Latin-American Stock Market Dynamics and Co-movement

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ABSTRACT

With the economic relevance of the relationships among emerging and frontier equity markets becoming increasingly significant, this paper investigates co-movement among returns from six Latin-American stock markets [Mexico (BMV), Brazil (BOVESPA), Chile (IPSA), Peru (IGBVL), Argentina (MERVAL), Venezuela (IBVC)] and also with the U.S. S&P 500 Composite index. In part, we employ Principal Component Analyses, to account for the maximum portion of the variance present in the returns by examining rolling windows with 8,6,4,3,2, and 1-year periods. We also investigate the incidence of structural breaks and co-movement, aiming to uncover the dynamics in co-movements among these markets. We find evidence of high co-movement among the Latin-American markets, and also with the U.S. markets. Venezuela and Mexico's equity markets are at the extremes. However, our results do not corroborate findings of clear evidence, reported in previous studies, of the U.S. having a leading role in the region.

JEL classifications: F21; G11; G15.

Key words: Co-movement; Correlation; Emerging and Frontier Stock Markets; Portfolio Diversification.

1. Introduction

One of the most worrying side-effects of increasing economic and financial globalization is financial contagion and unfavourable inter-market co-movement. Following 2007/8 global

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financial turmoil, academic, political and investor interest in international stock-market co-movements appears to have increased markedly (see Kizys and Pierdzioch, 2009; Madaleno and Pinho (2011); Lahrech and Sylwester, 2011, Pyun and An, 2016; Beetsma *et al*., 2017). It is worth noting, however, that while integration in banking and financial markets provide increased diversification options for investors, that same advantage of access to markets may also be a poison chalice for investors who are less informed about correlations among markets. Several studies, including seminal work by Forbes and Rigobón (2001), have discussed the apparent impacts of inter-market transmission of shocks, particularly in times of turbulence or crisis (a.k.a. *contagion*). Though reasons for some of these occurrences are fairly intuitive, due to the obvious economic and financial linkages between the countries, others are less so. For example, the well-documented effects of the 1998 Russian crisis on Brazil and other Latin-American stock markets even when no apparent (trade and financial) links existed between them (see for example Baig and Goldfajn, 2000). In those cases, even though, the Brazilian and Venezuelan stock markets were most affected by the Russian crisis, and were generally believed to be most vulnerable to a currency crisis or debt default, it is also well-documented that other stock markets in Latin-America were also heavily affected (see Forbes and Rigobón, 2001 among others). In the extant literature, geographical proximity, financial linkages and trade links have been cited as potential reasons for stock markets to co-move (see Madaleno and Pinho (2011); Didier *et al*. (2011)). Notably, Latin-American stock markets (market capitalization), during the last few decades, appear to have increased their worldwide exposure and international investors interest, even if somewhat volatile especially those of Brazil, Mexico and Chile and also some noticeable differences exist in the size of these markets (see Table 1).

[TABLE 1 HERE]

According to the Gross fixed capital formation (current US$) in these countries show a similar pattern, with Brazil having $289.2 in 2016, $321.3 billion in 2017 after reaching a high of $539.1 in 2011. At the other extreme is Peru, with a not-very-meagre $41.3 in 2016 and $43.5 in 2017.[2] An analysis of co-movement between these markets is therefore relevant for the international investor.

[2] See https://data.worldbank.org/indicator/NE.GDI.FTOT.CD?locations=BR-PE

As suggested above, Latin-American markets appear to be a good representation for emerging and frontier markets.[3] With increased economic and financial integration globally, and significant increases in investor interest in emerging and frontier market equity markets, have equity markets in Latin-American become more similar? Are they moving in sync with the US equity market? Is there a clear lead/lag relationship? Such analyses will complement findings by studies that analyse the impacts of U.S. monetary policy on foreign equities (see examples Wongswan, 2009; Chortareas and Noikokaris, 2017; Du, 2017), that there is a statistically significant effect of US monetary policy surprises on foreign equity indexes, but then explain only a small percentage of the foreign equity price movements.

Intuitively, analyses of issues relating to co-movement between these markets should hold huge interest for risk-averse investors aiming to hold well-diversified portfolios. More specifically, this study aims to address the following questions: First, do Latin-American markets co-move and how do these markets co-move with the BOVESPA (São Paulo Stock Exchange), the largest stock market in Latin-America which has been subject of several studies (see for example, Medeiros *et al*., 2009, which showed that return from the NYSE and BOVESPA were cointegrated and co-moved with each other). Second, across these markets, is there contagion or there is simply interdependence?[4] In order to address this issue it is important to clarify the impact of return shocks during periods of normality i.e. interdependence, from augmented effect originated from crises periods, i.e. contagion. Samarakoon (2011) posits that the propagation of shocks across markets is a continuous phenomenon that happens constantly. Within periods of crisis, shocks become amplified, and their effects across markets is likely to be distinctive from the effects during relatively stable time periods. The term interdependence, as defined by Forbes and Rigobón (2002), refers to co-movements during stable periods driven by strong linkages among markets. Here, in this study, we consider the consensus definition of contagion as a change in the international propagation of shocks caused by some country-specific factor. In other words, we adopt the definition of contagion as the increase in cross-country correlations during crisis times relative to more tranquil times.[5] Our study aims to address the questions above in an easily-assessable manner and contribute to the still developing debate regarding to what extent equity markets in Latin-America co-move.

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[3] See also Morana and Beltratti, (2008); Harrison and Moore (2009).

[4] The extant literature makes a distinction between Contagion and Interdependence (see examples including Dornbusch *et al.* (2000), Forbes and Rigobón (2002), Pesaran and Pick (2007) and Marçal *et al.* (2011).

[5] The definition we adopt matches that used by Forbes and Rigobón (2002) and also is similar to the 'very restrictive' definition of contagion by the World Bank.

The empirical methodology we employ is three-pronged. First, we employ Principal Component Analysis (PCA), which offers a natural metric to gauge the extent of convergence between the Latin-American equity markets. Second, to determine the similarity (or differences) in parameter instability and structural change across the market returns over time, we also perform a multiple structural break test (Bai and Perron, 2003a). Third, we investigate co-movement between each possible pairing of the market returns by constructing the co-movement between each pair of market returns, and crucially, at each point in time by computing a *z*-score of each market's returns (see Yetman, 2011). The multi-pronged approach, the inclusion of the U.S. in our study and the consensus in the results underscore our findings and provide several insights into the co-movement between the U.S. equity market and equity markets of Latin America.

The rest of the paper is structured as follows. Section 2 reviews some related extant literature. Section 3 presents the data and methods employed in this study, while Section 4 analyses the results and Section 5 concludes.

2. Literature Review

Against the background presented above, we note that the extant literature is quite eclectic. First, some have focussed on whether, and how, the transmission of economic and financial events (crisis) from one country's to other countries' stock markets occur. Second, of both academic and business interest is the relation to portfolio diversification. As widely known from Portfolio Theory, the expected benefits of portfolio diversification exist only when assets included in an investor's portfolio have negative or near-zero correlations among them. Thus, there will be no additional gains from diversifying a portfolio with assets from another country's stock market which are highly correlated with the original assets – in fact, the risk may increase. In other words, international portfolio diversification is advantageous to investors only if stock markets in different countries do not co-move in the same direction. Furthermore, others investigate how stock markets may present lead-lag relationships between two different stock markets, which may then allow an investor to exploit abnormal returns by trading shares from the lagging market based on the behaviour of share prices in the leading market.

Madaleno and Pinho (2011) find that geographically and economically closer markets exhibit higher correlation and more short-run co-movements among them. They also find that strong co-movement is mostly confined to long-run fluctuations and supports the contagion analysis. Further Didier *et al*. (2011) find that co-movement between stock market returns is largely driven by financial linkages. Even a casual review of these economies show that several economic, financial and trade linkages exist among the Latin-American economies which suggest that some interdependence is not unexpected. Moreover, geographical proximity, common language (except Brazil), trade agreements, such as Mercosur (Southern Common Market), ALADI (Latin American Integration Association), creation of MILA (Latin American Integrated Markets) by Chile, Colombia, Mexico and Peru and also the Andean Community of Nations (See Appendix I for additional information) lend support to this view. Rapach *et al*. (2013), investigate lead-lag relationships among monthly country stock returns and identify a leading role for the United States and conclude that "lagged U.S. returns significantly predict returns in numerous non-U.S. industrialized countries, while lagged non-U.S. returns display limited predictive ability with respect to U.S. returns" p.1658. Tonin *et al*. (2013) also examine the lead-lag effect between the stock market of the BRICs, and suggest that in periods before and after the 2007/8 global financial crisis, the Brazilian market is, for a short period of time not longer than two days, the leading BRICs stock market exchange. Therefore, for the astute investor, a well-diversified portfolio requires a clear understanding of how international stock returns co-move and the dynamics of any co-movements.

Interestingly, several studies, including Bekaert and Harvey (1995), Harvey (1995) and Korajczyk (1996) posit that equity markets in emerging and frontier economies appear to provide better diversification opportunities for investors having portfolios which include equity markets in high income countries, due to their low correlations with them. Moreover, given the impacts on investor wealth, expectations and subsequent investment decisions, stability of the financial system may be impacted and this should be of concern to policymakers. The finding by Didier *et al*. (2011) that co-movement between stock market returns is largely driven by financial linkages and that countries having more vulnerable financial sectors co-moved more with the U.S. market further warrants inclusion of the US market in analyses of Latin American stock markets.

