International Stock Markets Linkages: A Dynamic Factor Model Approach

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Abstract

This paper investigates international stock market dynamics and their linkages. It uses factor models to extract stock market indicators from common cyclical stock components of industrialized countries, emerging markets, the BRICT, and global stock markets. We find that the stock market indicators for these groups are correlated with each other and with the global market factor. The BRICT display the highest average stock return and are the least correlated with the others. The stock return indicators as well as the global stock market factor show close relationship with economic downturns, entering in bear phases around the beginning of recessions, and in bull phases mid-way through recessions, anticipating future economic recovery. We also find that the stock return indicators are more persistent and, therefore, more predictable than the stock market of individual countries. We study international linkages across these stock market groups through impulse response analysis and find that economic development levels play an important role in shock propagation. In particular, all stock market indicators respond positively to global factor shocks, with the least reactive group being the BRICT, and the most responsive being the emerging markets. Interestingly, the BRICT respond negatively to positive shocks to industrialized countries stock markets, indicating that the BRICT may have a role in hedging risk.

Keywords: Stock Market indicators, Stock Return, Global Markets, Dynamic factor Model, Market Integration, Country Risk, International Stock Return, Business Cycle, Recessions, BRIC, Emerging Markets, Euro Area.

JEL Classification Code: G1, C32

1. Introduction

In recent decades, global markets have become increasingly more integrated, with less international capital and trade restrictions and stronger financial linkages across countries. Some of the reasons are the establishment and development of the Euro Area, which unified major industrialized countries, the increased pool of countries that evolved as emerging economies, and the advances of the BRICT, which have become powerhouses of recent economic growth.[1]

Progressive globalization has led to a worldwide interest from governments and the private sector in conducting their activities in light of both national and international economic and financial conditions. Changes in economic fundamentals in different parts of the world can influence the competitive position of businesses and the effectiveness of local government policies, even of those not directly related to international operations. This integration impacts the performance of firms, and therefore their stock returns. Thus, there is a strong connection between international business cycles and stock markets.

This paper investigates the dynamics of international stock markets and their linkages. The performance of international stock markets is not directly observable, but it can be evaluated through the construction of indicators. We use dynamic factor models to extract common cyclical components from stock markets across countries as stock market indicators. We first model stock markets of group countries according to their economic development. We consider 24 of the most prominent markets, and group them as industrialized countries, emerging markets, and the BRICT. We then model each group of country as a function of an unobserved common factor and an idiosyncratic term. The unobserved dynamic factor summarizes underlying information common to the stock returns of the countries within the group, and separate out idiosyncratic movements that are specific to each country. Thus, as an outcome of the first approach we obtain three stock market indicators for the groups

[1] The countries included in the BRICT are Brazil, Russia, India, China and Turkey. The selection of these countries and those studied as emerging markets is discussed in section 2.1.

considered. We next use the framework to obtain a global stock market indicator based on data from all countries considered, and to examine the international linkages across country groups.

A large strand of literature traditionally uses correlation approach to study financial market linkages and contagion.[2] However, complex economic and financial systems cannot be appropriately described using only pair-wise correlation between countries. The comovement among markets might be driven by several factors hitting countries simultaneously or by common cyclical factors, which cannot be captured using pairwise correlation. Additionally, in order to study global linkages, the number of pair-wise correlation increases exponentially with the number of countries considered, which poses estimation difficulty.

The proposed dynamic factor model extracts common components of international economic movements and circumvent several problems faced by this traditional approach. The common factors representing stock market for groups of countries and global financial markets enable examination of their dynamics and interactions among a multitude of financial markets in a parsimonious way.

There is a vast literature studying comovements of business and financial cycles across countries starting with the earlier work of Mitchell [1927] and Morgenstern [1959]. Theoretical approaches were pioneered by Backus, Kehoe, and Kydland [1992, 1993] and Baxter and Crucini [1993], which propose international real business cycle models. The models generated some counterfactual results (e.g. negative output correlation), but served as background for later developments, such as in Kehoe and Perri [2002], Heathcote and Perri [2004], Iacoviello and Minettib [2006]. The results in these papers are divergent and the dynamics of international business cycles and crisis propagation are, thus, not conclusive.

Recent empirical literature on the relationship between international financial markets and business cycles also reaches divergent results.

[2] A more recent literature uses conditional dependence via copula-based framework or wavelet-based coherence measures, which circumvents some of the problems with pair-wise correlation approach.

Forbes and Rigobon [2001, 2002] study mechanisms of financial contagion, and find evidence of international interdependence but not contagion. Imbs [2004, 2006] and Davis [2014] study the relationship between financial integration and business cycle comovements and find a positive effect of the former on the latter. On the other hand, Kalemli-Ozcan, Papaioannou, and Perri [2013] and Kalemli-Ozcan, Papaioannou, and Peydro [2013] find a negative effect instead. Cheung, He, and Ng [1997] study the predictability of regional common components of stock markets for North America, Pacific Rim, and Europe, and find that only North America has some predictability over the other regions. Bekaert et al. [2009] study comovements in international stock return focusing at the country and industry sector levels and find an increase in return correlations for European stock markets but not for other countries. Bekaert et al. [2014] use factor model to study the dynamics of global stock markets during the 2008-2009 financial crisis, focusing on country and industry portfolios. They find small contagion effects from the U.S. or global markets but stronger contagion from equity markets to equity portfolios for countries with weak fundamentals. Kose, Otrok, and Whiteman [2003] use dynamic factor model to investigate global, regional, and country-specific business cycles and their comovements. They find that the world factor has a significant effect on the volatility of most countries, but regional business cycles do not.

More recently, Kose, Otrok, and Prasad [2012] argue that categorizing countries according to their geographic location has many pitfalls as countries within the same region might have very different fundamentals and, therefore, not share similar economic dynamics. These authors propose, instead, to categorize country groups according to their development level as industrialized, emerging markets, and other developing countries. They investigate the economic performance of these three groups and find that although country groups have become more integrated, global business cycles have become less important in contributing to the groups' business cycles.

In this paper we also classify stock returns into groups according to their economic development. However, as found in Bekaert et al. [2014] for international financial markets, and Kose, Otrok, and Prasad [2012] for global business cycles, there is recent evidence of decoupling of emerging economies from international global markets. We find evidence that this is primarily driven by the fact that the BRICT countries are considered together with other emerging economies, as discussed below. In our approach, we model separately stock markets for emerging economies and the BRICT, in addition to considering industrialized countries. This allows analysis of potential changes in the interactions of these different groups and international stock markets.

Our findings suggest that country specific stock markets are more correlated with their common group factor than with the countries within their group. We also find that the stock market factors from the group countries are correlated with each other, but a lot less than they are with the global market. The BRICT are the least correlated with the other groups and with the global markets. The stock market of these countries reflect their fundamentals, which seem to march to the beat of their own drums.

All stock return indicators as well as the global stock market index show a close relationship with recessions in the U.S. and Europe, usually decreasing substantially around the beginning of recessions - when income and earnings fall, and increasing mid-way through recessions, anticipating future economic recovery. Extensive empirical literature also finds evidence of systematic movements in stock returns related to business cycles. See for example, Whitelaw [1994], Hamilton and Lin [1996], Chauvet [1998/1999], Perez-Quiros and Timmermann [1998], Fama and French [1999], Chauvet and Potter [2000, 2001], Chauvet and Sun [2014], Chauvet, Senyuz and Yoldas [2015], etc.

The dynamic factors representing stock returns for the country groups and for the global market are more persistent and, therefore, more predictable than the stock market of individual countries. Idiosyncratic noise makes it difficult to detect the presence of predictable stock return components, as found in extensive literature. By construction, the dynamic factor model separates idiosyncratic noise from a common component underlying the observable stock returns, which is more predictable and more stable than country-specific stock market movements.

Further, BRICT stock returns are on average substantially higher than those from emerging markets and industrialized countries, while the stock return indicator for industrialized countries displays the lowest mean rate.

We study the lead-lag relationship across international markets through impulse response analysis. We find that countries with different economic development levels play different roles in shock propagation. In particular, all stock market indicators respond positively to a shock to the global stock market factor. The least reactive group to the global market is the BRICT, and the most responsive is the emerging markets. Interestingly, the BRICT respond negatively (positively) to a positive (negative) shock to the stock market of industrialized countries. This indicates that stock market of the BRICT may have a role in hedging risk in the stock market of industrialized countries.

The rest of the paper is organized as the follows. Sections 2 discusses the data and the proposed models, while Section 3 describes the estimation procedure. Section 4 reports the results for each of the country groups and for the global stock market. Section 5 discusses the linkages between these markets based on impulse response analysis, and Section 6 reports sensitivity tests. The last section concludes.

2. Modeling Stock Market Clusters and Global Stock Markets using Dynamic Factor Structures

2.1. Data

The dynamics of financial markets are examined using monthly stock returns from 24 countries. The representative market index selected for each country is the one with the largest market capitalization and longest time span. The countries selected can be categorized into three groups: 10 industrialized countries, the 4 BRIC countries with the addition of Turkey, and 9 emerging market economies. The sample studied was determined by the availability of data. The longest sample for which data are available for all countries is from September 1997 to August 2015. The data were obtained from Global Financial Data.[3] The complete list of data is described on Table 1.

