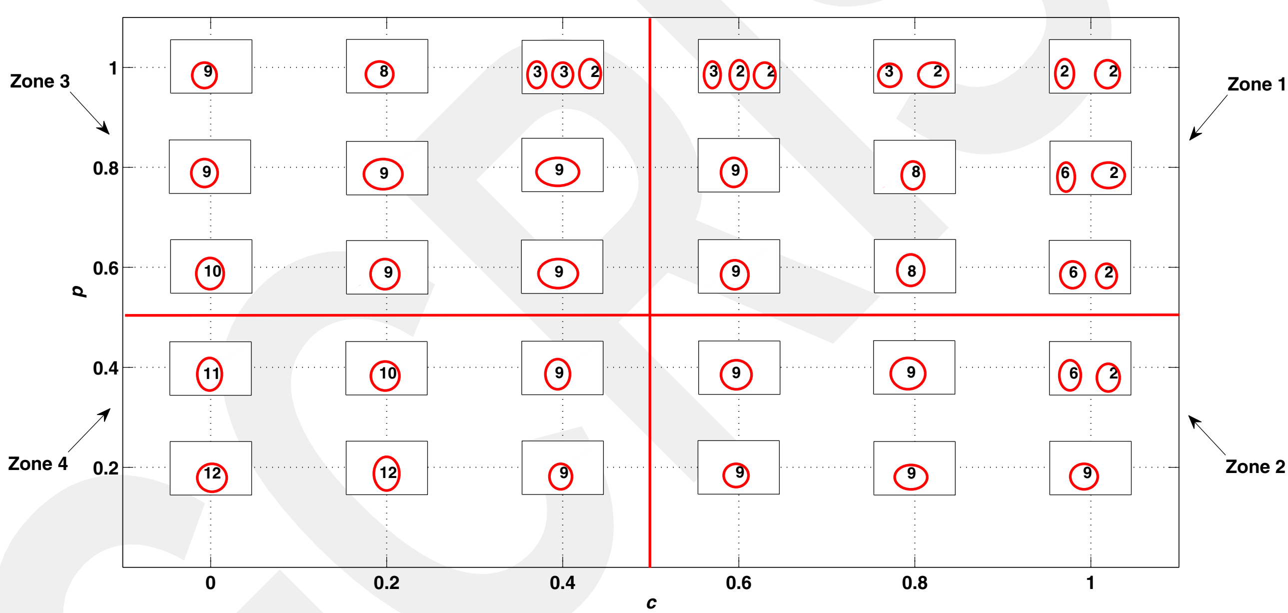

Fig. 14. Each box corresponds to a *p*-stable network for different (*p*, *c*) combination in phase 2. Each circle in a box denotes a cluster and the number in the circles represent the amount of countries belonging to that cluster. Total number in a box corresponds to the amount of countries belonging to that *p*-stable network.

Figs. 19–21 shows the annual averages of these ratios in phase 1 and phase 2. Accordingly, we obtain striking results.

For all these countries with full access to international financial markets, a cross-country comparison of net government debt to GDP and current account to GDP ratios shows that the distribution of these ratios within the clusters remains on average relatively stable passing from phase 1 to phase 2 (Figs. 20 and 21). Therefore, the heterogeneous picture is preserved for these macro-vulnerability

Table 3
Average statistics comparison of the network analysis between phases.

	Phase 1		Phase 2	
	Clusters/(*p*, *c*)	Countries/(*p*, *c*)	Clusters/(*p*, *c*)	Countries/(*p*, *c*)
Zone 1	1.00	5.33	1.67	7.33
Zone 2	1.00	9.50	1.17	8.83
Zone 3	1.11	8.78	1.22	8.89
Zone 4	1.00	12.67	1.00	10.50