The seminal studies on the topic focus on several strands. A first wave focus on investigating co-movements between developed stock markets (see Eun and Shim, 1989; Bessler and Yang, 2003; Fraser and Oyefeso, 2005; Goetzmann, Li and Rouwenhorst, 2005). The second wave of studies concentrated on co-movements between developed and emerging stock markets where they explored the interrelationships between these two groups (see Valadkhani, Chancharat and Harvie, 2008; Evans and MacMillan, 2009). A third group of studies has been concerned with co-movements between emerging markets, generally belonging to a common continent or geographical region. Since a generalized literature review on stock market co-movement can be easily accessed in the extant literature, this section briefly discusses directly relevant studies i.e. those focussing on co-movements involving the emerging markets in countries belonging to Latin American and the neighbouring Caribbean region.

Christofi and Pericli (1999) investigate the short-run dynamics between five major Latin-American stock markets (Argentina, Brazil, Chile, Colombia and Mexico) by estimating the joint distribution of stock returns. Employing a vector autoregressive (VAR) model with innovations and following an exponential GARCH process over a five year period (1992*m*5 - 1997*m*5), they find that these countries have significant first and second moment time dependencies and that these markets reveal stronger volatility than mean spillovers. Further, they suggest that these markets are likely to exhibit stronger volatility spillovers than other regions of the world. Meric *et al*. (2001) examine the stability of correlations and the benefits of international portfolio diversification for an American investor by investing in the four largest Latin American markets (Argentina, Brazil, Chile and Mexico), during, and after, the 1987 stock market crash – when the Dow Jones Industrial Average fell by 508.32 points (or 22.6%), and lost *circa* US$500 billion in one day, the largest one-day percentage drop in history. They use principal components analysis to study changes in co-movement patterns of the selected equity markets from the pre-crash period to the post-crash period and *during* the post-crash period. They also apply Box's *M*-statistic to study the inter-temporal stability of the variance–covariance matrix of the equity market index returns. For the 1991-1993 sample period, they find that correlations increase over time and that there are no significant gains for holding a domestically well-diversified U.S. portfolio over holding a well-diversified portfolio of Latin-American stocks. Accordingly, they argue that investment in Latin-America should be made through a careful selection of countries and securities instead of the purchasing of a broad index of Latin-American stocks. Lopes and Migon (2002), aiming at measuring the transmission of shocks by cross-market correlation coefficients and following Forbes and Rigobón's (2001) notion of 'shift-contagion', combine traditional factor model techniques with stochastic volatility models to study the dependence among Latin-American stock price indexes and the North-American index. Modelling factor variances using a multivariate stochastic volatility structure and allowing factor loadings, in the factor model structure, to have a time-varying structure to capture changes in the series' weights over time, they conclude that their results show that some contagion is present in most of the series' covariance during periods of economic instability or crises. Fujii (2005) studies the causal linkages among several emerging stock markets in Asia and Latin America since 1990, using daily observations of stock indices and the GARCH family of econometric models. Using residual cross-correlation function tests to investigate cross-market causality both in the first and second moments of the stock returns, the study finds significant causal linkages both within each region and across the two regions. Moreover, the rolling test results suggest that the significance of the causality varies considerably over time and that the causal linkages become stronger at the time of major financial crises. Lorde, Francis and Greene (2009) analyse co-movement, common features and efficiency across three Caribbean Community (CARICOM) stock markets over 1991 to 2006 i.e. the stock markets of Barbados, Jamaica and Trinidad and Tobago. Analysing cointegration and common features among the three markets analysed, they do not find evidence of either long-run or short-run co-movement, or common features. They conclude that the three exchanges analysed are *weakly efficient*, that these markets are segmented, and that there may be benefits from regional diversification of security portfolios. Harrison and Moore (2010), analysing co-movement in five Caribbean stock markets (Barbados, Jamaica, Trinidad and Tobago, The Bahamas and Guyana), employ common factor analysis, obtained by principal component analysis. They divide their sample period in 10-year, 5-year and 3-year windows and test for co-movement in different periods to determine changes that might have taken place from one period to the next. They also use impulse response functions after specifying a vector autoregressive model to test for co-movement between the five markets during the sample period. Their study concludes that both tests fail to find any evidence of co-movement between the exchanges over the entire sample period, however they find evidence of periodic co-movement, particularly between exchanges in Barbados, Jamaica and Trinidad and Tobago. De Barba and Ceretta (2011) exploring the potential time-varying behaviour of long-run stock market relationships among four Latin American emerging capital markets (Brazil, Argentina, Chile and Mexico) and the U.S., consider the period of Global Financial Crisis (GFC) of 2007/2008. The authors test for cointegration using the Engle-Granger method before, during and after the crisis period. Their results suggest that Latin-American equity markets seem to respond differently to shocks in U.S. stock markets in the long-run. They posit that relationships between Argentina and Brazil and the United States have changed over time, as their markets have become more integrated; however, Chile’s and Mexico’s relationships with the U.S. did not change significantly during or after the crisis period. Their study therefore concluded that, for international diversification, each country should be analysed individually, and that analysing Latin America as a group could lead to misguided conclusions about international diversification opportunities.

3. Data and Methods

3.1 Sample and Data

We analyse the monthly returns, constructed from the monthly closing price indices from six Latin American stock exchange markets i.e. Merval (Argentina), Ibovespa (Brazil), IPSA (Chile) BMV (Mexico), IGVBL (Peru), and IBVC (Venezuela).[6] In addition, we use the *S&P 500* as a benchmark index, to assess the influence of the USA stock market on these Latin American markets. Specifically, the monthly returns represented in continuous compounding form and, accordingly calculated as $R_{it} = \Delta \ln p_{it}$, where Δ is a first difference operator, ln is the natural log operator, p_{it} is the stock market index of country i in period t. Our sample period extends from 1993m4 to 2016m3 and all data series were obtained from Thomson Reuters *DataStream*®.

3.1.1 Descriptive statistics

The summary statistics of the data (1993m4-2016m3) is reported in Table 2. Here, we highlight a few notable observations. Brazil and Venezuela appear to have the highest mean returns, 2.78% and 3.51% respectively, whereas the lowest mean returns were in Peru (1.16%) and Chile (0.72%). When the USA's *S&P* composite index is considered, in relation to the six Latin-American markets, it yields the lowest mean return (0.56%) suggesting that, in terms of returns, opportunities exist for international portfolio diversification in the region. The highest volatilities, measured by the standard deviation, are observed in Argentina (10.97%) and Brazil (12.00%), whereas the lowest volatilities are found in the Chilean (4.64%) and Mexican (6.91%) markets. Therefore, higher associated risk can be inferred in the former two markets and lower associated risk in the latter two. The U.S. market again exhibits a lower standard deviation. With respect to the distribution of returns, all of the selected markets present non-normal returns, according to the Jarque-Bera test. A majority of these markets, during the period analysed, exhibit negative skewness, suggesting that the proportion of months with negative returns tends to be higher than those with positive returns. Notably, the exceptions are Brazil and Venezuela, which have positive skewness.

[TABLE 2 HERE]

From Table 2, the data also highlights that all of these markets have leptokurtic distributions, suggesting 'fat tailed risk' in their returns. Finally, the correlation matrix reported in Table 3

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[6] Although some references situate Mexico in North America, the United Nations locates Mexico in Central America. See: http://unstats.un.org/unsd/methods/m49/m49regin.htm#americas

suggests the potential of the region for diversification with the Venezuelan market the most promising one for portfolio diversification due its lower correlation with the other markets. Interestingly also, with the exception of Mexico, the correlation coefficients of the individual countries with the USA's *S&P* composite index are all below 0.5. Figure 1 shows the mean returns and volatilities for the six Latin America markets plus the USA and in general the adage of high returns followed by high risks is present.

[TABLE 3 HERE]

[FIGURE 1 HERE]

3.2 Methods

3.2.1 Principal Components Analysis

In this study, we consider an alternative way to assess co-movement based on a common factor framework, which we implement using Principal Components Analysis (PCA). The approach offers a natural metric for the extent to which convergence of a set of times series, in the case of this research stock market returns, has occurred. It is worth noting here that the PCA has often been referred to in many statistical texts as a special case of Factor Analysis. However, PCA and Factor Analysis, as usually defined, are quite distinct techniques. The confusion may be related to the fact that both PCA and Factor Analysis aim to reduce the dimensionality of a set of data, but they differ in the techniques employed in doing so.[7]

Originally developed by Hotelling (1933), is concerned with explaining the variance-covariance structure of data through a few linear combinations of the original variables. Its general objectives are two-fold i.e. *Data reduction* and *Interpretation*. Although the original data set contains p variables, often much of the variability can be accounted by a smaller number m of principal components, where there is (almost) as much information in the m new variables (principal components) as in the original p variables. Thus, data reduction means that the original data set consisting of n observations on p variables is reduced to one consisting of n observations on m principal components. In general, p components are necessary to represent the total system variability, but there are many situations where much of the variability can be represented by a reduced number m of components. If so, there is nearly as much information in the m components as in the original p variables. The m principal components can then substitute the original p variables so that the original data set is reduced to a data set of n measurements on m principal components (Tsay, 2005).

[7] For a more detailed description and further details, see Jackson, J. E. (1991). 'A User's Guide to Principal Component Analysis', John Wiley and Sons.

