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International Financial US Linkages: Networks Theory and MS-VAR Analyses

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Abstract

This paper aims to examine the impact of the Global Financial Crisis on portfolio investment flows, as well as on stock market activity. Network Theory is used to analyze structural changes of foreign portfolio investment flows (FPI) to a sample of 13 developed countries and 6 emerging Latin American countries. Additionally, using daily data from 2003 to 2015, the dynamics of returns are analyzed to test whether the US market influenced these markets or vice versa; univariate (MS-AR) and multivariate (MS-VAR) regime-switching models are used. The evidence confirms the presence of two different regimes, low volatility and a high volatility for all markets. Findings suggest strengthening local productive and financial institutions in order to anchor FPI. The MS-(V)AR study is limited to stock markets from the Americas and Europe. Previous literature has not applied the innovative and complementary methodologies employed here to analyze financial crisis impacts on FPI flows. We conclude that US financial markets keep a close financial relationship with the most important European and American countries' stock markets, both by receiving and delivering FPI, and in addition influencing the behavior of stock indexes.
JEL Classification: C58, F65, G01, G15, N20
Keywords: crisis, Network theory, Foreign portfolio investment flows, MS-AR, MSs-VAR

Vínculos financieros internacionales de EE. UU.: Teoría de redes y análisis MS-VAR

Resumen

Nuestro objetivo es examinar el impacto de la crisis financiera mundial en los flujos de inversión de portafolio, así como en la actividad bursátil. La teoría de redes analiza cambios estructurales en los flujos de inversión de portafolio (FPI) extranjeros para una muestra de 13 países desarrollados y 6 economías emergentes latinoamericanas. Además, utilizando datos diarios de 2003 a 2015, se estudia la dinámica de los rendimientos accionarios para comprobar si el mercado estadounidense influyó en los demás mercados, o viceversa. Modelos univariados MS-AR y multivariados MS-VAR sobre cambio de régimen confirman la presencia de dos regímenes, baja y alta volatilidad, para todos los mercados. Los resultados sugieren fortalecer las instituciones productivas y financieras para anclar los FPI extranjeros. El análisis MS-VAR se limita a mercados accionarios de las Américas y Europa. Investigaciones anteriores no han aplicado las metodologías innovadoras y complementarias aquí empleadas para analizar los efectos de la crisis financiera en los FIP, Concluimos que el mercado accionario de Estados Unidos mantiene una estrecha relación

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Resumen

con los mercados bursátiles más importantes de Europa y las Américas, tanto recibiendo, como otorgando FPI, y además influyendo en los índices bursátiles.
Clasificación JEL: C58, F65, G01, G15, N20
Palabras clave: crisis, Teoría de redes, Flujos de inversión en cartera extranjera, MS-AR, MSs-VAR

1. Introduction

Increased trade of goods and services derived from globalization processes has led to greater interdependence among countries. In addition to traditional direct investments, portfolio investments and stock exchange markets linkages became important benchmarks of global financial interdependence. However, during the last two decades, its extraordinary growth has been asymmetric and subject to severe booms and collapses. Moreover, their evolving patterns changed abruptly due to the Global Financial Crisis (GFC). Allegedly, negative foreign portfolio investments (FPI) changes around the world were largely influenced by United States which is the largest destiny and origin of this type of investments.

Table 1. World Portfolio Flows Trends
(Billions current US Dollars)

Year	Flow
1960	$ 0.2
1971	$ 0.7
1972	-$ 11.6
1982	$ 4.7
1983	$ 21.0
1984	$ 19.4
1993	$ 178.1
1994	$ 121.2
1995	$ 120.2
2000	$ 647.4
2001	$ 373.1
2002	$ 187.7
2003	$ 485.4
2004	$ 543.3
2005	$ 905.5
2006	$ 900.9
2007	$ 843.7
2008	-$ 166.9
2009	$ 840.4
2010	$ 801.4
2011	$ 283.3
2012	$ 831.4
2013	$ 807.3
2014	$ 1,108.137
2015	$ 175.7