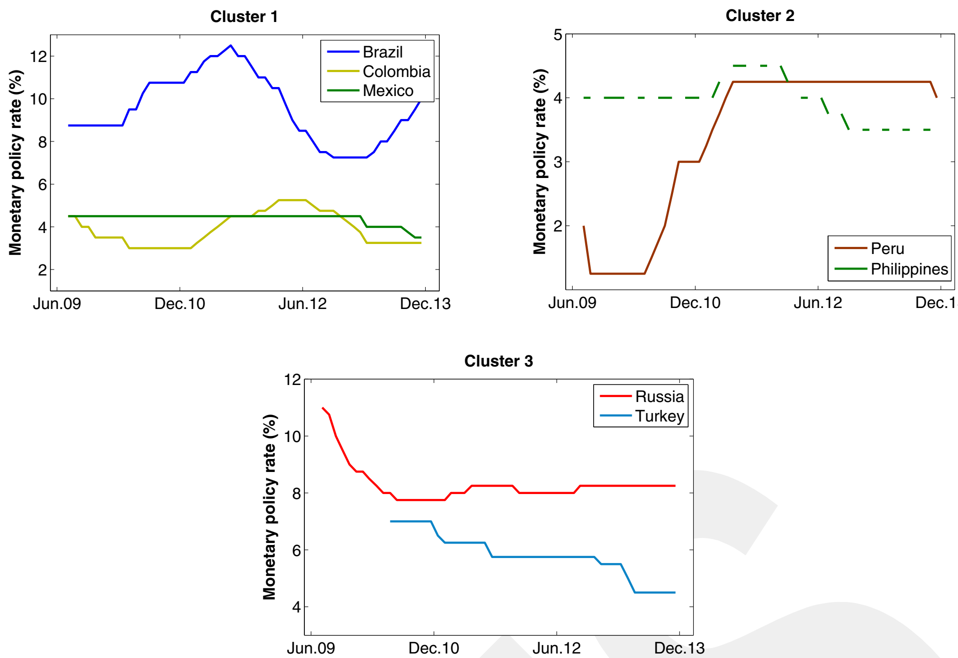

Fig. 15. Monetary policy rates of the emerging countries within the same clusters in phase 2 (Panama is not included in Cluster 2 due to its unique monetary system i.e. it has no central bank).

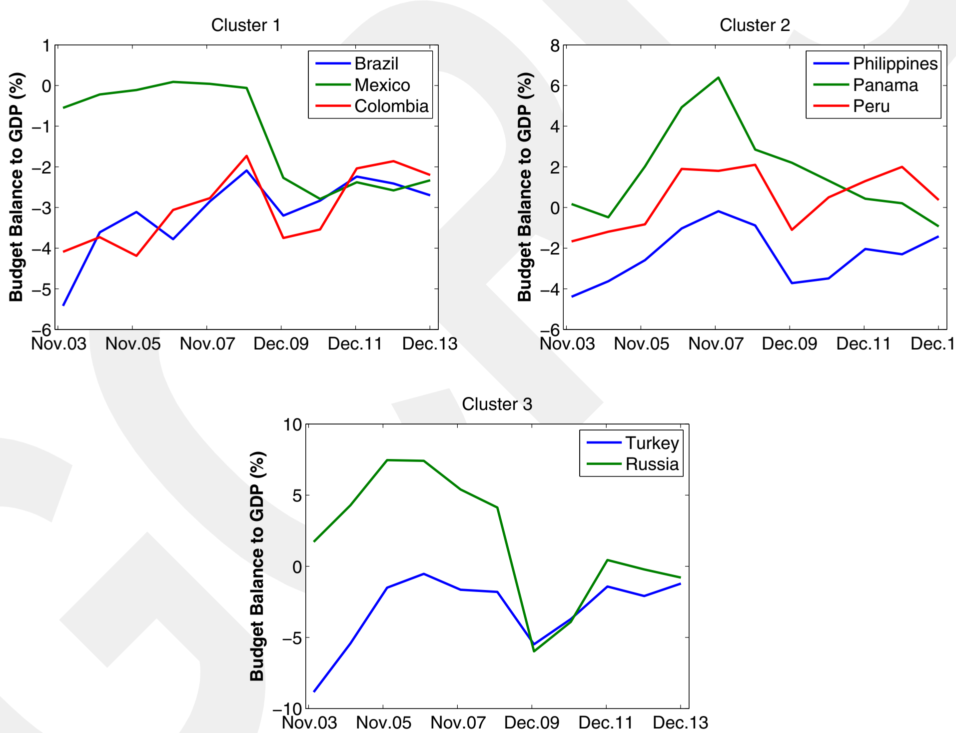

Fig. 16. End of year budget balance to GDP ratios of the emerging countries within the same clusters.