Let $y=\{y_{it}\}$ be a vector of stock market indicators for country $i=1,\ldots,n$ for period $t=1,\ldots,T$, which are determined by a set of factors (components) f

$$y_{it} = \sum_{j=1}^{X} \lambda_{ij} f_{jt} + \varepsilon_{it} \qquad y_{it} = \lambda_i f_{it} + \varepsilon_{it} \tag{1}$$

where λ_i are the factor loading coefficients associated with each of the f common factors, and ε_{it} it is a white noise identically and independently distributed error term.

Becker and Hall (2009) show that a set of variables converge if the general factor representation given by Equation (1) can be constrained to a single factor. In this study, we obtain each of the X common factors by Principal Component Analyses (PCA) which represents the maximum portion of the variance for the chosen stock exchanges. Using the calculated monthly returns, we employ PCA to test for convergence over the sample period considered. We follow the definition of convergence from Becker and Hall (2009) which is based on the value of the $\%R^2$ of the first principal component, this value is a measure of the total variation in returns explained by the first factor.[8] The closer this value is to one, the greater the degree of convergence between the returns. In addition, if the $\%R^2$ over the first period is less than that in some subsequent period 2, then convergence has accelerated over the selected interval. Thus, the convergence is used as a measure of co-movement.

3.2.2 Multiple Structural Breaks test

The testing for parameter instability and structural change in regression models have been fundamental in applied econometric work; dating back to Chow (1960), who tested for regime change at *a priori* known dates using an *F*-statistic. As *a priori* known dates may not be clear to relax the requirement that the candidate break date be known, Quandt (1960) modified the Chow framework to consider the *F*-statistic with the largest value over all possible break dates. Others, including Andrews (1993) and Andrews and Ploberger (1994) deducted the limiting distribution of the Quandt (and related) test statistics.

Based on those previous methodologies, Bai (1997) and Bai and Perron (1998, 2003a, 2003b) determined theoretical and computational results that further extended the Quandt-Andrews framework by allowing to test for *multiple* unknown breakpoints. In this study, we consider the case of a pure structural change regression model with *T* periods and *m* potential

[8] Becker and Hall, 2009 (p.88) present this definition: "Convergence is taking place between a vector of 2 or more series over any given period 1 to T if the $\%R^2$ of the first principle component calculated over the period 1 to T/2 is less than the $\%R^2$ of the first principal component calculated over the period T/2 to T".

breaks (resulting $m+1$ regimes), for observations $T_j, T_j+1, \ldots, T_{j+1}-1$ for the regimes $j = 0, \ldots, m$ given by:

$$y_t = Z_t' \delta_j + \varepsilon_t \qquad (2)$$

The Z variables have coefficients that are regime specific.[9] In such cases, computation of the estimates of Equation 3 can be completed by simply employing the Ordinary Least Squares (OLS) approach, segment by segment, without constraints. Bai and Perron (1998) depict global optimization procedures for distinguishing the *m* multiple breaks which minimize the sums of square residuals (SSR) of the regression model in Equation (2). The multiple breakpoint tests may be broadly separated into three categories i.e. i) tests that use global maximizers for the breakpoints; ii) tests that employ sequentially defined breakpoints; and iii) hybrid tests which combine the two approaches. The tests can be performed allowing different serial correlation in the errors, different distribution for data and the errors across sections or stating a common structure. In this study, we apply the global maximizer approach in line with recommendations by Bai and Perron (2003a, p.15): "The problem is that, in the presence of multiple breaks, certain configurations of changes are such that it is difficult to reject the null hypothesis of 0 versus 1 break, but it is not difficult to reject the null hypothesis of 0 versus a higher number of breaks (this occurs, for example, when 2 changes are present and the value of the coefficient returns to its original value after the second break)." In such cases the sequential procedure breaks down.

Briefly for a specific set of *m* breakpoints, such as $\{T\}_m = (T_1, \ldots, T_m)$, we minimize

$$S(\beta, \delta | \{T\}) = \sum_{j=0}^{m} \left\{ \sum_{t=T_1}^{T_{t+1}-1} y_t - X_t' \beta - Z_t' \delta_j \right\} \qquad (3)$$

Using standard least squares regression to find the estimates $\hat{\beta}, \hat{\delta}$ in the case of a partial structural model; or $\hat{\delta}$ for a pure structural change model. Bai and Perron show that the number of comparison models increases rapidly in both *m* and *T* and derived practical algorithms for computing the global optimizers for multiple breakpoint models. These global break point estimates are then utilized as the benchmark for several breakpoint tests.

Bai and Perron (1998, 2003a) present a further generalization of the Quandt-Andrews (test (Andrews, 1993) in which tests for equality of the across multiple regimes. For a test of the null of no breaks against an alternative of breaks, an *F*-statistic is applied to assess the null hypothesis that $\delta_0 = \delta_1 = \cdots = \delta_{l+1}$ as below:

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[9] Bai and Perron (2003a) present a partial structural version of the model where variables which do not vary across regimes can also be considered.

$$F(\hat{\delta}) = \frac{1}{T}\left(\frac{T-(l+1)q-p}{kq}\right)(R\hat{\delta})'(R\hat{V}(\hat{\delta})R')^{-1}R\hat{\delta} \quad (4)$$

Where $\hat{\delta}$ is the optimal *l-break* estimate of δ, $(R\delta)' = (\delta_0' - \delta_1', \ldots, \delta_l' - \delta_{l+1}')$, and $\hat{V}(\hat{\delta})$ is an estimate of the variance covariance matrix of δ which may not suffer from serial correlation and heteroscedasticity depending on assumptions regarding the distribution of the data and the errors across segments.

A singular test of no breaks versus an alternative of *l* breaks assumes that the alternative number of breakpoints, *l*, is pre-determined. As is often the case, the precise number of breaks is not known; the Bai and Perron (BP) approach proposes the *double maximum tests* - two tests of the null hypothesis of no structural break against an the alternative of an unknown number of breaks, given some upper bound *M*. The first, UD_{max}, an equal-weighted version of the test, chooses the alternative that maximizes the statistic across the number of breakpoints. The second test, WD_{max}, employs weights to the individual tests such that the marginal *p-values* are equal across values of *M*. BP recommend that 5 breaks should be sufficient for most empirical applications, and provide the appropriate critical values for *M=5* and also options of a 5%, 10% and 15% sample trimming. BP also show that critical values appear to vary little when the upper bound *M* is greater than 5.[10] In this study, we test the individual stock market returns for multiple structural breaks using the "*Global L Breaks versus None*" option and explore similarity in number of breaks and, as consequence, infer some form of evidence of co-movements across these markets. Recent empirical applications relevant to this current work include Cuestas, Filipozzi and Staehr (2015, 2017).

3.2.3 Dynamic co-movement

Aiming to analyse dynamic co-movement between the markets, we deviate from the widely-used Pearson Correlation Coefficient (PCC), which though simple has a major limitation with high frequency data, in particular due to the narrowness of the time-specific information it provides. In this study, we follow Yetman (2011b), who proposes an improvement based on a *z*-score.[11] In brief, the co-movement, at time *t*, between the returns *R* of markets *i* and *j* can be estimated by the product of their respective *z*-scores (see Equation 5):

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[10] Bai and Perron(2003a) provide additional critical values for 20% (M=3) and 25% (M=2)

[11] For some empirical applications, see Bin *et al.* (2012) and Sirichand and Coleman (2015); and Yetman (2011a) for a theoretical background. Also, Yetman (2011b) points out, up to one-degree of freedom correction, the average of the co-movements in each time period as given by Equation (1) will equal the PCC, i.e. $\frac{1}{T}\sum_1^T \rho_t^{ij} = \frac{T-1}{T}\rho^{ij}$, where the PCC follows a Student's t-distribution.

$$\rho_t^{ij} = \frac{(R_{it}-\bar{R}_i)}{\sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(R_{it}-\bar{R}_i)^2}} \cdot \frac{(R_{jt}-\bar{R}_j)}{\sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(R_{jt}-\bar{R}_j)^2}} = z_{it}.z_{jt} \qquad (5)$$

We estimate Equation (5) for each possible pairing, i.e. the six markets plus the US market (i.e. ${}^7C_2$ or 21 pairs, the ρ^{it} across time. Positive estimates of ρ^{it} imply co-movement whereas negative values imply movement in opposite directions. In any one case, the relative size of the *z*-score indicates the strength of the co-movement. In line with the aims of this study, we are also interested in the proportion of the time that we observe co-movement between each market pair. For our purposes, a simple events study will suffice – we consider three periods: 2000*m*1-2006*m*12 as the *pre*-event period; 2007*m*1-2008*m*12 as the event window; and 2009*m*1-2016*m*3 as the *post*-event period. The proportion of times that positive estimates of the co-movement is observed is calculated and reported in Table 7 and, based on this, we are able to posit on whether there is any noticeable change in the periods of co-movement across any market pair.

4. Results and Discussion

4.1 Principal Components Analysis (PCA)

Table 4 reports the PCA results for the whole sample and for 8-, 6-, and 4-year rolling windows. For the whole sample period, the first principal component is able to explain approximately 49.79% of the variance in the data without the U.S. market, and 48.99% with the U.S. market. This result suggests that most of the variance in stock market return indices in Latin America cannot be attributed to one factor over the whole sample period. Furthermore the inclusion of the U.S. appears to have no substantial effect the increment is less than 1%. One clear implication is that there is incomplete convergence over the period and as a result, the study attempts to assess whether convergence has been period-specific or increasing over time.