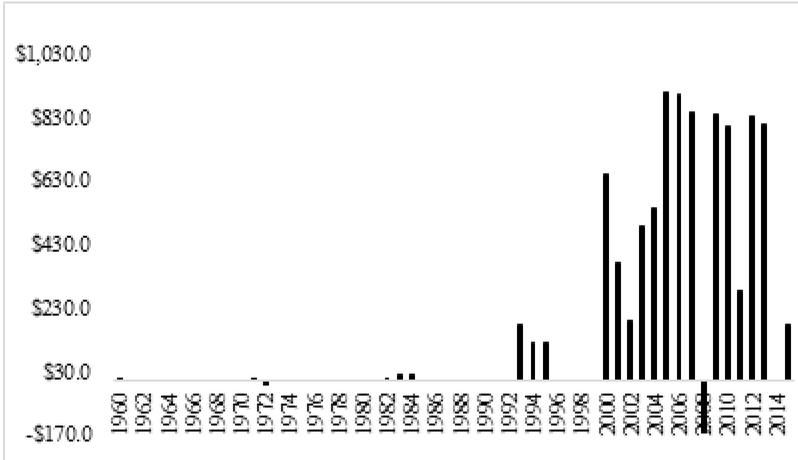

Figure 1. World Portfolio Flows Trends
Source: World Bank: Portfolio equity, net inflows

Table 1, complemented with Figure 1, summarizes the long run irregular trends of world portfolio investments, quoting some representative years. Before the 1971 fall of the Bretton Woods Agreement and beyond FPI, remained moderate, albeit in 1972 there was a severe reversal of -US$11.59 billion dollars. During the debt crisis of the 1980's FPI began to grow steadily, albeit in 1984 there was a reversal from of US$21.03 to 19.38 billion. Take-off really took place in the following decade, but in 1994 and 1995 reversals took place again with respect to 1993. Since year 2000 to the present, which comprises 203; 208; and 2015, years of our study, the behavior of FPI has been very erratic, growing to a maximum of US$1,108.137 trillion by 2014, but falling rashly to only US$175.740 billion in 2015.

It is important to mention that, a significant part of FPI focused on stock markets. Consequently, the GFC affected them generating abrupt swings in asset prices, high volatility periods and higher correlation levels among stock markets. This fact is the point of departure for our research. It aims to examine changes in the direction and importance of portfolio flows for key years previous, during and after the GFC: 2003; 2008; and 2015. These key years were chosen to isolate the 2008 crisis year of the effects of the dot com crisis (2001) and to avoid by 2015 the height of the Eurozone debt crisis (2010-2012).[2] Furthermore, considering the impacts of the GFC on the behavior of stock markets, it aims to analyze the U.S. dynamic linkages with the 18 most important economies of Europe and the Americas from 2003 to 2015, using daily data. To accomplish these goals, first, Network Theory is used to analyze Foreign Portfolio Investment (FPI) flows among the 19 countries in the sample, stressing the U.S. relationships with the rest of the countries. Second, the MS-AR and MS-VAR models are used to prove whether the US equity market influenced European and other American stock markets or vice versa.

We hypothesize that the U.S. financial markets kept a close financial relationship with the most important markets from Europe and the Americas: 1) by leading the reception, direction and volume of FPI, and 2) influencing other stock indexes behavior.

This paper contributes in methodologic terms proposing a, relatively, innovative approach in the finance field, i.e. networks analysis, and by employing MS-AR and MS-VAR modeling. The research includes two complementary methodologies, first, because network analysis provides a static and graphic approach which shows in detail how Foreign Portfolio Investment Flows patterns (volume by year) changed since the Global Financial Crisis,

[2]Our twofold analyses focus on the 2008 Great Recession identified with the subprime crisis. Some authors recognize both the subprime and Eurozone debt crises conforming one phenomenon.

above all, in terms of outgoing and incoming flows to the US. On the other hand, MS-AR and MS-VAR models are used to analyze the influence on and of the US stock market (daily price indices) in terms of the other stock markets. In comparison with the network analysis, MS-AR provides a dynamic graphic tool to analyze high and low volatility periods in the stock markets. Combining these two models gives a complete view, from the general (FPI) to the specific (stock market) perspective. In this sense, the study also promotes the understanding about the US linkages with the main stock markets from Europe and the Americas, in terms of FPI flows and stock markets behavior. Findings are important for risk managers, policy makers and investors, in terms of investment strategies and international asset allocation.

We designed our work into five sections. In the second section we recall recent research papers network flows, and on MS-AR and MS-VAR works employed for stock market research. The third section describes the methodology. The fourth section presents the empirical evidence. Finally, section five presents some conclusions.

2. Recent Related Literature

As previously pointed out, two major and interrelated catalysts of financial globalization have constituted cross-border financial flows and investments in stock markets. Their extreme volatile patterns became a symptom and manifestation of the GFC which has been subject to extensive research. Nevertheless, although network theory has been amply used in other sciences, including some successfully applications in various areas of economics, the literature on financial networks is still at an initial phase (Allen & Babus, 2009; Battison et al, 2016a). Moreover, most of the existing research applying network theory has mainly dealt with banking and financial institutions (Allen & Gale, 2000; Battison et al., 2016b; Braverman Minca; 2018; Kojaku et al, 2018; Fukker, 2018), management (Sharma Chopra, 2013; D'Arcangelis & Rotundo, 2016), insurance (Lin, Yu & Peterson, 2015) and financial regulation (Tennant, 2017; Battison, 2016a).