ratios. Similarly, the annual values of these ratios given in Figs. 17 and 18 do not present any promising result on explaining the reasons for the clustering scheme in our analysis.[11]

However, we observe a level-wise converge in budget balance to GDP ratios for the countries within the same cluster in phase 2 (Fig. 16). This convergence is also validated by comparing the

[11] For example, in the case of current account deficit to GDP ratio in cluster 3 (Russia and Turkey), while Russia is being challenged to improve on a weak growth outlook in phase 2 without having serious current account deficit problems (still having surplus in every year post-crisis), Turkey is being challenged to address potential sudden stop problems in capital flows as the country is struggling with short term capital flows compensating for a shortfall in foreign direct investments and long term external borrowing in the same period. Similarly, valid explanations can also be given for the other clusters in explaining the poor explanatory performance of the current account deficit to GDP and net government debt to GDP ratios.

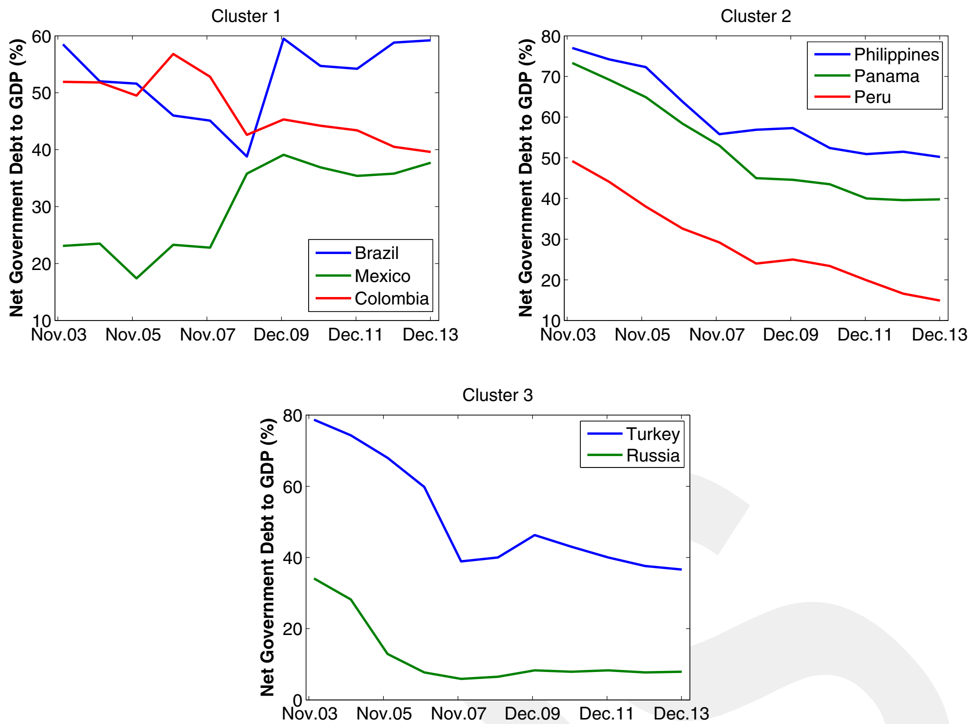

Fig. 17. End of year net government debt to GDP ratios of the emerging countries within the same clusters.

average budget balance to GDP ratios in phase 1 and 2, except the case of Philippines (Fig. 19).

Not only level-wise, but direction-wise the budget balance to GDP ratio outperforms the others in terms of explaining the clustering scheme in phase 2. Simple correlations show that the mean co-movement degree of budget balance to GDP ratio in cluster 1, cluster 2 and cluster 3 are 0.60, 0.49 and 0.92, respectively. Whereas the same averages for net government debt to GDP are significantly lower than the budget balance to GDP ratio and are −0.02, 0.44 and 0.32 for cluster 1, cluster 2 and cluster 3, respectively. Similar case is also observed for the current account deficit to GDP ratio, except the case of cluster 2.