[3] See https://www.globalfinancialdata.com/

The acronym BRIC was coined in the early 2000s by Jim O'Neil, former chairman of Goldman Sacks, to represent Brazil, Russia, India, and China, as those countries were developing at a fast pace, and were predicted to soon become global economic powers. The BRIC became a formal institution during its first Summit in 2009. In 2011 South Africa was considered as a member, although O'Neil and many others criticized the move since South Africa's economy and population are too small to be part of the group. Emerging countries that have largest potential future GDP PPP (in purchasing power parity terms) and the highest predicted long run growth have been named N-11, the Next Eleven countries.[4] Notice that South Africa is not included in this group. From these 11 countries, South Korea and Turkey have the highest GDP per capita and Human Development Index (HDI) as of 2016.[5] We have initially considered South Korea and Turkey to extend the group of BRIC but the economic development of South Korea took place a lot earlier than those in the group (in the 1980s), and the cyclical movements of this country are not coincident with the ones in BRIC. For this reason, we include only Turkey with the BRIC and coined it BRICT.

We selected emerging markets according to their level of economic development in terms of GDP PPP per capita, HDI, trade openness, and development of financial markets.[6] We considered several other emerging economies but their inclusion or exclusion did not alter the results. We chose then a parsimonious representation, with the top 9 emerging countries according to these metrics (Table 1).[7]

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[4] The N-11 are Bangladesh, Egypt, Indonesia, Iran, Mexico, Nigeria, Pakistan, Philippines, South Korea, Turkey, and Vietnam.

[5] The data for GDP per capita are obtained from the World Bank: World Development Indicators http://databank.worldbank.org/data/reports.aspx?source=2&country=MEX&series=&period= . The data for HDI are obtained from the United Nations Development Programme - Human Development Index http://hdr.undp.org/en/content/human-development-index-hdi-table.

[6] These metrics are obtained from the World Bank http://wits.worldbank.org/openness-to-trade-visualization.html; https://data.worldbank.org/

[7] The emerging countries are: Chile, Hong Kong, Korea, Malaysia, Mexico, Peru, Singapore, Taiwan, Thailand. Note that although Hong Kong and Singapore have

The series studied are one hundred times the first difference of the log of the stock price index for each country, which yield stationary stock returns (based on Dickey-Fuller tests).

developed stock markets, they are still considered as emerging economies based on their economic development level.

Table 1 - List of Variables: Stock Market Indices

Country	Representative Index
Industrialized	
Canada	S&P Toronto Stock Exchange 300 Composite
France	France Continuous Assisted Quotation All-tradable Index
Greece	Athens Stock Exchange General Index
Germany	Composite Deutscher Aktienindex
Italy	Banca Commerciale Italiana Index
Japan	Nikkei 225
Portugal	Oporto Portuguese Stock Index-20
Spain	Madrid Stock Exchange General Index
UK	Financial Times-Actuaries All-Share Index
USA	Dow Jones Industrial Average
BRIC	
Brazil	Ibovespa Brasil Sao Paulo Stock Exchange Index
China	Shanghai Stock Exchange Composite
India	Bombay Stock Exchange Sensitive Index
Russian	Moscow Interbank Currency Exchange Composite
Turkey	Istanbul Menkul Krymetler Borsas Index
Emerging Markets	
Chile	General Stock Price Index
Hong Kong	Hong Kong Hang Seng Composite Index
Korea	Korea Stock Exchange Stock Price Index
Malaysia	Kuala Lumpur Stock Exchange Composite
Mexico	Price and Quotes Index
Peru	Indice General de la Bolsa de Valores de Lima
Singapore	Singapore FTSE Straits-Times Index
Taiwan	Taiwan Stock Exchange Weighted Index
Thailand	Thailand Stock Exchange of Thailand General Index

2.2 The Dynamic Factor Models

We use unobserved dynamic factor structures to model international stock market dynamics. The model extracts common cyclical movements across stock market indices from several different countries. We propose two approaches: first, we categorize stock markets into three groups, according to their economic development levels as industrialized countries, emerging market countries, and the BRICT (Model 1). We then model each group of country as a function of an unobserved common factor and an idiosyncratic term. The unobserved dynamic factor summarizes underlying information common to the stock returns of the countries within the group, and separate out idiosyncratic movements that are specific to each country. We repeat this for each of the three groups. Thus, as an outcome of the first approach we obtain three stock return factors, which are estimated indicators of stock markets for the three country group considered. Next, we model the global stock market factor by extracting a common factor from stock returns of all 24 countries considered all at once (Model 2).

2.2.1 Model 1- Stock market clusters

We first extract common factors representing stock market dynamics of the three country groups *h* = industrialized, the BRICT, and emerging markets. The stock market of each country within the group shares a common group-specific factor, f_t^h, and displays idiosyncratic movements that are country specific, $\varepsilon_{i,t}^h$. The model is cast in state-space form, with the measurement equations relating the observed stock market indices for each country to the unobserved common factor, representing the country groups *h* as:

$$y_{i,t}^h = \lambda_i^h f_t^h + \varepsilon_{i,t}^h \tag{1}$$

where $y_{i,t}^h$ are the observed monthly stock market return of country *i* at time *t* belonging to the group *h*, and f_t^h is the unobserved stock return group factor. λ_i^h are the factor loadings, which represent the sensitivity of the stock market factor to the observed variable *i*. The country-specific idiosyncratic term is assumed to be normally distributed, $\varepsilon_{i,t}^{h} \sim i.i.d.N(0, \sigma_{i,h}^{2})$.

The factors are assumed to follow an *AR(1)* process, according to the transition equation:

$$f_t^h = \mu^h + \varphi^h f_{t-1}^h + u_t^h \tag{2}$$

where $u_t^h \sim N(0,1)$ is the common group factor shock. We set the variance of the factor to one as a normalization to provide a scale for the factor. Thus, the units of the data do not affect the factor or the model parameters.

2.2.2 Model 2 – Global stock market

We obtain the global dynamic common factor representing stock returns of all countries considered by modeling:

$$y_{i,t}^g = \lambda_i^g f_t^g + \varepsilon_{i,t}^g \tag{3}$$

where $y_{i,t}^g$ are the observed monthly stock market return of country *i* at time *t*, f_t^g is the unobserved global stock return factor. λ_i^g are the factor loadings, and the country-specific innovations are $\varepsilon_{i,t}^g \sim i.i.d.N(0, \sigma_{j,g}^2)$. The global factor follows an *AR(1)* process, with transition equation:

$$f_t^g = \mu^g + \varphi^g f_{t-1}^g + u_t^g \tag{4}$$

where $u_t^g \sim N(0,1)$ is the common global stock market factor shock

Since the factors obtained in Model 1 and Model 2 summarize information common to different variables and cannot be directly observed, a scale must be provided to allow for their interpretation as a normalization. We assign a scale to the stock return factors by setting its variance to unity. Notice that none of the time series properties of the dynamic factor or the correlation with its components is affected by the choice of the parameter scale.

3. Estimation

The factors are constructed using the Kalman filter, which allows estimation of the unobserved state vector and parameters. The filter calculates the course of the state vector (the common dynamic factors), using only observations on $y_{i,t}$. It computes recursively one-step-ahead predictions and updating equations of the dynamic factors and the associated mean squared error matrices. The filter provides the conditional mean and variance of the state vector at time *t*, and based on them evaluates the conditional likelihood of the observable variable. The filter evaluates this likelihood function, which can be maximized with respect to the model parameters using an optimization algorithm. Based on information available through time *t*, the algorithm yields as outputs predictions of the stock market common factors, $E(f_t|I_t)$, where I_t is the information set at *t*. That is, the filter computes the maximum likelihood estimate of the unobserved factor at *t*, given information at *t*.[8]

4. Results

We estimate the stock market factors for the three groups of countries and the global stock market factor at the monthly frequency from 1997.09 to 2015.08.

The adequacy of the model specifications is examined through tests of the idiosyncratic errors. We use Brock, Dechert, and Scheinkman's [1987] BDS test to check their *i.i.d.* assumption. The diagnostic tests indicate that the specification selected is adequate for all equations in both models 1 and 2. The BDS test fails to reject the *i.i.d.* hypothesis for the residuals. In addition, the autocorrelation functions for the disturbances in the measurement equations are within the limit of two times their asymptotic standard deviation, and the pairwise covariance between the disturbances is close to zero.

These results imply that all common cyclical information underlying stock returns from the countries considered are captured by the dynamic

[8] The estimation procedure is described in more detail in the appendix available upon request.

factors, and the peculiarities of each individual market are the residual noise captured by the idiosyncratic errors.

4.1. International Stock Returns - Contemporaneous Relationship

The estimates of the models obtained through numerical maximization of the conditional log likelihood function are presented in Tables 2 and 3, which report results for the dynamic factor model for each group of countries, and for the global stock market factor, respectively. The tables also show the correlation of each of the components with the factors.

As it can be observed, the mean growth rate of stocks for the BRICT (μ^{BRICT}=0.138) is substantially higher than emerging markets (μ^{EMK}=0.047) and industrialized countries (μ^{IND}=0.032). This is consistent with the opening and development of these countries' financial markets and accelerated economic growth they experienced until the late 2000s.