To identify whether stock market co-movement is episodic, we provide a series of rolling windows periods respectively (8, 6, 4, 3, 2 and 1-year) for the first principal component for the Latin American stock exchanges without and with the inclusion of the U.S. market. For the 8, 6, and 4 years rolling windows it appears to have an indication of increasing convergence peaking when episodes of crises and international macroeconomic policy instability are embedded in the rolling window. For example, for the 8-year rolling window the highest periods of convergence can be flagged between 1997-2005 and 2004-2012. Notably, both periods contain major economic shocks such as the 1997/98 Asian Financial crisis, the 1999-

2001 Dot-Com bubble; the 1999 Brazilian Currency devaluation; the 2008-2009 Global Financial Crisis and the more recent 2011/12 Greek sovereignty debt crisis. The 6 and 4 years rolling windows appears to reassure this pattern of increasing co-movement apex during periods of economic and financial distress. These initial findings seems to be in line with studies from Forbes and Rigobón (2001), Barba and Ceretta (2010) Romero-Meza *et al*. (2015), Coronado *et al*. (2015) who also identify this behavioural pattern within Latin American countries. As most studies in this area traditionally include the USA, we also present the results by including it, however the analysis augmented by the USA market does not appear to increase or decrease the co-movement between the 7 stock exchanges with marginal differences being noticeable when analysing the rolling windows.

[TABLE 4 HERE]

To a certain extent this may imply that countries with smaller cultural distance have higher stock market co-movement as reported by Lucey and Zhang (2009). Figures 2 – 4 graphically illustrate the results from Table 4 where these patterns can be also seen.

[FIGURE 2 HERE]

[FIGURE 3 HERE]

[FIGURE 4 HERE]

Table 5 summarises the results for the shorter periods rolling windows respectively i.e. 3, 2, and 1 year. By examining these windows, we may expect the episodic periods of increasing and decreasing co-movements and their links with the occurrence of economic and financial shocks to be more prominent. It is fairly evident that the initial pattern of increasing convergence peaking during times of economic and financial distress is also repeated for shorter periods rolling windows. Particularly the 3- and 2-year rolling windows suggest a link of these co-movements during 1996-1999, 1997-2000, 1998-2001, 2006-2009, 2007-2010 and 2008-2011 for the 3 years rolling windows and similar results being replicated for 2 years windows. The 1-year rolling windows peaks suggest links with the Russian Crisis, Brazilian Real devaluation and the Global Financial Crisis. Besides as argued by Graham *et al*. (2012) the wave of financial sector liberalisation in these markets in the past few decades might have contributed to this development. Again those periods coincide with:

- *The 1997/98 Asian crisis:* During July 1997, the Thailand government was forced to switch from a U.S. dollar pegged currency to a free floating currency on the Thai baht.

The massive currency devaluation spread to neighbouring countries, leading to severe capital outflows in most of the developing world.

- *The 1998 Russian Crisis:* On August 17th 1998, the Russian government devalued its currency, defaulted on domestic debt, and ceased payments on foreign debt, leading to the Rubble crisis or so-called *Russian flu*.

[TABLE 5 HERE]

[FIGURE 5 HERE]

[FIGURE 6 HERE]

[FIGURE 7 HERE]

- *The 2007/08 Global Financial Crisis:* Although the origins of the subprime crisis can be traced back to August 2007, the financial panic was triggered in July 2008, after the rescue of Fannie Mae, Freddie Mac, and Bear Stearns, followed by the bankruptcy of Lehman Brothers and the multimillion rescue plan announced by the US government.

Finally, events including the junk bond rating assigned on Irish bank bonds by Moody's in April 2011, Portugal's rescue in May 2011 and the sharp increase in Greek CDS after the rejection of the European bailout plan by the former Greek Prime Minister Georgios Papandreou leading to the sovereign crisis debt are also noteworthy. These trends can also be seen is Figures 5, 6, and 7. We note here too that the inclusion of the US market appears not to have significant influence on the level of co-movement among the six Latin America markets.

4.2 Structural break analyses

This section focusses on the results of the multiple break point tests developed by Bai and Perron (2003). In order to apply the tests, we specified a multiple regression equation (Eq. 6) for each of the six Latin American markets over the whole sample, with and without the USA.

$$Y_{jt} = \alpha_t + \sum_{k=1}^{6} \beta_{kt} X_{kt} + \varepsilon_t \qquad (6)$$

In Equation 6, Y_j is the return in country *j* in which the multiple break test is considered, and X_k are the returns in the other countries *k* = 1,…., 6.

In order to overcome potential problems of heteroskedasticity and serial correlation we employ the Newey-West (1987) estimator to the covariance matrix. In total, we allowed a maximum number of five breaks based on the sample size; we also employed a 15% trimming and 5% significance level. As described in Section 3, we apply the *Global L Breaks vs. None* approach, using an *F*-statistic and *Double Maximum test* which involves maximisation both for a given number of breaks *l* across various values of the test statistic for *l*. The hypothesis can be summarised as H_0: No structural breaks and H_A: Alternative number of unknown breaks up to an upper bound ($m=5$). Table 6 below summarises the results:

[TABLE 6 HERE]

A preliminary but crucial observation is that, in general, the breaks are similar across the markets and the inclusion of the USA – as with the PCA analysis – does not appear to have a clear distinctive effect. This is quite an interesting and important result in this study, as there is a full body of literature that states be the USA market the leading market in terms of co-movements within the region.[12] The findings so far from the convergence and structural break analyses appear to suggest that this may not be the case, and the whole of these American markets tend to be synchronised without a distinct lead-lag relationship. An important consideration is that emerging Latin American equity markets have become pivotal to international investors, especially to USA investors, since the late 1980s and during the 1990s since these countries started to liberalise their equity markets during these periods. Moreover, the substantial increase in bilateral trade (see Hornbeck, 2004) between these countries and the USA since 1992 has attracted the attention of not only investors and policymakers but also of academic researchers studying the impact of international trade on equity market correlations.[13] Johnson and Soenen (2003) find a high percentage of contemporaneous association between Latin-American equity markets and the USA equity market. Moreover, they find that a high trade share with the USA has a strong positive impact on equity market co-movements. Forbes and Chinn (2004) show that direct trade flows are a relevant determinant of cross-country linkages. Chen and Zhang (1997), studying the relationship between bilateral trade and cross-country return correlations, find that countries with more trade to a region tend to have higher return correlations with that region. In our analyses, we also point out that the periods covered by the identified breaks also suggest alignment with periods of regional/global financial and macroeconomic instability and may be used as a robustness check for the PCA results that tend

[12] We tested for multiple structural breaks between each country and the USA only and with the exception of Chile all the remaining countries did show any identified break at 5% significance level.
[13] Bi-lateral trade (on exports and imports) data compiled from Thomson Reuters DataStream during this current study confirm the increase. For brevity though, these tables have not been included here, but can be made available upon request.

to signal an increase in co-movement during periods of instability. The tests in the subsequent section aim to further test this view of increasing comovement.

4.3 Correlation Dynamics

Employing Equation 5, we estimate all the possible pairings of the ρ_t^{ij}, for the seven markets. Following this, we are then able to graphically illustrate and examine the behaviour of these cross-market co-movements over time (See Figures 8 and 9). Positive entries ($\rho_t^{ij} > 0$) represent co-movement, whereas negative entries ($\rho_t^{ij} < 0$) imply the markets move in opposite directions. Some notable observations are highlighted below. First, the estimated *z*-scores appear to show stronger co-movement during periods of economic crises. For example, the 1998 and 2007/8 crises are clearly captured across all the possible pairings as periods of higher co-movement, which corroborates the results found in the PCA analyses above. This lends support to earlier findings by Forbes and Rigobón (2001) *vis-à-vis* the impacts of the transmission of shocks from one market to another, particularly in times of turbulence. Second, across all the 21 (i.e. ${}^7C_2$) possible pairings, the markets appear to be fluctuating around the zero mark over most of the period. The relevance of this co-movement for investors is crucial, so in order to ascertain the proportion of the sample period over which co-movement is found between any pair, Table 7 reports the percentage of positive entries. The results of this exercise suggest that, typically, there is over co-movement between the markets in over 60% of the time analysed. The exception, though, appears to be the Venezuelan stock market which seems to commove with the other markets the least i.e. around 50% of the entire period. In other words, risk-averse investors in these Latin-American markets may, in theory, include the Venezuelan market in their portfolios to improve diversification.[14] Did the markets commove more or less following the 2007/8 global financial crisis? Analyses of an *ad-hoc* pre-crisis (2001*m*1 – 2006*m*12) and post-crisis (2009*m*1 – 2016*m*3) periods, do not present a clear pattern for all the markets. However, on the one hand, an indicative observation is that the larger markets of Brazil, Argentina and Mexico appear to commove even more following the crisis and in line with the findings of Samarakoon (2011) indications of a bi-directional co-movement with the U.S. On the other hand, the smaller markets, particularly Venezuela appears to demonstrate even less co-movement with the other markets following the crisis. This observation buttresses

[14] We, however, note the continuing economic and political turmoil in Venezuela since the institution of the Bolivarian Republic by ex-president Hugo Chavez (1954-2013) and his successors.

the point made earlier that risk-averse investors can improve diversification of their portfolios by combining Venezuelan equities with the other Latin-American assets.