Accordingly, among three key macro-vulnerability indicators, budget balance to GDP ratio performs significantly better than others in explaining the determinants of the markets segmentation of EM sovereign bond markets after the recent global financial crisis.

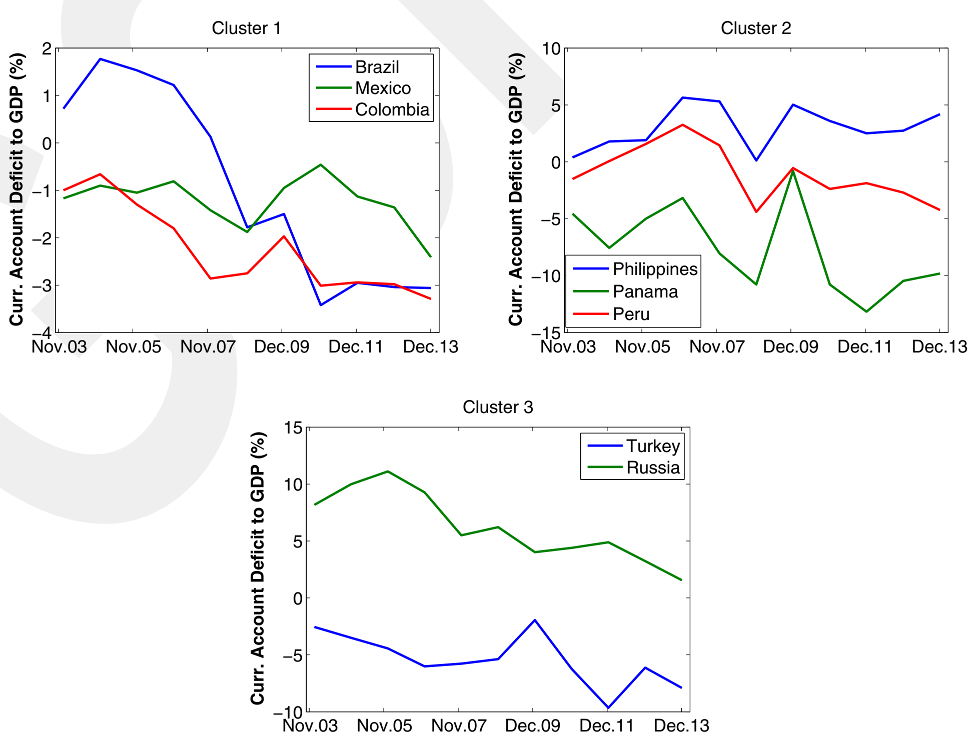

Fig. 18. End of year current account deficit to GDP ratios of the emerging countries within the same clusters.

Table 4
Cross country correlations between annual changes in analyzed macro-variables.

	Brazil	Mexico	Colombia	Philippines	Panama	Peru	Turkey	Russia
Panel A: Cross-correlations between annual changes in budget balance to GDP ratios within clusters 1, 2 and 3								
Brazil (C1)	1	0.57	0.46					
Mexico (C1)		1	0.78					
Colombia (C1)			1					
Philippines (C2)				1	0.45	0.68		
Panama (C2)					1	0.33		
Peru (C2)						1		
Turkey (C3)							1	0.92
Russia (C3)								1
Panel B: Cross-correlations between annual changes in net government debt to GDP ratios within clusters 1, 2 and 3								
Brazil (C1)	1	−0.09	0.24					
Mexico (C1)		1	−0.22					
Colombia (C1)			1					
Philippines (C2)				1	0.34	0.22		
Panama (C2)					1	0.75		
Peru (C2)						1		
Turkey (C3)							1	0.32
Russia (C3)								1
Panel C: Cross-correlations between annual changes in current account deficit to GDP ratios within clusters 1, 2 and 3								
Brazil (C1)	1	0.07	0.57					
Mexico (C1)		1	0.27					
Colombia (C1)			1					
Philippines (C2)				1	0.65	0.87		
Panama (C2)					1	0.60		
Peru (C2)						1		
Turkey (C3)							1	−0.43
Russia (C3)								1

Note: C1, C2 and C3 denote clusters 1, 2 and 3 respectively.