Idiosyncratic noise makes it difficult to detect the presence of predictable stock return components, as found in extensive literature. By construction, the dynamic factor model separates idiosyncratic noise from a common component underlying the observable stock returns. The dynamic factors representing stock returns for the country groups and for the global market are persistent – the first-order autoregressive coefficients of the factors are statistically significant and higher in magnitude than the ones of their components. Thus, the stock return common factors are more predictable than the stock market of individual countries. One of the reasons for their higher persistence is their lower variance compared to the variance of the individual countries' return, as the model extracts the signals (factors) from the noise in the observed stock return series.

The BRICT stock return indicator is the most persistence of all groups ($\varphi^{BRICT} = 0.276$), and even more persistent than the global stock market indicator ($\varphi^{Global} = 0.200$). Thus, surprisingly, these countries have the most predictable stock market factor among all the other groups.

All markets display relatively high correlations with their group stock market factor,[9] and they are generally even more correlated with the common factor than with each other. This indicates that the structure of the common stock market indicator is not merely imposed on the financial variables by assuming large idiosyncratic noise terms. On the contrary, the dynamic factor captures an underlying common cyclical movements highly correlated with stock returns of all countries considered (Tables 2 and 3).

[9] The one exception is Brazil. The main reason is that Brazil stock market factor shows a stronger correlation at leads rather than contemporaneously with the BRICT stock market factor.

Table 2 – Maximum Likelihood Estimates for Model 1: Stock Market Factors for Industrialized Countries, Emerging Market Countries, and the BRICT 1997:09 – 2015:08

	Industrialized Countries		**Emerging Markets**		**BRICT**	
Factor Mean	0.03243		0.04732		0.13759	
φ_1	0.17042		0.24206		0.27586	
Factor Loading	USA	3.742	Hong Kong	6.024	China	2.796
	Japan	3.593	Singapore	5.931	Russia	8.280
	UK	3.725	Taiwan	4.842	India	4.147
	Germany	5.605	South Korea	5.725	Brazil	1.080
	France	5.170	Malaysia	4.432	Turkey	7.190
	Italy	5.397	Thailand	6.052		
	Canada	3.354	Mexico	4.682		
	Spain	5.113	Chile	2.952		
	Portugal	4.586	Peru	4.959		
	Greece	6.044				
Standard Deviation-Idiosyncratic Terms	USA	2.479	Hong Kong	4.055	China	7.491
	Japan	4.484	Singapore	2.862	Russia	8.355
	UK	1.789	Taiwan	5.003	India	5.762
	Germany	2.332	South Korea	6.274	Brazil	8.560
	France	1.404	Malaysia	4.935	Turkey	9.840
	Italy	2.791	Thailand	5.576		
	Canada	2.995	Mexico	4.456		
	Spain	2.990	Chile	3.333		
	Portugal	3.887	Peru	7.051		
	Greece	7.752				
Correlation with Factor	USA	0.8482	Hong Kong	0.8676	China	0.4330
	Japan	0.6397	Singapore	0.9398	Russia	0.8564
	UK	0.9159	Taiwan	0.7337	India	0.7150
	Germany	0.9375	South Korea	0.7079	Brazil	0.0824
	France	0.9788	Malaysia	0.7037	Turkey	0.7213
	Italy	0.9033	Thailand	0.7721		
	Canada	0.7603	Mexico	0.7614		
	Spain	0.8777	Chile	0.6984		
	Portugal	0.7804	Peru	0.6071		
	Greece	0.6326				

Table 3 – Maximum Likelihood Estimates for Model 2: Global Stock Return Estimated from All Country Data
1997:09 – 2015:08

	Global Factor					
Factor Mean	0.0460					
φ_1	0.1998					
Factor Loading	USA	3.915	Hong Kong	5.375	China	2.519
	Japan	3.808	Singapore	4.943	Russia	6.972
	UK	3.707	Taiwan	4.509	India	4.255
	Germany	5.324	South Korea	5.219	Brazil	0.919
	France	4.820	Malaysia	3.428	Turkey	6.903
	Italy	5.037	Thailand	4.743		
	Canada	3.633	Mexico	4.514		
	Spain	4.934	Chile	2.627		
	Portugal	4.324	Peru	4.562		
	Greece	6.044				
Standard Deviation-Idiosyncratic Terms	USA	2.140	Hong Kong	4.985	China	7.631
	Japan	4.276	Singapore	4.480	Russia	9.787
	UK	1.779	Taiwan	5.359	India	5.792
	Germany	2.869	South Korea	6.765	Brazil	8.585
	France	2.297	Malaysia	5.741	Turkey	10.244
	Italy	3.366	Thailand	6.822		
	Canada	2.605	Mexico	4.678		
	Spain	3.237	Chile	3.629		
	Portugal	4.156	Peru	7.358		
	Greece	7.722				
Correlation with Factor	USA	0.894	Hong Kong	0.751	China	0.3215
	Japan	0.684	Singapore	0.759	Russia	0.595
	UK	0.919	Taiwan	0.663	India	0.608
	Germany	0.898	South Korea	0.627	Brazil	0.101
	France	0.919	Malaysia	0.527	Turkey	0.573
	Italy	0.850	Thailand	0.587		
	Canada	0.830	Mexico	0.712		
	Spain	0.854	Chile	0.602		
	Portugal	0.743	Peru	0.541		
	Greece	0.639				

Table 4 reports the pairwise contemporaneous correlation of stock market factors. The global stock market is highly correlated with stock returns of all groups, but particularly with the stock market of industrialized countries.

Interestingly, the stock market indicator for the group countries are correlated with each other, but a lot less than they are with the global market indicator. The BRICT are the least correlated with the other groups and with global markets. The stock market of these countries reflect their fundamentals, which seem to march to the beat of their own drums. In fact, some recent studies show that the BRICT economic movements are negative related with those of industrialized countries. This is particularly the case since the Great Recession in 2008-2009, in which most countries had a subsequent sluggish recovery. The BRICT, on the other hand, experienced a deep but shorter economic contraction, and a stronger recovery. As a result, the stock markets in these countries received a large inflow of capital as investors were hedging against the slow recovery in industrialized countries.

Table 4 – Contemporaneous Correlation between Stock Return Common Factors

Stock Return Common Factors	Global	Industrialized	Emerging Markets	BRICT
Global	1.000	0.973	0.834	0.703
Industrialized	0.973	1.000	0.699	0.631
Emerging Markets	0.834	0.699	1.000	0.637
BRICT	0.702	0.631	0.637	1.000

Figure 1 shows shaded areas representing recessions in the U.S. as dated by the NBER Business Cycle Dating Committee, and recessions in the Euro Area as dated by the Center for Economic Policy Research

(CEPR).[10] The U.S. and the Euro Area experienced two economic recessions each in the period studied, in which one was common to both. The 2001 U.S. recession had as some of the culprits a slowdown in manufacturing production and a crash in the stock market in 2000. Although the Euro Area did not experience a recession in 2001, their economy had a low growth during this period. The second recession in the U.S. – the Great Recession in 2008-2009, spread internationally affecting the Euro Area, which also experienced a recession during this period. This recession is associated with a severe crisis in the housing market and financial markets. The Euro Area had and additional recession, in 2011-2013, related with the European sovereign debt crisis, particularly resulting from structural economic problems in Greece, Spain, Italy, and Portugal.

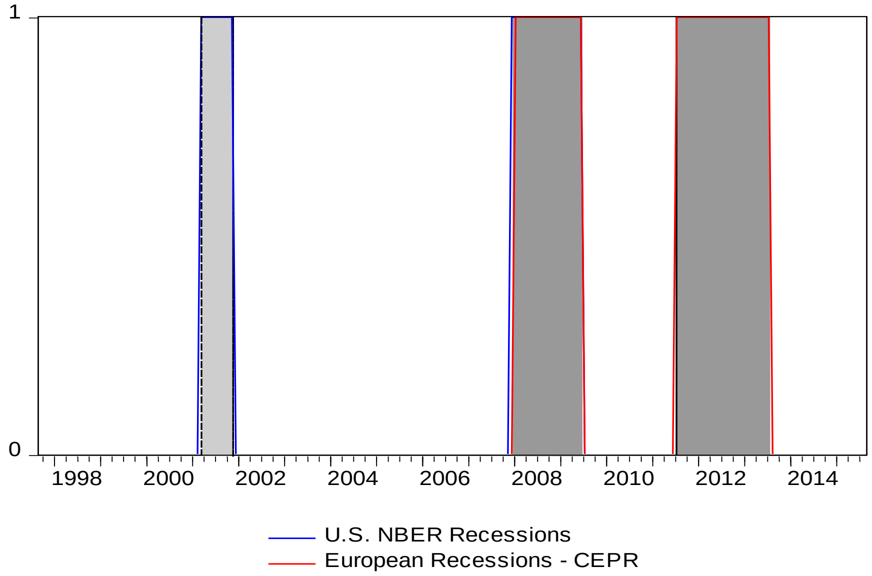

Fig. 01 - U.S. Recessions as Dated by the NBER (Lighter Shaded Area and blue line, and Europe Recessions as Dated by the CEPR (Darker Shaded Area and red line)

Even though most of the individual countries studied do not have 'official' recession dating, extensive literature shows that most of them

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[10] The recession dating by these institutions is considered as the official beginning and ending of recessions in the U.S. and Euro Area.

also experienced either a slowdown or a recession in 2001 and in 2008-2009.[11] This is in line with our findings that all stock return factors as well as the global stock market factor show a close relationship with recessions in the U.S. and Europe, usually decreasing substantially around the beginning of recessions - when income and earnings fall, and increasing mid-way through recessions, anticipating future economic recovery.