[FIGURE 8 HERE]

[FIGURE 9 HERE]

[TABLE 7 HERE]

5. Conclusions

In this study, we have used the monthly returns, constructed from the monthly closing price indices from six Latin American stock exchange markets [Merval (Argentina), Ibovespa (Brazil), IPSA (Chile) BMV (Mexico), IGVBL (Peru), and IBVC (Venezuela)] and the U.S. *S&P500* market index to examine to what extent the Latin-American equity markets co-move with each other and also with the US equity market. First, our results suggest that, *post*-2009, irrespective of the equity market choice, an inclusion of the Venezuelan equity market in investor portfolios is likely to increase the benefits of diversification. It is worth noting Venezuela's recent political and economic problems may lessen some investors' willingness to invest there. Mexico, on the other hand, appears to co-move the most with the other markets, implying least portfolio diversification benefits. Second, *post*-2009, with the exception of Venezuela, the Latin-American markets co-move with the US market over 60% of the time with the highest degree of co-movement being with Mexico (the Mexican trading is completely concurrent with the US, opening and closing at the same times). This highlights the possible impact of the North American Free Trade Agreement (NAFTA) in the Mexican equity markets, as reported by Lahrech and Sylwester (2013) who found increased linkages between the two markets due to the trade agreement. Third, we find that, *post*-2009, co-movement with the US equity market appears to have decreased across the markets compared to the 2001-2006 period.

In an era of easier large capital inflows, this study underscores the importance of understanding interdependencies among Latin-American markets and also with the US in order to make reliable and profitable portfolio decisions. The implication from this study, for investors, is that optimal (limited risk) portfolios of Latin-American equities can be obtained by including Venezuela, and despite the relatively high degree of co-movement with the US market, we do not find evidence to support the US markets having a clear leading role across the Latin-American markets. As mentioned earlier, in practice, international investors are not likely to ignore the potential role of the political and economic situation in Venezuela.

Arguably, technological advances in trading allied to high frequency trading and instantaneous exploitation of asset prices discrepancies may have blurred the lead-lag process.

For policy makers, the observed levels of co-movement between the US and these Latin American equity markets underscore the relevance of considering and being prepared for contagion effects when formulating policies relating to financial regulation and international capital flow controls. It suggests that equity market disturbances in the US and other countries in the region are more likely to be transmitted to the other countries, which may then have adverse consequences for the stability of the financial system. In particular this is so for Mexico, but less so for Venezuela. One natural extension of this paper will be a more close investigation of the economic factors behind the differences in the observed links and co-movements and also to determine to what extent differences arise across these Latin American markets.

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APPENDIX

APPENDIX I: Regional blocs and linkages in Latin-America

1. *Mercosur:* A sub-regional bloc officially established in March 1991, and follows the framework of the European Economic Area (EEA). The bloc aims to substantially reduce trade barriers among their members, so as to increase trade and cooperation. The main objective is to establish zero trade tariffs between members, paving the way for the creation of a single currency. The membership includes South American countries: Argentina, Brazil, Paraguay, Uruguay and Venezuela. Recently, though, Venezuela's membership has been under scrutiny and Bolívia, Chile, Columbia, Equador, and Peru are considered associate members.

2. *MILA (Latin American Integrated Markets):* The Latin American Integrated Market (MILA) is the result of an agreement signed by the Santiago Stock Exchange, the Colombia Stock Exchange and the Lima Stock Exchange, along with the CSDs Deceval, DCV and Cavali, who in 2009 started the process of setting up a regional market to trade equities from the three countries. After several months of working together, in

which the main actors from all three markets and government authorities of each country played an important role, MILA began operating on May 30th, 2011; thereby opening up a world of opportunities for investors and brokers from Chile, Colombia and Peru, who can now purchase and sell shares from the three stock markets through a local broker. Mexico became a member in December 2014.

3. *The Andean Community of Nations (formerly Andean Pact):* Created in 1969 to integrate member countries economically and culturally, towards the formation of a common Latin American market, to enhance the interests of member countries in agreements with other economic blocks or international organizations. Membership includes Bolivia, Colombia, Ecuador and Peru, with Brazil, Argentina, Chile, Paraguay and Uruguay as associate members.

Table 1: Market Capitalization of Listed Domestic Companies

Country	Market Capitalisation (x 10^{10} USD)		
	June' 06	**June' 11**	**June' 16**
Brazil	71.00	123.00	75.90
Argentina	5.12	4.36	6.36
Peru	4.00	8.19	8.11
Mexico	34.80	40.90	35.10
Chile	17.40	27.00	21.2
U.S.	1,960.00	1,560.00	2,740.00

Source: *DataStream*®; Market capitalization for Venezuela only available for 2001 and 2002, as 0.62×10^{10} USD and 0.397×10^{10} USD respectively.

Table 2: Descriptive Statistics of Monthly Returns of Latin American/USA Stock Exchanges (1993*m*4 – 2016*m*3)

	R_{ARG}	R_{BRA}	R_{CHI}	R_{MEX}	R_{PER}	R_{USA}	R_{VEN}
Mean	0.012684	0.027780	0.007187	0.012058	0.011598	0.005611	0.035087
Median	0.016751	0.018594	0.004074	0.015266	0.009105	0.011004	0.016394
Maximum	0.430373	0.607421	0.162710	0.176613	0.325410	0.102307	0.653863
Minimum	-0.500619	-0.483385	-0.240741	-0.349814	-0.466485	-0.185636	-0.514268
Std. Dev.	0.109712	0.120019	0.046354	0.069077	0.089158	0.042890	0.116758
Skewness	-0.486209	0.842841	-0.240285	-0.924552	-0.290449	-0.840500	0.712876
Kurtosis	6.431791	7.362720	6.256907	6.508462	6.948004	4.680077	7.465323
Jarque-Bera	145.7819	250.6492	124.1899	180.2223	182.4646	64.72144	251.7612
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	3.488110	7.639502	1.976322	3.315981	3.189552	1.543129	9.648924
Sum Sq. Dev.	3.298071	3.946878	0.588752	1.307414	2.178076	0.504047	3.735295
Observations	275	275	275	275	275	275	275

Notes: In this table, R_{ARG}, R_{BRA}, R_{CHI}, R_{MEX}, R_{PER}, R_{USA} and R_{VEN} represent returns for the stock markets in Argentina, Brazil, Chile, Mexico, Peru, the USA and Venezuela respectively.

Table 3: Correlation Matrix

	R_{ARG}	R_{BRA}	R_{CHI}	R_{MEX}	R_{PER}	R_{USA}	R_{VEN}
R_{ARG}	1.000000						

R_{BRA}	0.387671	1.000000					
	(6.948778)	-----					
	[0.0000]	-----					
R_{CHI}	0.452669	0.495466	1.000000				
	(8.387921)	(9.424567)	-----				
	[0.0000]	[0.0000]	-----				
R_{MEX}	0.609024	0.482527	0.437989	1.000000			
	(12.68700)	(9.102447)	(8.049978)	-----			
	[0.0000]	[0.0000]	[0.0000]	-----			
R_{PER}	0.501499	0.467503	0.517870	0.445914	1.000000		
	(9.577590)	(8.738109)	(10.00236)	(8.231374)	-----		
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	-----		
R_{USA}	0.441665	0.431138	0.418852	0.598349	0.389235	1.000000	
	(8.133813)	(7.895027)	(7.621315)	(12.33889)	(6.981819)	-----	
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	-----	
R_{VEN}	0.207184	0.095667	0.153671	0.194099	0.160322	0.167057	1.000000
	(3.499173)	(1.587968)	(2.569582)	(3.269222)	(2.683673)	(2.799573)	-----
	[0.0005]	[0.1135]	[0.0107]	[0.0012]	[0.0077]	[0.0055]	-----

Notes: In this table, R_{ARG}, R_{BRA}, R_{CHI}, R_{MEX}, R_{PER}, R_{USA} and R_{VEN} represent returns for the stock markets in Argentina, Brazil, Chile, Mexico, Peru, the USA and Venezuela respectively. Entries in ( ) and [ ] represent the t-statistic and *p*-values respectively.

Table 4: R-Square First Principal Component NoUSA and USA (8,6 and 4 Years Rollling Windows)																				
Full Sample	1994M04-2016M03																			
NOUSA	0.4979																			
USA	0.4899																			
8-years Windows	1993-2001	1994-2002	1995-2003	1996-2004	1997-2005	1998-2006	1999-2007	2000-2008	2001-2009	2002-2010	2003-2011	2004-2012	2005-2013	2006-2014	2007-2015	2008-2016				
NOUSA	0.557	0.5699	0.5783	0.5981	0.6058	0.5878	0.4751	0.4912	0.5347	0.5699	0.5803	0.5835	0.5791	0.5544	0.5421	0.5467				
USA	0.5244	0.5415	0.5566	0.5754	0.582	0.5737	0.4792	0.5035	0.5507	0.5806	0.5861	0.5956	0.5914	0.5681	0.5578	0.5624				
6-years Windows	1993-1999	1994-2000	1995-2001	1996-2002	1997-2003	1998-2004	1999-2005	2000-2006	2001-2007	2002-2008	2003-2009	2004-2010	2005-2011	2006-2012	2007-2013	2008-2014	2009-2015	2010-2016		
NOUSA	0.5608	0.5835	0.6178	0.6186	0.6155	0.6033	0.4725	0.4883	0.4744	0.4847	0.5814	0.5991	0.6014	0.6008	0.5872	0.567	0.4873	0.4689		
USA	0.5294	0.5476	0.5916	0.5911	0.5882	0.5823	0.4792	0.5036	0.4908	0.4953	0.5899	0.6055	0.6079	0.6148	0.6032	0.5835	0.4992	0.4846		
4-years Windows	1993-1997	1994-1998	1995-1999	1996-2000	1997-2001	1998-2002	1999-2003	2000-2004	2001-2005	2002-2006	2003-2007	2004-2008	2005-2009	2006-2010	2007-2011	2008-2012	2009-2013	2010-2014	2011-2015	2012-2016
NOUSA	0.4221	0.4732	0.6423	0.6753	0.6798	0.6331	0.4561	0.4802	0.4718	0.4809	0.4726	0.51	0.6151	0.6296	0.6257	0.625	0.5448	0.4623	0.4425	0.4444
USA	0.3764	0.437	0.6263	0.6382	0.6469	0.6029	0.4614	0.506	0.4956	0.4962	0.4725	0.5023	0.6205	0.638	0.6334	0.6413	0.5629	0.4857	0.4682	0.4442