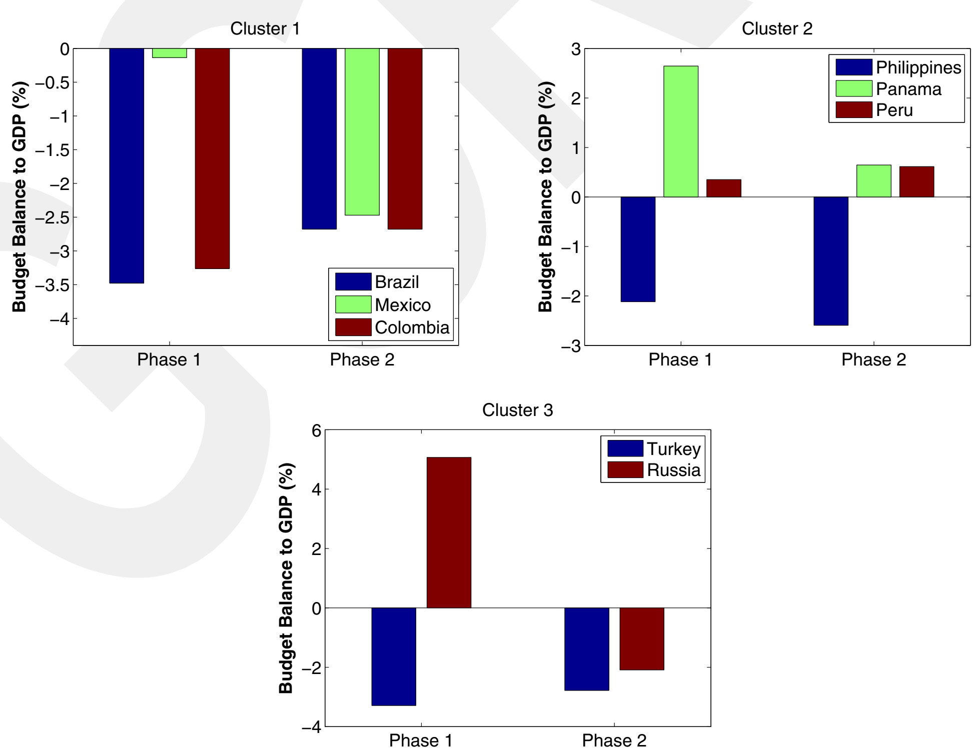

Fig. 19. Annual averages of budget balance to GDP ratios of the emerging countries within the same clusters in phase 1 and phase 2.