Periods in which stock returns are substantially negative (bear markets) are generally related to economic recessions. However, they also take place during economic expansions, possibly reflecting weak economic growth, economic or political instability, wars, sectoral contractions, negative sentiment, etc.

Figure 2 plots the global stock indicator factor, which is obtained from all the 24 countries considered, Figure 3 plots the industrialized stock return indicator, emerging market return indicator, and the BRICT return indicator, while Figure 4 compares the global stock market factor with the group factors. The international movements in stock returns are highly correlated with the ones from industrialized countries, displaying similar mean rate. Emerging market average returns were above the global returns in the late 1990s and slightly below since. The BRICT factor returns, on the other hand, are above the global returns throughout the sample, but particularly so until the 2008 recession.

Global stock market returns experienced five bear markets in the period studied, as did the industrialized countries. Global returns fell substantially during the U.S. and Euro Area recessions in 2001, 2008-2009 and in 2011-2013. International markets also crashed in 1998, related to the contagion of the Asian currency crisis to the BRICT in mid-1998, and the losses of the giant U.S. hedge fund Long-Term Capital Management (LTCM). Global returns also fell substantially in 2002, during the slow recovery from the 2001 recession.

[11] Brazil has its own Business Cycle Dating Committee (CODACE), which has established that this country experienced recessions in 2001, 2003, 2008-2009, and 2014-present.

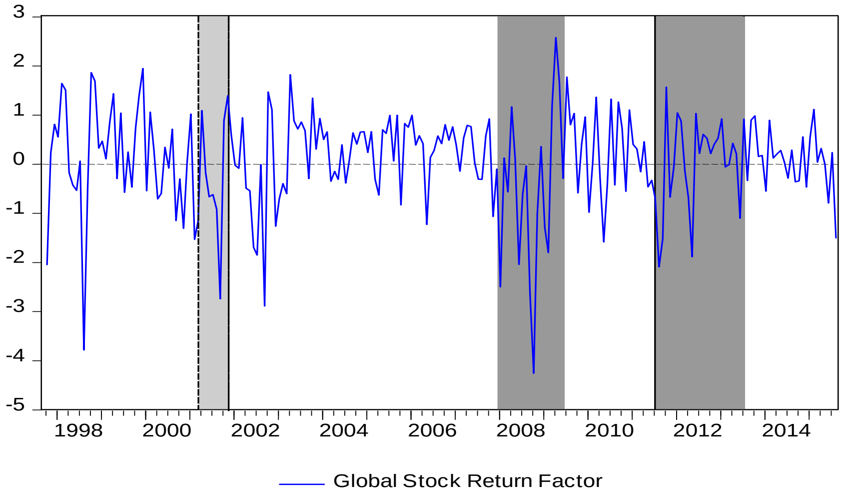

Fig. 02 – Global Stock Return Common Factor for All 24 Countries, U.S. Recessions as Dated by the NBER (Lighter Shaded Area and Doted Line), and Euro Area Recessions as Dated by the CEPR (Darker Shaded Area)

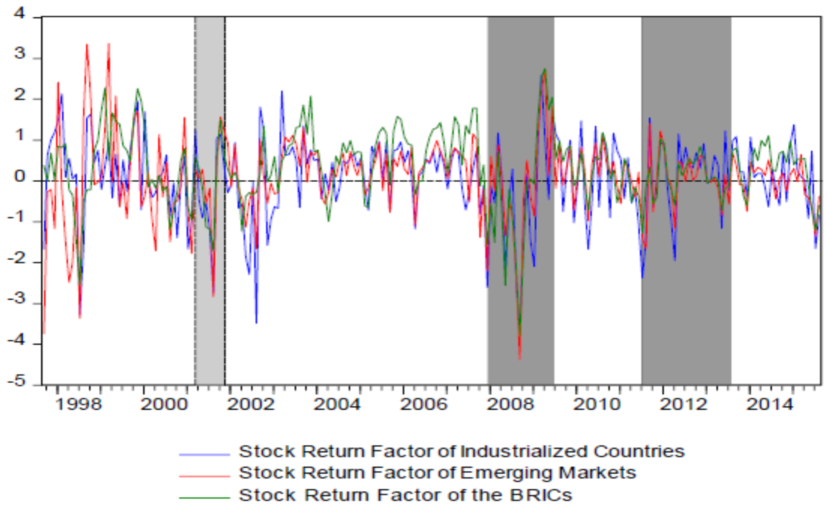

Fig. 03 – Stock Return Common Factors of Industrialized Countries, Emerging Markets, and the BRICT, U.S. Recessions as Dated by the NBER (Lighter Shaded Area and Doted Line), and Europe Recessions as Dated by the CEPR (Darker Shaded Area)

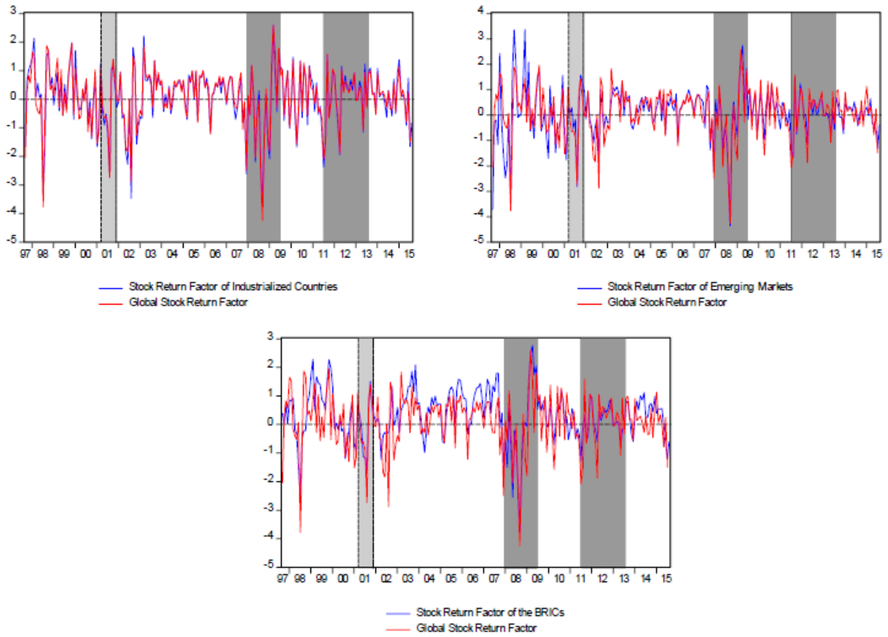

Fig. 04 –Stock Return Factor of Industrialized Countries, Stock Return Factor of Emerging Markets, and Stock Return Factor of the BRICT Compared with the Global Stock Return Common Factor, U.S. Recessions as Dated by the NBER (Lighter Shaded Area and Doted Line), and Europe Recessions as Dated by the CEPR (Darker Shaded Area)

The countries with the highest correlation with the global stock market are Singapore, Hong Kong, U.S. and Canada, while the ones with the lowest correlation are Greece, China, Russia, and Brazil. The latter are some of the ones with the largest volatility as measured both by their total variance and by the variance of their idiosyncratic errors. This will be discussed in more detail for each factor in the next sections.

4.2 Stock Market Clusters - Country Groups

Table 2 shows the maximum likelihood estimates of the factor loadings and standard deviation of the idiosyncratic noises for the country groups. The factor loadings characterize the direct structural relation between the unobservable variable f_t and the observable variables y_t. The parameter

λ_t can be interpreted as a reverse regression coefficient since it measures the sensitivity of f_t to changes in y_t. The variance of the stock return factor is set to one for normalization, as explained above. Thus, the sign of the factor loadings indicates the direction of the relation between the stock return of each country with their respective stock return group indicator.

Additionally, from equations (1)-(4), it can be derived that the factor loading of the observed series *i* is directly proportional to the difference between the variance of series *i* and the variance of its idiosyncratic term. Thus, the higher the total variance of the stock markets of a country compared to its estimated country specific variance, the higher is its factor loading. The intuition is that the common factor separates the signal - the common correlation across the different countries, from their idiosyncratic noise.

4.2.1 Stock Market Factor of Industrialized Countries

Figure 5 shows the stock return indicator of the industrialized countries, together with U.S. recessions and Euro Area recessions, while Figure 6 displays the stock return indicator of industrialized countries contrasted with each of its 10 country components. The stock return indicator of industrialized countries falls in the beginning of recessions and increases a couple of months before its end. It decreases during economic expansions as well. In particular, it falls below 2%[12] during the U.S. stock crash in 1998, and during the slow recovery of the U.S. economy in 2002. During this time Europe also displayed weak economic growth, but not sufficiently low to be classified as a recession.

[12] This corresponds to a fall below its mean minus two standard deviations.