Table 5: R-Square First Principal Component NoUSA and USA (3, 2 and 1 Year Rollling Windows)

3-years Windows	1993-1996	1994-1997	1995-1998	1996-1999	1997-2000	1998-2001	1999-2002	2000-2003	2001-2004	2002-2005	2003-2006	2004-2007	2005-2008	2006-2009	2007-2010	2008-2011	2009-2012	2010-2013	2011-2014	2012-2015	2013-2016		
NOUSA	0.4361	0.4017	0.4851	0.7061	0.6983	0.6881	0.4681	0.4686	0.4674	0.4709	0.4734	0.5019	0.5249	0.6302	0.6448	0.6504	0.5629	0.5183	0.4489	0.4037	0.4454		
USA	0.3869	0.3557	0.4764	0.6832	0.6635	0.6506	0.461	0.4878	0.5003	0.4975	0.4708	0.4916	0.5196	0.6357	0.6522	0.6587	0.5828	0.5475	0.4818	0.4023	0.4428		
2-years Windows	1993-1995	1994-1996	1995-1997	1996-1998	1997-1999	1998-2000	1999-2001	2000-2002	2001-2003	2002-2004	2003-2005	2004-2006	2005-2007	2006-2008	2007-2009	2008-2010	2009-2011	2010-2012	2011-2013	2012-2014	2013-2015	2014-2016	
NOUSA	0.5182	0.4118	0.3601	0.6176	0.733	0.7117	0.5115	0.488	0.4695	0.4544	0.4348	0.5116	0.5084	0.5464	0.6311	0.6757	0.5816	0.5441	0.5282	0.3843	0.3923	0.5145	
USA	0.4555	0.3602	0.333	0.59	0.7202	0.669	0.4907	0.4956	0.4912	0.5025	0.4356	0.4917	0.5027	0.543	0.6329	0.6842	0.5819	0.5774	0.5717	0.3877	0.3852	0.5215	
1-year Window	1993-1994	1994-1995	1995-1996	1996-1997	1997-1998	1998-1999	1999-2000	2000-2001	2001-2002	2002-2003	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016
NOUSA	0.4622	0.536	0.441	0.3913	0.7117	0.7582	0.4339	0.5711	0.4868	0.5468	0.3531	0.4937	0.5158	0.584	0.5437	0.6821	0.6094	0.5723	0.5857	0.5236	0.3585	0.4861	0.5557
USA	0.4854	0.46	0.4486	0.366	0.6997	0.7413	0.3738	0.5816	0.4939	0.5623	0.3606	0.4631	0.4918	0.5853	0.5213	0.6786	0.5973	0.5927	0.6385	0.5299	0.3507	0.5048	0.5653

Notes: The highlighted entries indicate the high values of the PCA.

Table 6: Bai and Perron (2003a) Multiple Breaks Test Results

Number of Breaks											
COUNTRY	**Sequential F-Statistic**	**UDMAX**	**WDMAX**			**COUNTRY**	**Sequential F-Statistic**	**UDMAX**	**WDMAX**		
Argentina	*5**	*4**	*4**			**Mexico**	*5**	*3**	*5**		
Initial Date Breaks	*1997M9*	*2001M8*	*2005M1*	*2008M10*	*2012M11*	**Initial Date Breaks**	*1996M11*	*2000M4*	*2003M11*	*2008M4*	*2011M11*
Argentina with USA	*5**	*5**	*5**			**Mexico with USA**	*5**	*3**	*5**		
Initial Date Breaks	*1996M12*	*2001M7*	*2005M1*	*2008M10*	*2012M11*	**Initial Date Breaks**	*1996M12*	*2000M5*	*2003M11*	*2007M4*	*2010M12*
COUNTRY	**Sequential F-Statistic**	**UDMAX**	**WDMAX**			**COUNTRY**	**Sequential F-Statistic**	**UDMAX**	**WDMAX**		
Brazil	*0**	*5**	*5**			**Peru**	*5**	*2**	*2**		
Initial Date Breaks	*1996M12*	*2000M5*	*2005M2*	*2008M8*	*2012M1*	**Initial Date Breaks**	*1996M11*	*2000M5*	*2003M12*	*2007M8*	*2011M8*
Brazil with USA	*0**	*5**	*5**			**Peru with USA**	*5**	*2**	*2**		
Initial Date Breaks	*1996M11*	*2000M5*	*2005M2*	*2008M8*	*2012M1*	**Initial Date Breaks**	*1996M11*	*2000M5*	*2003M12*	*2007M8*	*2011M8*
COUNTRY	**Sequential F-Statistic**	**UDMAX**	**WDMAX**			**COUNTRY**	**Sequential F-Statistic**	**UDMAX**	**WDMAX**		
Chile	*2**	*4**	*5**			**Venezuela**	*0**	*3**	*4**		
Initial Date Breaks	*1996M10*	*2000M3*	*2003M11*	*2008M4*	*2011M12*	**Initial Date Breaks**	*1996M11*	*2000M4*	*2007M1*	*2011M5*	
Chile with USA	*5**	*5**	*5**			**Venezuela with USA**	*0**	*3**	*4**		
Initial Date Breaks	*1996M11*	*2000M5*	*2004M9*	*2008M4*	*2011M9*	**Initial Date Breaks**	*1996M11*	*2000M4*	*2007M1*	*2011M5*	
COUNTRY	**Sequential F-Statistic**	**UDMAX**	**WDMAX**								
USA	*5**	*2**	*5**								
Initial Date Breaks	*1996M12*	*2000M9*	*2004M2*	*2007M7*	*2010M12*						

Notes: * indicates 5% significance level. The initial date breaks embeds the period until the month before the start of the next break.

Table 7: Percentage of positive estimates of ρ_t^{ij} (co-movement) – full sample, pre-crisis and post-crisis.

Country pair	**Full Sample (1993*m*5-2016*m*3) [%]**	***Pre*-Crisis (2001*m*1-2006*m*12) [%]**	***Post*-Crisis (2009*m*1-2016*m*3) [%]**
Number of Obs.	275	84	87
Argentina - Brazil	69.09	65.48	68.97
Argentina - Chile	60.00	58.33	54.02
Argentina - Mexico	70.91	63.10	75.86
Argentina - Peru	64.00	64.29	62.07
Argentina - Venezuela	58.55	66.67	**47.13**
Argentina – U.S.	65.82	64.29	66.67
Brazil - Chile	69.09	64.29	72.41
Brazil - Mexico	69.82	69.05	74.71
Brazil - Peru	68.73	65.48	72.41
Brazil - Venezuela	53.82	63.10	**48.28**
Brazil – U.S.	67.64	75.00	65.52
Chile - Mexico	67.27	69.05	70.11
Chile - Peru	67.64	65.48	67.82
Chile - Venezuela	54.91	58.33	**45.98**
Chile – U.S.	65.82	76.62	67.82
Mexico - Peru	66.18	72.62	70.11
Mexico - Venezuela	51.27	55.95	**41.38**
Mexico - USA	73.82	82.14	70.11
Peru - Venezuela	55.27	54.76	**52.87**
Peru – U.S.	59.64	66.67	60.92
Venezuela – U.S.	53.45	59.52	**45.98**