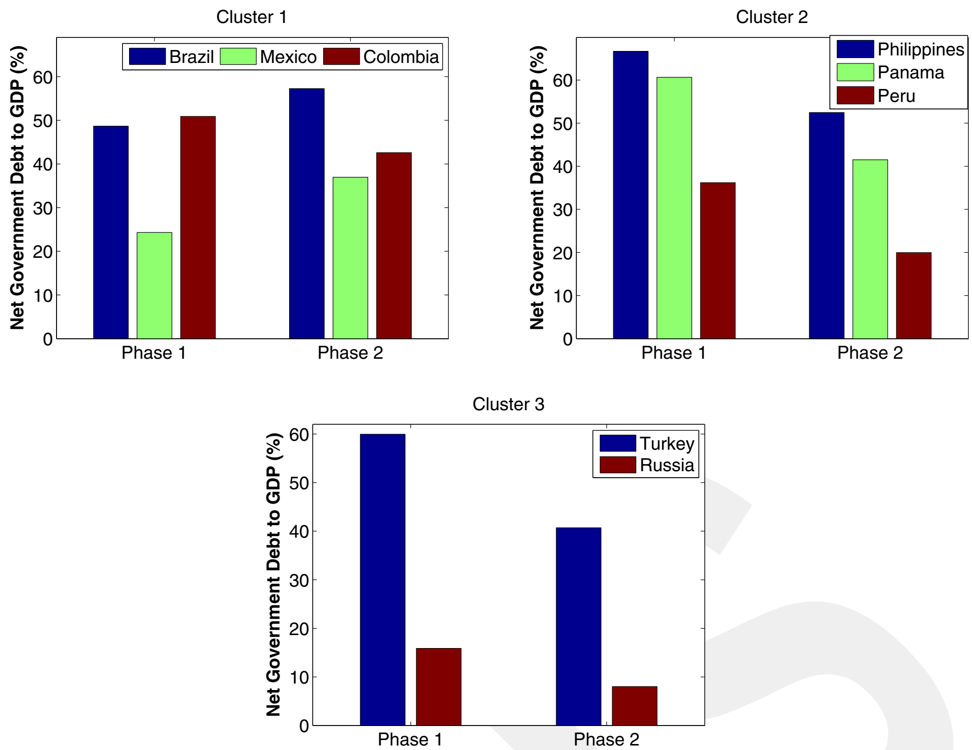

Fig. 20. Annual averages of net government debt to GDP ratios of the emerging countries within the same clusters in phase 1 and phase 2.

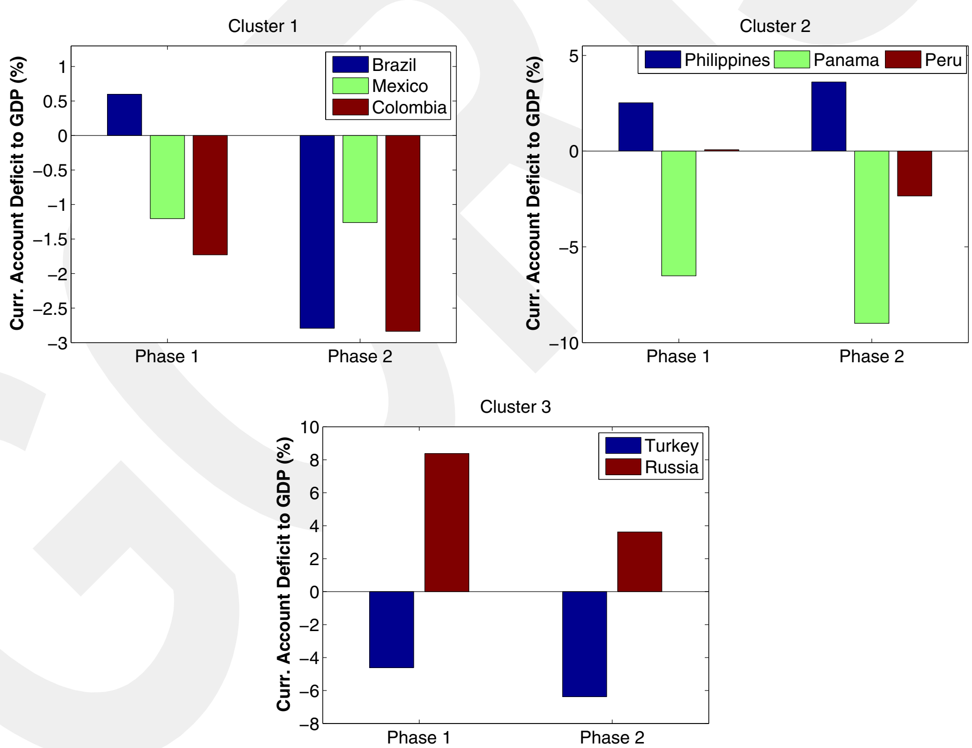

Fig. 21. Annual averages of current account deficit to GDP ratios of the emerging countries within the same clusters in phase 1 and phase 2.

4. Conclusion

The quantitative easing policy that has been launched by the 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 flows to 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.

In further attempts to search for the main factors that determine markets segmentation of EM sovereign bond markets, except from the geographical factor, we focus on the key indicators for macroeconomic vulnerability; namely net government debt to GDP, current account deficit to GDP, and budget balance to GDP ratios. Accordingly, we show that among these key macro-vulnerability indicators, budget balance to GDP ratio outperforms others significantly and present satisfactory evidence in explaining the post-crisis segmentation.

Although the results depend critically on the sample period used,[12] 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 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.[13] 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 findings are in line with those provided by the Fed in the sense that emerging market economies cannot be considered as a whole after the global financial crisis. Accordingly, international investors should not think of 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 results. 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 policy-makers and investors.