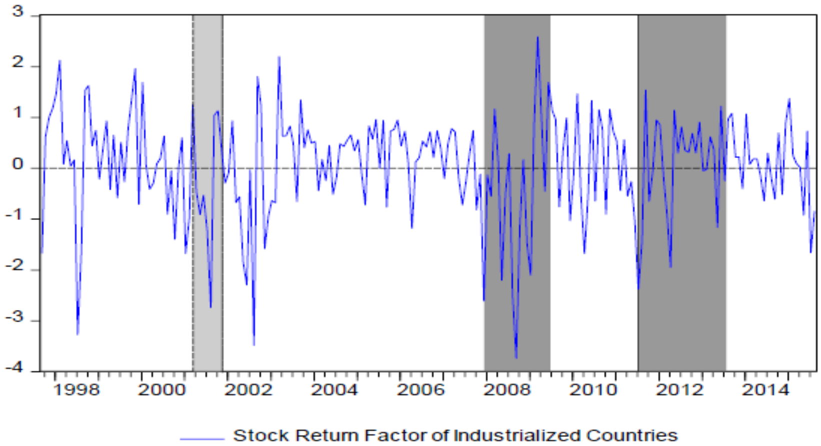

Fig. 05 – Stock Return Common Factor of Industrialized Countries, U.S. Recessions as Dated by the NBER (Lighter Shaded Area and Doted Line), and Europe Recessions as Dated by the CEPR (Darker Shaded Area)

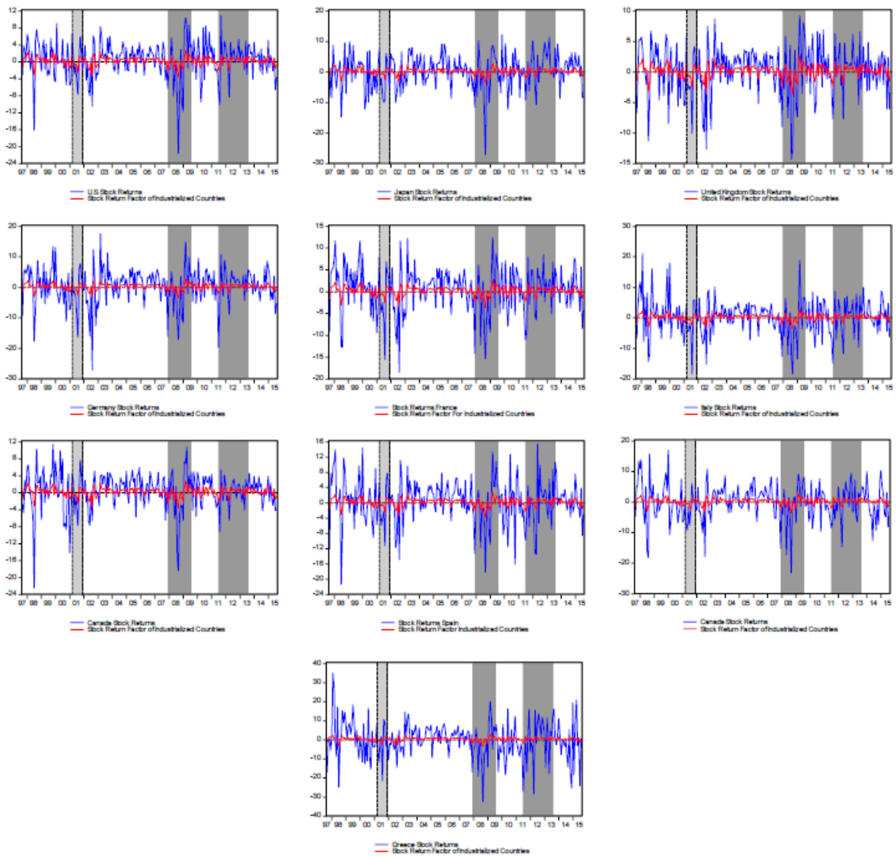

Fig. 06 – Industrialized Countries: Stock Return Common Factor and Country Specific Stock Returns, U.S. Recessions as Dated by the NBER (Lighter Shaded Area and Doted Line), and Europe Recessions as Dated by the CEPR (Darker Shaded Area)

As seen in Table 2, the country with the largest estimated factor loading is Greece (6.044), which implies that changes in Greece's stock market affect the most the stock market of industrialized countries, as represented by the common dynamic factor. This is partially related to the high Greece's country risk and volatility. The volatility of Greece's idiosyncratic stock return ($\sigma^h_{Greece} = 7.752$) is almost 8 times higher than the volatility of the common stock return factor of industrialized countries ($\sigma^h_u = 1$) (Table 2, Figure 6). Germany' market also strongly contributes to movements in the common stock market factor of the industrialized countries, with a factor loading of 5.606 and idiosyncratic stock return volatility, $\sigma^h_{Germany} = 2.332$.

All markets display relatively high correlations with the stock market of industrialized countries, ranging from 0.63 to 0.98 – and generally they are even more correlated with the industrialized stock indicator than with each other. The highest correlated markets with the stock market of industrialized countries are France (0.98), followed by Germany (0.94), U.K. (0.92), and Italy (0.90). On the other hand, Greece and Japan's markets have the lowest correlation with the common factor. That is, contemporaneously, Greece is the market that most affect the stock market of industrialized countries, but Greece's market idiosyncratic movements dominate its own dynamics. This is also the case for Portugal and Japan.

The dynamic factor representing stock returns for all industrialized countries have a higher significant first-order autocorrelation coefficient ($\hat{\rho}(1)$ =0.170), than the individual countries.[13] That is, although the estimated industrialized stock return factor is highly correlated with all industrializes countries, it is also more persistent and, therefore, more predictable than the stock return for each country itself. The country specific stock returns of most industrialized countries show low persistence, with a first order autocorrelation, $\hat{\rho}(1)$, not statistically significant at the 10% level. Interestingly, the exceptions are the stock returns for France ($\hat{\rho}(1)$ =0.141), the U.S. ($\hat{\rho}(1)$ =0.141), and Portugal ($\hat{\rho}(1)$ =0.219), which are more persistent than the other countries, with first order correlations statistically significant at the 5% level.

[13] The only exception is Portugal, which has an autoregressive coefficient slightly higher.

4.2.2 Stock Market Factor of Emerging Markets

Figure 7 shows the stock return factor of the emerging markets together with recessions in the U.S. (NBER) and recessions in Europe (CEPR). A feature that stands out is that the stock market of emerging economies displays high volatility in the late 1990s. There was a sharp drop in 1997-1998 related to the currency crisis experienced by the Asian Tigers (Thailand, Malaysia, Korea, and Hong Kong)[14]. This was followed by a substantial recovery in 1999. Since then, stock returns in emerging markets became much less volatile. Interestingly, it has since been more stable, displaying less bear phases than the other groups, including industrialized countries and the overall global stock markets. In fact, emerging market stock factor did not enter any bear market phases outside recessions, in contrast with industrialized countries and the BRICT, and it did not fall much during the Euro Area recession in 2011-2103.

The countries with the largest factor loadings are Thailand, Hong Kong, and Singapore, which are also the countries with the largest correlation with the common factor (Table 2). The country with the lowest factor loading is Chile, which as expected, has also the lowest difference between the total variance of returns and the variance of its idiosyncratic term. Chile's market has responded more to internal strong economic fundamentals than to the common cyclical movements in other emerging stock markets (Figure 8).

[14] Singapore and Taiwan were the least affected countries by the currency crisis.

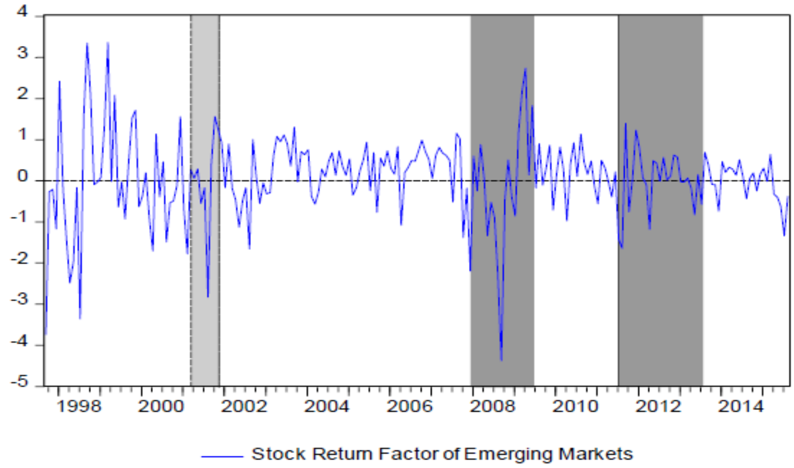

Fig. 07 – Stock Return Common Factor of Emerging Markets, U.S. Recessions as Dated by the NBER (Lighter Shaded Area and Doted Line), and Europe Recessions as Dated by the CEPR (Darker Shaded Area)