Figure 1: Stock market Mean Returns and Standard deviations

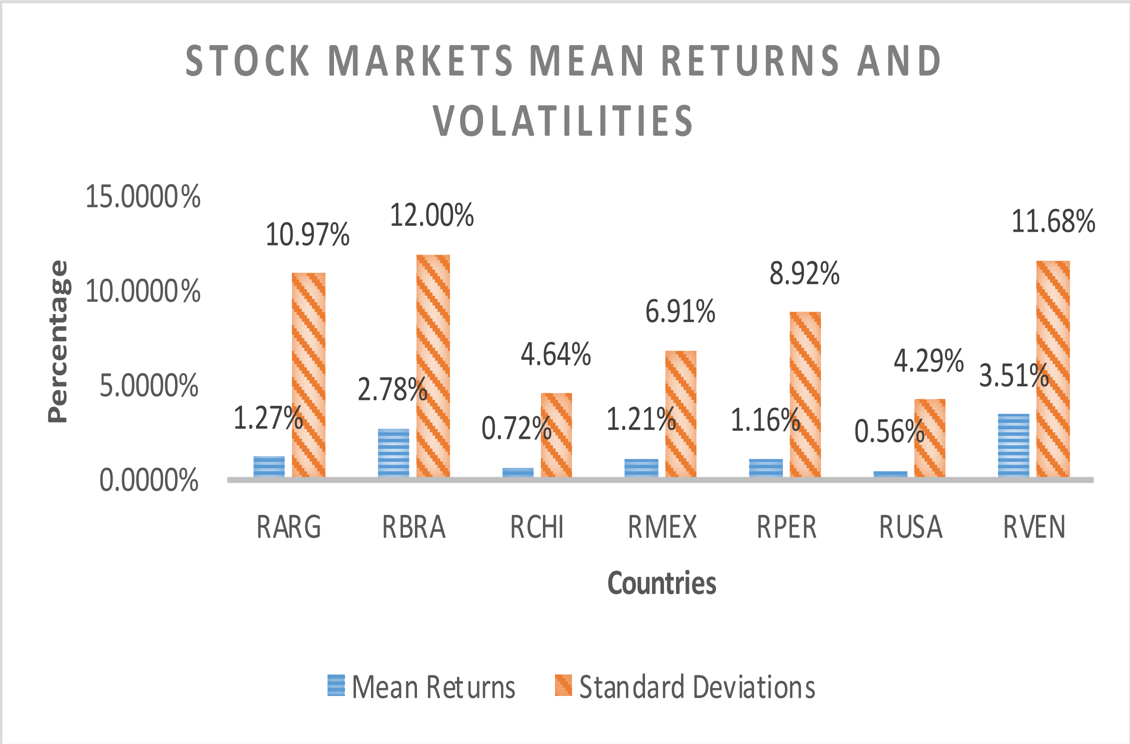

Figure 2: PCA 1st Component Results 8-Years Windows

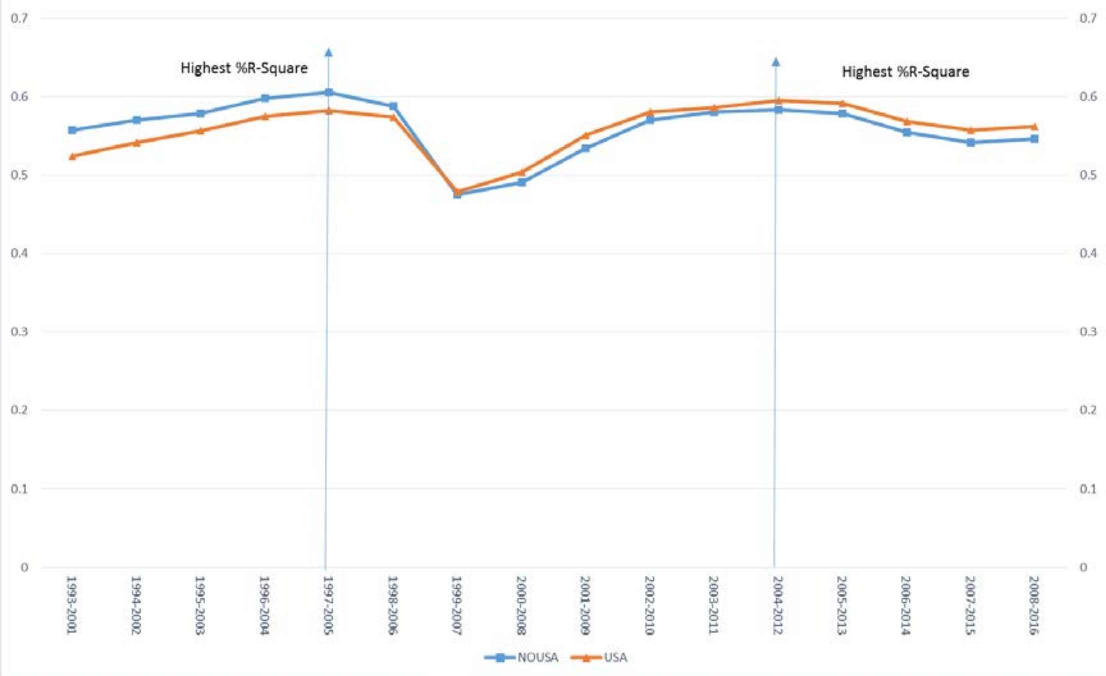

Figure 3: PCA 1st Component Results 6-Years Windows

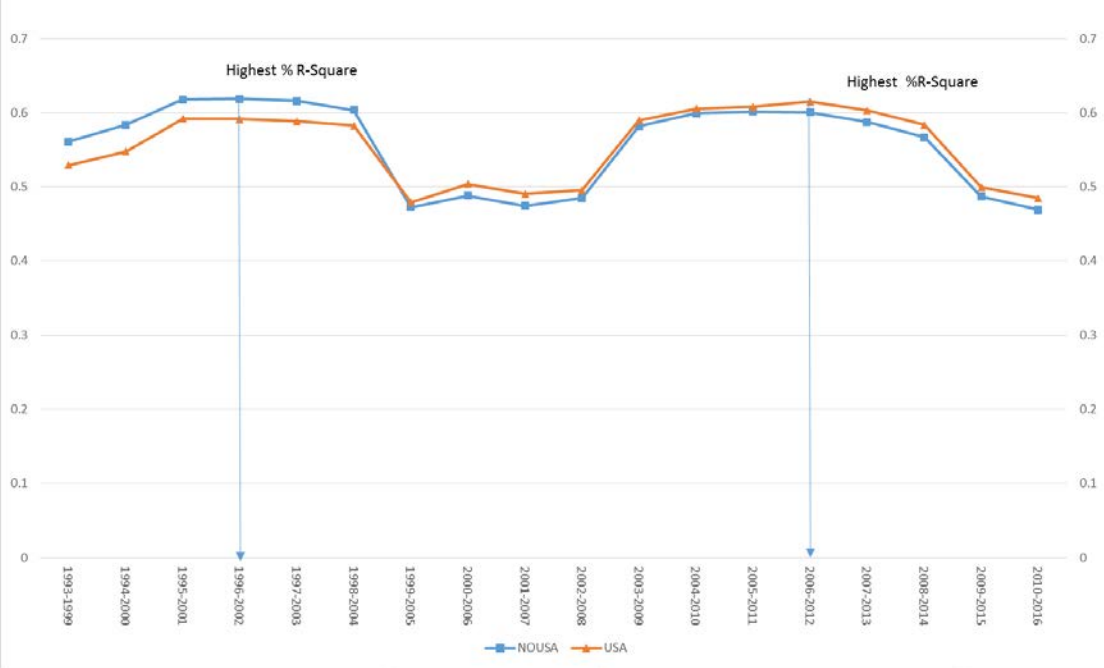

Figure 4:PCA 1st Component Results 4-Years Windows

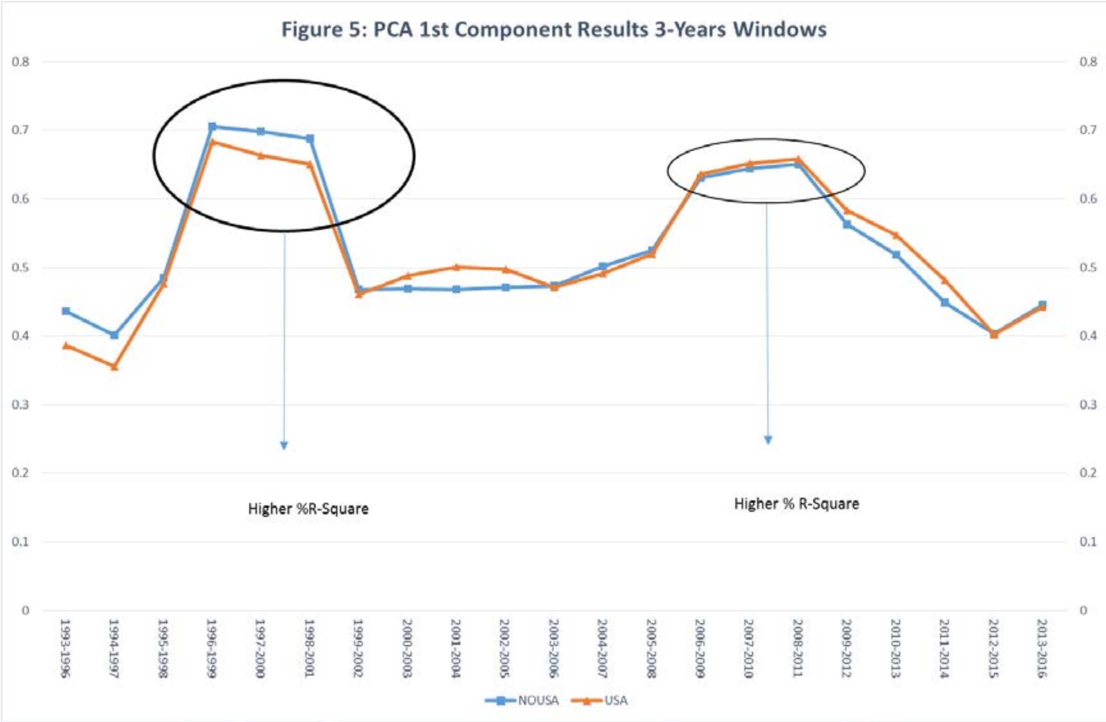
Figure 5: PCA 1st Component Results 3-Years Windows
Higher %R-Square
Higher % R-Square
NOUSA
USA