[12] They might have been different if the sample extended until, say, end 2015.

[13] 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.

Appendix A. Time-varying descriptive statistics of the DCC matrix R_t

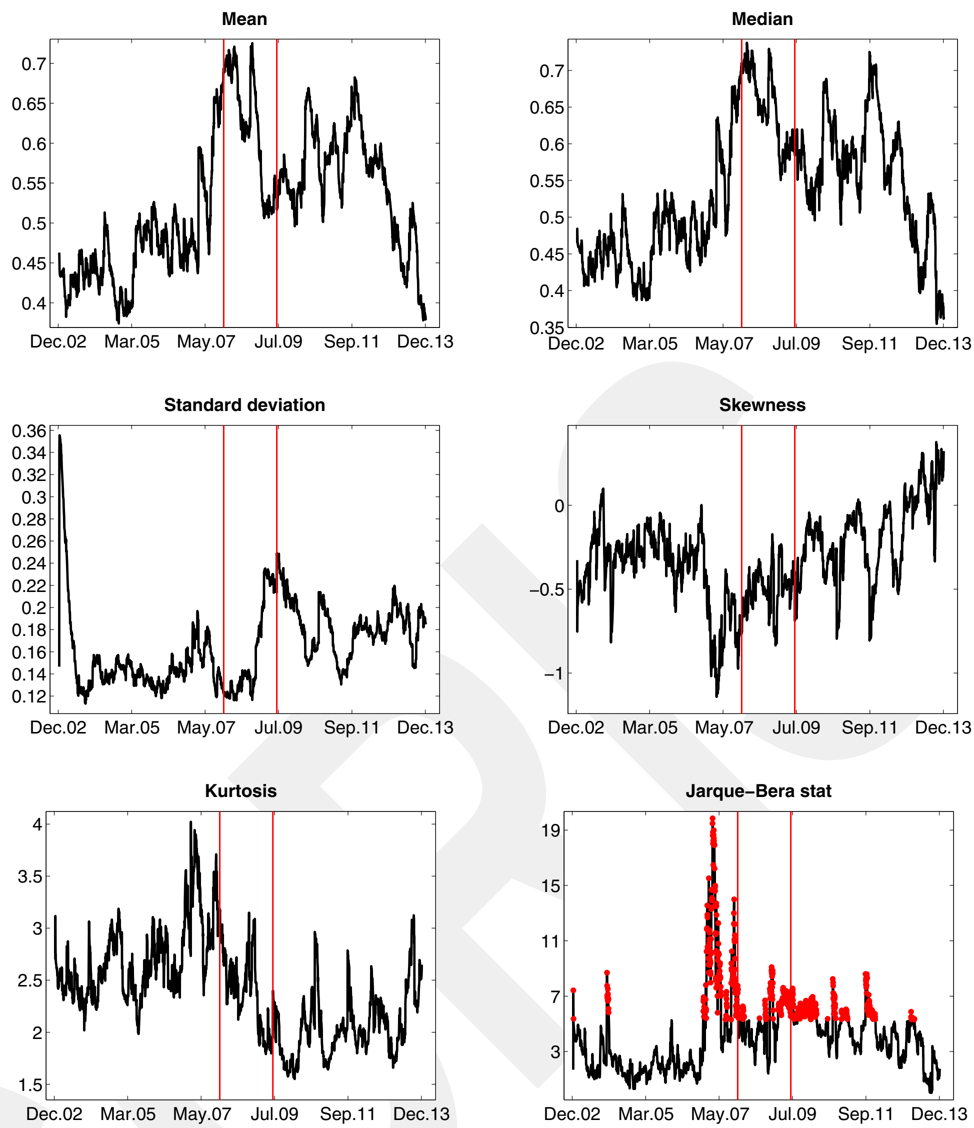

Fig. A1. Time-varying descriptive statistics of the dynamic conditional correlation matrix R_t. Red vertical lines split the pre-crisis, crisis and post-crisis periods according to NBER. Red points in the J–B stat denote the rejection of normality at 5% significance level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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