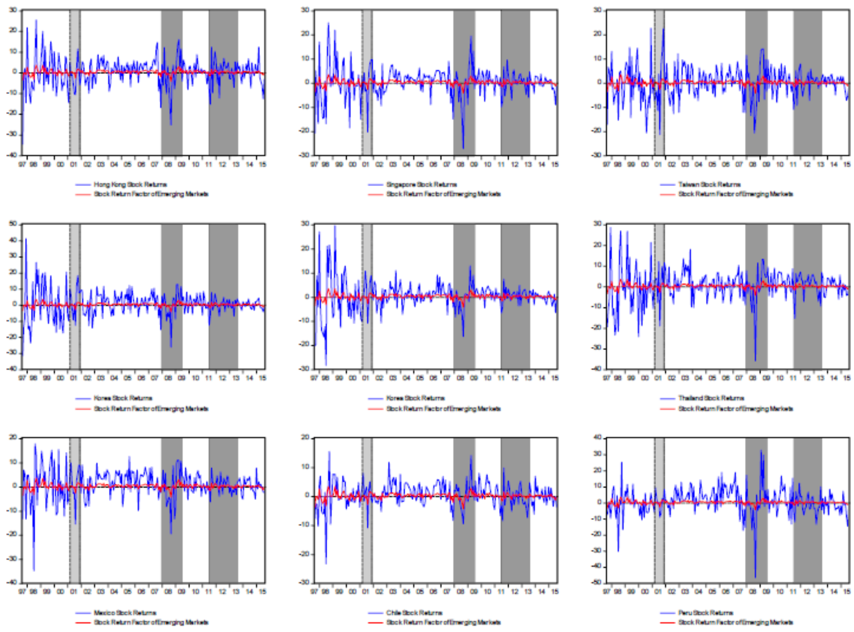

Fig. 08 – Emerging Markets: Stock Return Common Factor and Country Specific Stock Returns, U.S. Recessions as Dated by the NBER (Lighter Shaded Area and Doted Line), and Europe Recessions as Dated by the CEPR (Darker Shaded Area)

4.2.3 Stock Market of the BRICT

Figure 9 shows the stock return factor of the BRICT, recessions in the U.S. (NBER) and recessions in Europe (CEPR), and Figure 10 shows the BRICT factor compared with each of the stock returns of its 4 components. The BRICT are the group of countries with the largest average stock return (0.138), which is four times higher than stock returns in industrialized countries and three times higher than in emerging markets.

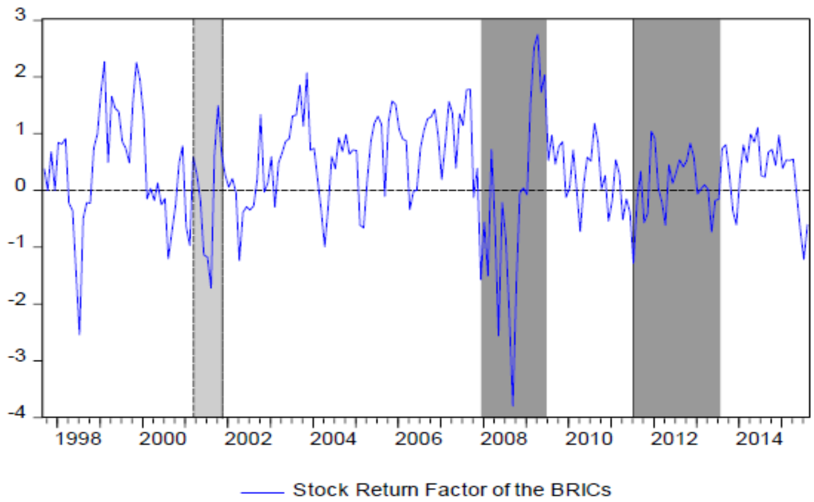

Fig. 09 – Stock Return Common Factor of The BRICT, U.S. Recessions as Dated by the NBER (Lighter Shaded Area and Doted Line), and Europe Recessions as Dated by the CEPR (Darker Shaded Area)

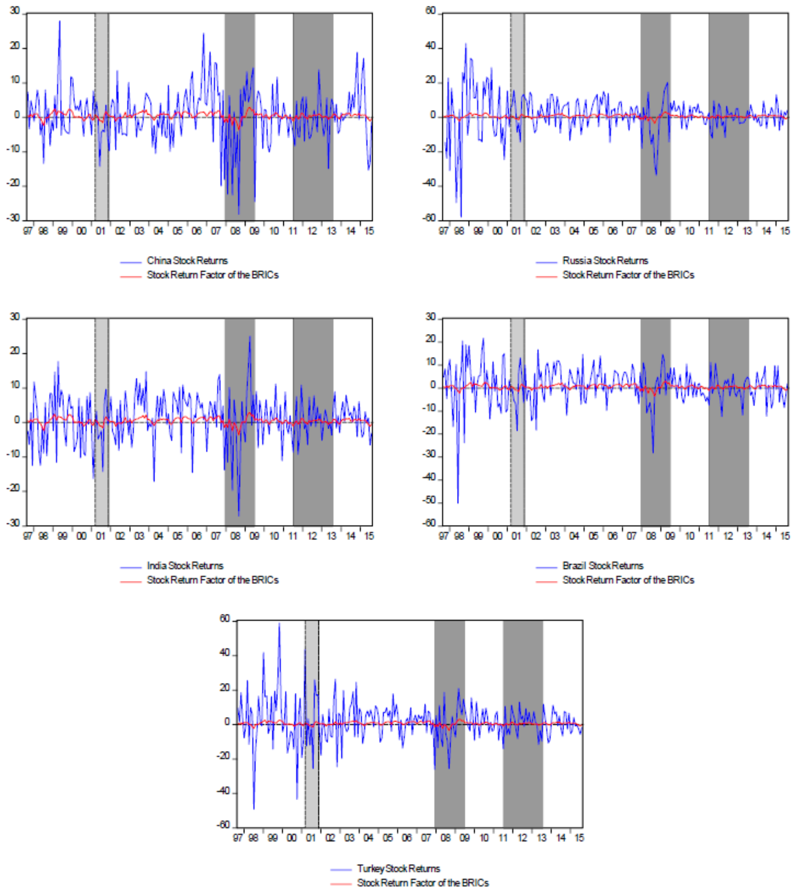

Fig. 10 – The BRICT: Stock Return Common Factor and Country Specific Stock Returns, U.S. Recessions as Dated by the NBER (Lighter Shaded Area and Doted Line), and Europe Recessions as Dated by the CEPR (Darker Shaded Area)

As the emerging markets, the BRICT stock return factor was also very volatile in the late 1990s. Although the BRICT stock markets were not contemporaneously affected by the 1997 Asian currency crisis, there was a contagion effect later in most of the BRICT, starting with Russia. The Asian crisis severely impacted Russia foreign exchange reserves, which together with other political and structural economic problems led Russia to have a currency crisis a year later, in mid 1998. As a result, Russia stock market crashed in 1998, which increased the country risk of the other BRICT members. Brazil and Turkey's stock market also crashed in mid-1998, which was the largest fall for these countries in the whole sample. China and India markets were less affected by this early crisis.

Subsequently, the BRICT stock factor experienced a strong bull market in 1999-2000, when both the stock factor and the country specific stock markets had the largest rate of returns in the sample studied. China also had a strong bull market between 2006-2008. The BRICT factor had a mild bear market in 2001 and a strong fall during the Great Recession in 2008-2009. In particular, China and India were strongly affected by both recessions. Stock returns in the BRICT have shown a strong recovery right after the crisis, but the average return has been lower than its past record since the Great Recession, in spite of the fact that the BRICT did not experience a bear market during the Euro Area recession in 2011-2013.

The country with the largest factor loading in the BRICT factor is Russia, while Brazil has the lowest. This is consistent with the fact that Russia has the largest difference between its total variance and its idiosyncratic variance, while Brazil has the lowest.

A feature that stands out from the BRICT factor is that it has a lot higher correlation with its country components than the BRICT countries have with each other. In fact, the stock returns of the BRICT countries are not very correlated with each other, as their markets strongly respond to their idiosyncratic movements. Finally, the BRICT factor is surprisingly more persistent than the industrialized factors and emerging market factors and, therefore, more predictable.

5. International Stock Market Linkages – Lead-Lag Relationship

5.1 Vector Autoregressive Model

In order to study the linkages across international stock markets, we consider a parsimonious VAR model that includes the variables whose dynamic interrelationship we want to investigate. The relationship across markets is represented by the p^{th}-order vector autoregression (VAR-p):

$$\mathbf{Z}_t = \mathbf{a} + \mathbf{A}_1\mathbf{Z}_{t-1} + \ldots + \mathbf{A}_p\mathbf{Z}_{t-p} + \mathbf{v}_t \qquad (5.1)$$

with $\mathbf{v}_t \sim (0, \Theta)$,where $\mathbf{Z}_t^{'}$ is an *nx1* vector containing the values that the *n* stock return factors take at date *t*, $\mathbf{A}_j$ is the *n x n* coefficient matrices with *j= 1, . . . ,p,* $\mathbf{a}^{'}$ is the *nx1* vector of constants, and $\mathbf{u_t}$ is the *nx1* vector of disturbances. Equation (5.1) describes the response of each of the stock return factors to changes in the other variables in the system.