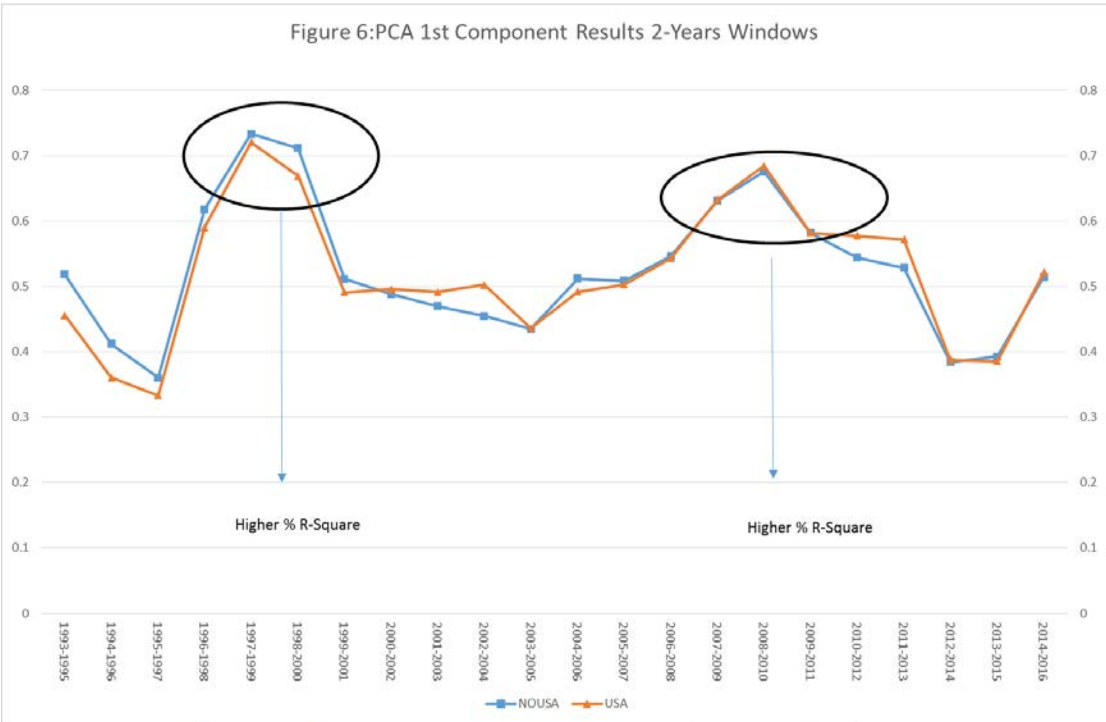
Figure 6:PCA 1st Component Results 2-Years Windows
Higher % R-Square
Higher % R-Square
NOUSA
USA

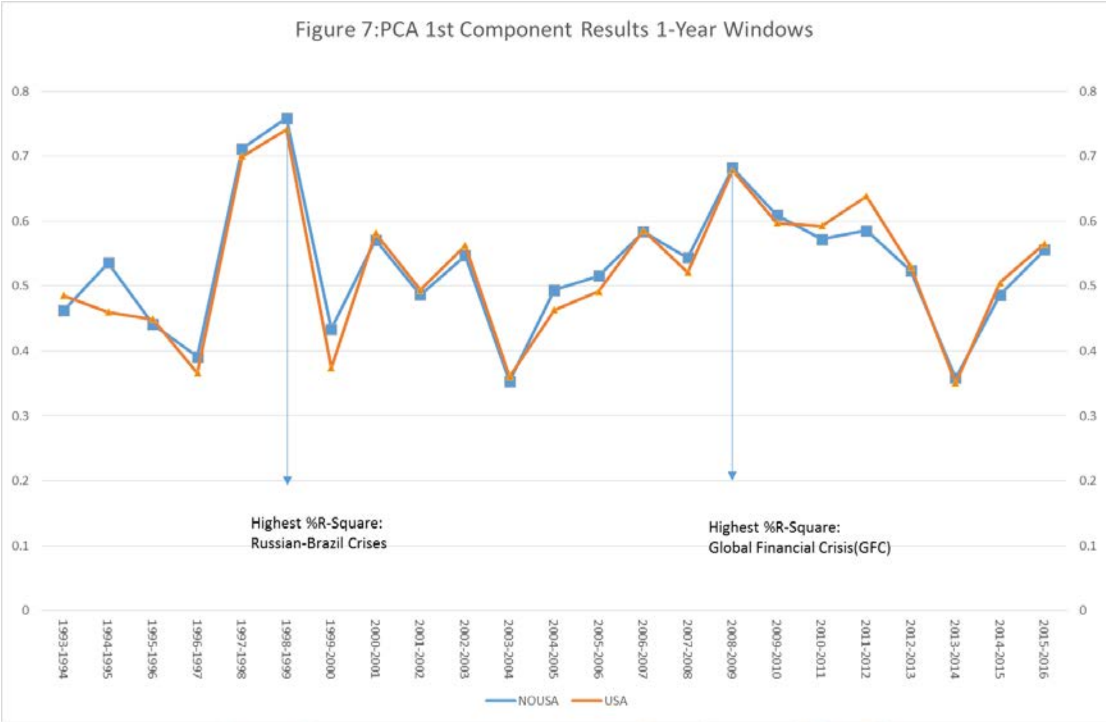

Figure 7:PCA 1st Component Results 1-Year Windows
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Highest %R-Square:
Russian-Brazil Crises
Highest %R-Square:
Global Financial Crisis(GFC)
1993-1994
1994-1995
1995-1996
1996-1997
1997-1998
1998-1999
1999-2000
2000-2001
2001-2002
2002-2003
2003-2004
2004-2005
2005-2006
2006-2007
2007-2008
2008-2009
2009-2010
2010-2011
2011-2012
2012-2013
2013-2014
2014-2015
2015-2016
NOUSA
USA

Figure 8: Estimates of comovement, ρ_t^{ij} (Set I: Argentina and Brazil versus other markets)

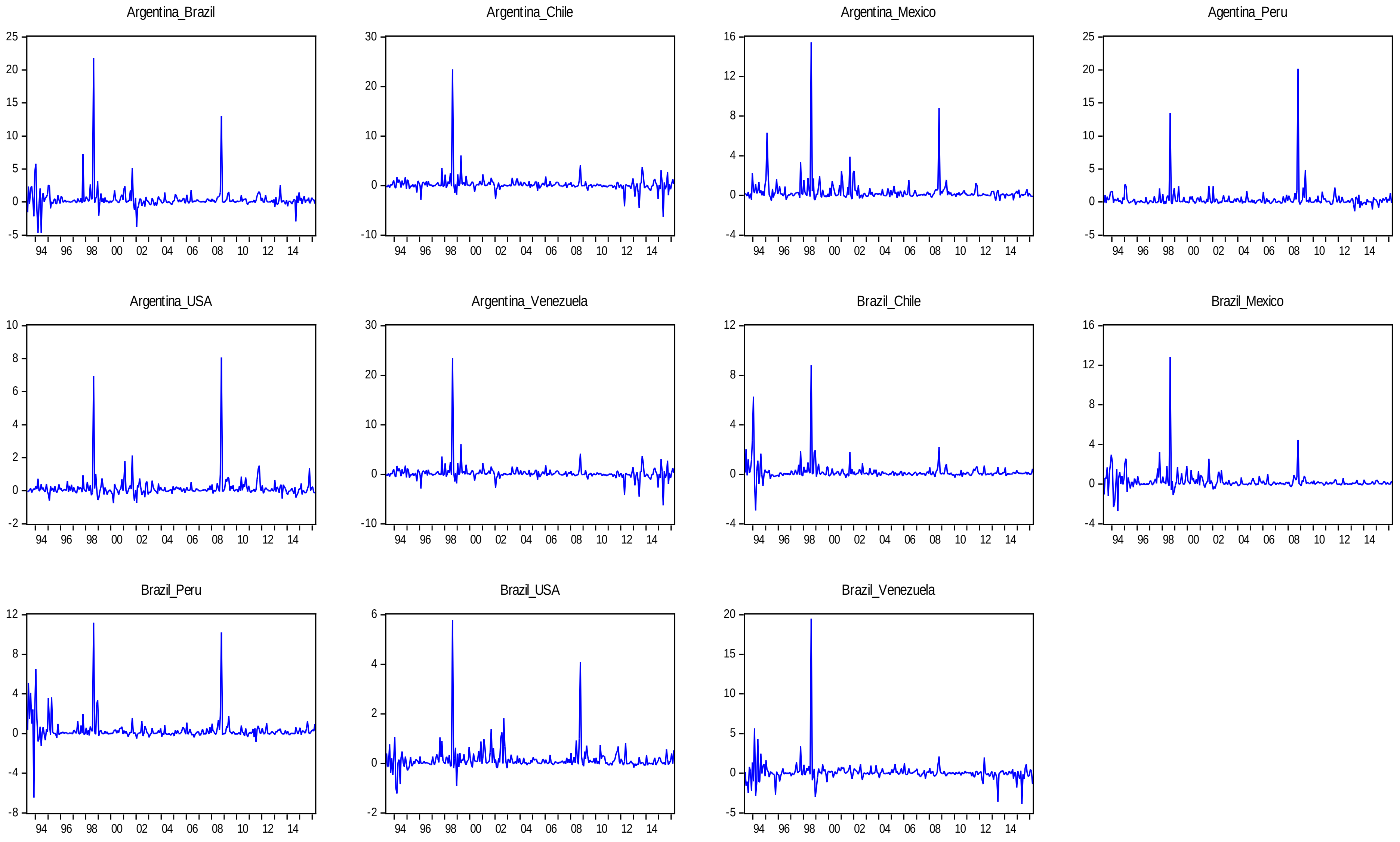

Figure 9: Estimates of comovement, ρ_t^{ij} (Set II: Chile, Peru, Mexico, Venezuela versus other markets)