The model identification conditions are formulated based on Swanson and Granger's [1997] method, which uses the notion of 'instantaneous causality' [see e.g. Lütkepohl 1990] to identify the causal structure for the innovations. Assume that the innovations of the VAR can be arranged as follows:

$$\mathbf{u}_{1t} = \mathbf{v}_{1t}; \mathbf{u}_{2t} = \gamma_2 \mathbf{u}_{1t} + \mathbf{v}_{2t}; \cdots; \mathbf{u}_{nt} = \gamma_n \mathbf{u}_{n-1,t} + \mathbf{v}_{nt}.$$

This structure can be represented by a causal graph as: [15]

$$\begin{array}{ccccccc} \mathbf{u}_{1t} & \rightarrow & \mathbf{u}_{2t} & \rightarrow & \cdots & \rightarrow & \mathbf{u}_{nt} \\ \uparrow & & \uparrow & & & & \uparrow \\ \mathbf{v}_{1t} & & \mathbf{v}_{2t} & & \cdots & & \mathbf{v}_{nt} \end{array}$$

This graph means, for example, that $\mathbf{u}_{2t}$ may be expressed as a function of $\mathbf{u}_{1t}$, $\mathbf{u}_{3t}$ as a function of $\mathbf{u}_{2t}$, etc. Swanson and Granger (1997) show that this causal ordering implies that $E(\mathbf{u}_{ht}\mathbf{u}_{kt} \,|\, \mathbf{u}_{lt}) = 0$ for $h < l < k$, with $h < n$, and suggest testing the partial correlation between $\mathbf{u}_{ht}$ and $\mathbf{u}_{kt}$ conditional on $\mathbf{u}_{lt}$ in order to recover the causal ordering empirically. For example, given $\mathbf{u}_{3t} = \gamma_3 \mathbf{u}_{2t} + \mathbf{v}_{3t}$ and $E(\mathbf{u}_{2t}\mathbf{v}_{3t}) = 0$, the condition $E(\mathbf{u}_{1t}\mathbf{u}_{3t} \,|\, \mathbf{u}_{2t}) = 0$ implies that given $\mathbf{u}_{2t}$ the variable $\mathbf{u}_{1t}$ does not help to predict $\mathbf{u}_{3t}$. Conversely, if $\gamma_3 \neq 0$, $E(\mathbf{u}_{2t}\mathbf{u}_{3t} \,|\, \mathbf{u}_{1t}) \neq 0$ and the variable $\mathbf{u}_{2t}$ helps to predict ('cause') $\mathbf{u}_{3t}$.

The method suggests that the best specification is the one in which global stock market and stock returns of industrialized countries respond with a lag to shocks to stock markets in emerging markets and in the BRICT. Emerging markets and the BRICT, on the other hand, respond to all contemporaneous and lagged variables in the system.

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[15] Note that the causal graph with the arrows pointed forward implies the same restriction on the conditional expectation as the arrows pointed backward, and, therefore, the direction of the graph is not identified.

5.2. Impulse Response Functions

We first estimate a VAR system that includes the stock market factors representing the three country groups: industrialized countries, emerging markets, and the BRICT. The BIC and AIC tests indicate that the best lag structure for this specification is $p=2$. The relative short lag is due to the fact that stock markets react promptly to shocks and do not display high dependency with the past.

The impulse response functions are shown in Figure 11. We find that the stock market of industrialized countries has a strong positive response to a positive shock in stock returns of emerging markets and of the BRICT. A shock to the BRICT has a higher impact on industrialized countries in terms of magnitude and duration compared to shocks to emerging markets (third row).

The dynamic impacts of a positive shock in the stock market of industrialized countries are shown in Column 3. Interestingly, emerging markets and the BRICT show a statistically significant stronger negative response, particularly 3 months after the shock. This support evidence that stock market of the BRICT has some hedge component to industrialized countries, as capital flows from industrialized countries to the BRICT when the former is hit by negative shocks and vice versa.

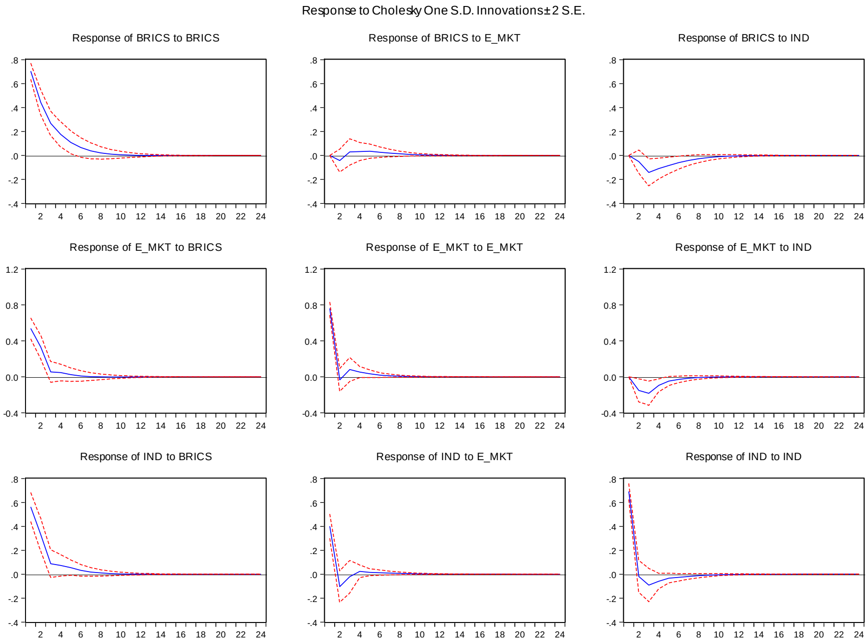

Fig. 11 – Impulse Response Functions for Industrialized Countries Stock Return Factor, Emerging Markets Stock Return Factor, BRICT Stock Return Factor – Full Sample

We investigate this finding further by estimating the VAR system for expansion and recession phases in the U.S. and Europe. The responses during recession phases are not statistically significant as there are not enough recession observations (*t=18*).[16] However, there is statistically significant response during expansions (Figure 12). The negative response of BRICT and emerging markets to a positive shock in stock returns in industrialized countries is stronger for the full sample (including both expansions and recession phases) than during expansions phases. This indicates that some of the negative response is due to movements during recession phases.

[16] Results for recession are not shown for parsimony but available upon request.

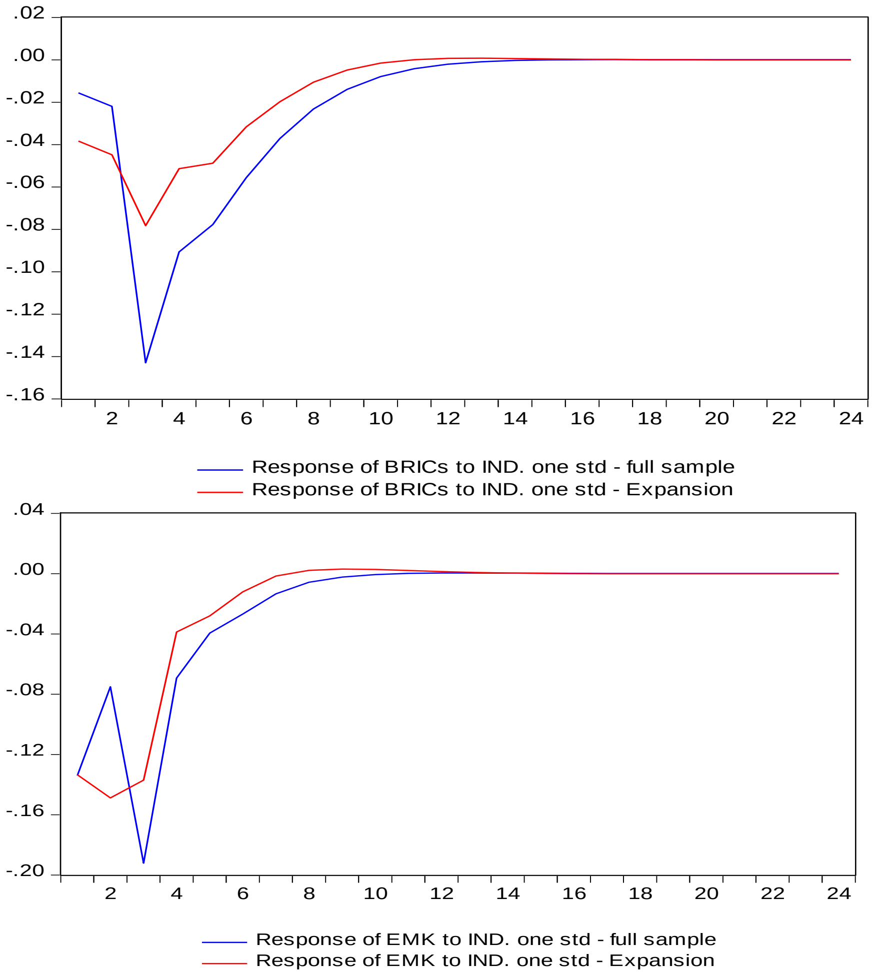

Fig. 12 – Impulse Response Functions for Industrialized Countries Stock Return Factor, Emerging Markets Stock Return Factor, BRICT Stock Return Factor – Expansion Phases in the U.S. and Euro Area

We extend the analysis to examine the effect of global stock markets on the group country factors by estimating a VAR with four variables. Swanson and Granger [1997] method suggests that global stock return factor responds with a lag to shocks to all market. The BIC and AIC tests also indicates a lag structure *p=2* for this specification.

Figure 13 shows the impulse response function of the variables in the system to a shock to global stock market returns.

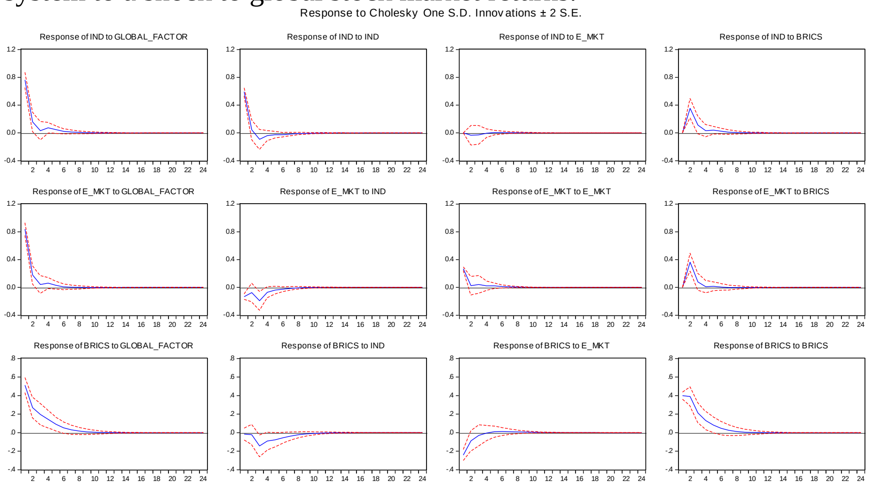

Fig. 13 – Impulse Response Functions – VAR with Global Stock Returns, Industrialized Countries Stock Return Factor, Emerging Markets Stock Return Factor, BRICT Stock Return Factor

All stock markets show an immediate rise in the first period with a positive shock to global stock returns. The effect is short-lived, with the rise lasting only one period, and returning to zero after 3 or 4 periods. The least reactive group to the global market is the BRICT, and the most responsive is the emerging markets.

6. Sensitivity Analysis

We have estimated several different specifications. The most relevant are discussed in this section.

First, we have estimated VAR specifications including different lags. Although the impulse response functions show more oscillations, the results overall results are qualitatively very similar to the ones presented in the previous sections.

Second, we have estimated the factor models for different samples as there is availability of longer sample for some countries. We have not chosen them for our primary analysis because it would preclude inclusion of several countries that only have shorter sample spams. In particular, we estimated all dynamic factor models starting in 1994. In this case, Russia data are dropped because it is available only after 1997. We find that the results are striking similar, and not sample dependent, as shown in Figures 14 and 15.

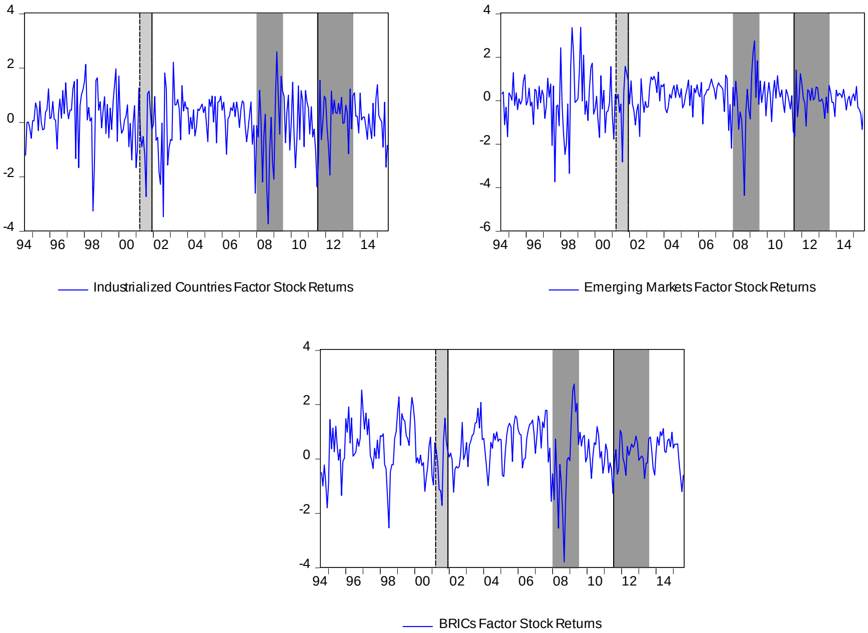

Fig. 14 – Industrialized Countries Stock Return Factor, Emerging Markers Stock Returns Factor, BRICT Stock Return Factor for the extended sample:1994:08 – 2015:08

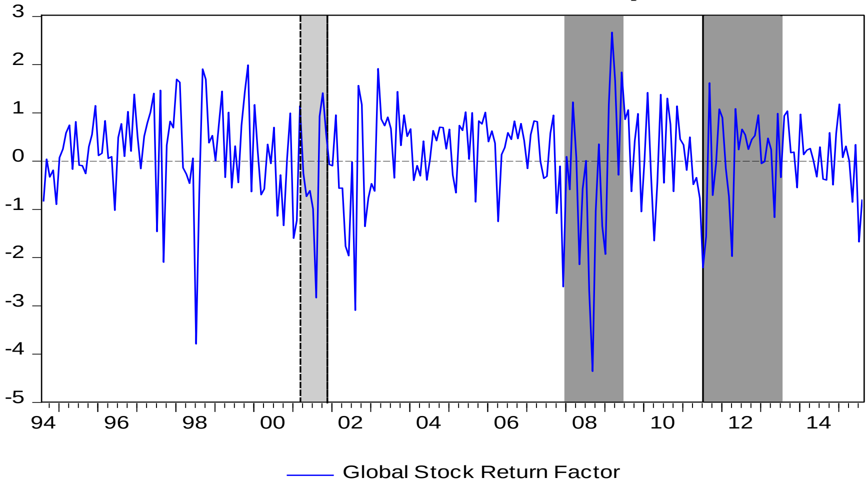

Fig. 15 – Global Stock Return Common Factor for All 24 Countries, Global Stock Return Common Factor for Group Factors for the extended sample:1994:08 – 2015:08

Finally, we have also estimated the global stock return factors from the factors obtained in equations (2.1) to (2.4), instead of extracting them from each of the 24 individual countries. As it can be seen in Figure 16, the global market factors obtained from these distinct methods are strikingly similar, indicating that the results are robust across different specifications.

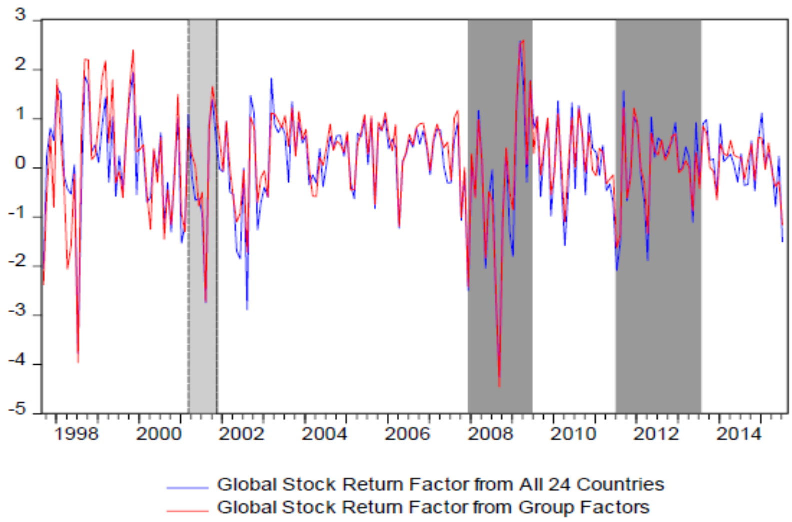

Fig. 16 – Global Stock Return Common Factor obtained from the Stock Return Common Group Factors

7. Conclusions

This paper uses dynamic factor structure to model and investigate the linkages of country group stock returns and global financial markets. In particular, we group countries according to their development level and extract indicators of stock markets in industrialized countries, emerging economies, and the BRICT. We also build a global stock market factor.

The results indicate that stock market of country groups are correlated with each other and with the global stock market, much more so than individual countries are with each other. We also find that all markets respond to major economic recessions, entering in a bear phase around their beginning and entering a bull phase towards the middle of the economic contraction, predicting its end.

Further, although we find that the BRICT countries are correlated with the other markets, they tend to have more distinct features. In particular, the BRICT stock returns display the highest mean and are the most persistent - therefore, most predictable compared to the other country groups and to the global market factor.

We examine international linkages through impulse response analysis. We find that the stock market of country groups with different development levels play distinct roles in the propagation of shocks. In particular, the BRICT tend to respond less to global stock market shocks, while emerging economies are the most sensitive to changes in the world markets. Finally, we find that positive (negative) shocks to stock returns of industrialized countries have a negative (positive) impact on the BRICT. That is, the stock market of BRICT countries might attract capital hedging against conditions in the stock markets of industrialized countries.

Overall, the results indicate that the BRICT show some distinct dynamics compared to other emerging economies and industrialized countries. We find that some of the evidence in the literature of decoupling or decreasing in market integration arises from not considering separately the peculiarities of the BRICT compared to other emerging economies.

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