Dealing directly with stock exchanges activity, networks theory research is limited and regarding international capital flows is absent, which underlines the importance of this paper. Nevertheless, it is worth mentioning recent works by Baitinger and Papenbrock (2017), Sandoval Junior (2017) and Výrost, Lyóska and Baulmöhl (2019). The former, propose to overcome the limitations of conventional mean-variance thinking; they introduce a model dealing with financial networks, and their active management which compares mutual-information-based networks with correlation-based networks on a stand-alone basis and in the framework of investment strategies in course.

In turn, Sandoval Junior (2017) develops dynamic networks based on correlations and transfer entropy employing both log-returns and volatilities for near 100 stock market indexes for the 2000 to 2016 period. These networks are analyzed employing node strength based on correlation, as well as on in and out node strengths transfer entropy. His evidence shows that node strengths peak at the height of both the GFC of 2008 and the Eurozone debt crises of 2010-2012. Additionally, Sandoval Junior's results dealing with volatilities also present considerable ties between the exchange indexes of Middle Eastern countries. Finally, Výrost, Lyóska, and Baulmöhl (2019) propose centralization measures from financial networks to improve portfolio returns in an out-of-sample framework. In their network, nodes are represented by assets, while edges are based on long-run correlations. Their sample includes 45 assets and the data covers the 1999-2015 period.

Regarding the impact of the GFC on asset prices, recent studies by Tella, Yinusa and Olusola (2011), Gabriel and Manso (2014), and Yildirim (2016) must be mentioned. In an interesting paper, Tella, Yinusa and Olusola (2011) test if efficiency of the Cairo, Johannesburg and Lagos stock markets changed as a result of the global economic crisis, as well as due to any delayed effect of the crisis. Applying EGARCH models their evidence reveals that those stock markets remained inefficient; additionally, some contagion with some lag effect following the height of the crisis was found. Gabriel and Manso (2014) examine the case of 12 European and non-European countries, focusing in the short-run. Their analysis includes October 4, 1999 to June 30, 2011. Gabriel and Manso employ a set of empirical tests including a vector autoregressive model, Granger causality tests, and impulse-reaction functions. Their empirical evidence shows that the GFC contributed to strengthen interdependence among stock markets. In a similar line of research, Yildirim (2016) analyzes the impacts of global financial conditions on five emerging markets: Brazil, India, Indonesia, South Africa, and Turkey. Yildirim employs a structural vector autoregressive model with a block exogeneity procedure which uses high-frequency daily data and Bayesian inference. His evidence confirms that global financial risk shocks impact significantly several local securities: government bond yields, equity prices, credit default swaps spreads, and exchange rates; these impacts differ significantly across the five countries under study and are strongly related to their local macroeconomic fundamentals. The effects differ considerably across countries and assets. These country differentiations are strongly related to local macroeconomic fundamentals. Finally, global financial risk shocks have a greater immediate effect on local currency government bond and credit default markets rather than on foreign exchange and stock markets.

Several studies have analyzed US economic and financial linkages with other countries during the GFC period. Some studies analyze the impact of US monetary policy decisions on various financial markets (Chen, Filardo, He & Zhu, 2016; Georgiadis, 2016; Yan, Phylaktis & Fuertes, 2016; Lien, Lee, Yang & Zhang, 2018; Yunus, 2018; Kang, Kim & Suh, 2019); effects of oil prices on the US stock markets (Fang, Chen & Xiong, 2018; Basher, Haug & Sadorsky, 2018) and the relationship among the US stock markets and European stock markets (Panda & Nanda, 2017; Golab, Jie, Powell & Zamojska, 2018).

Valls Ruiz (2014) treats comprehensively this issue in her doctoral thesis. Essentially, she examines the nature of volatility spillovers from the U.S. markets; the impact of U.S. macroeconomic announcements on returns, volatility and correlations considering the phenomenon of asymmetric volatility and incorporating the period of financial turmoil caused by the GFC. Valls Ruiz focus her study on emerging Southeast Asian markets. She also examines volatility transmission among the stock and main currency markets from Southeast Asia. Regarding volatility, all markets are impacted by their own past shocks and volatility, most of them responding asymmetrically; additionally, spillovers from US volatility do affect the dynamics of conditional variances of returns of the Asian countries in the sample. Finally, her evidence also shows that the GFC scarcely changed volatility transmission patterns; her study also finds that the level of correlations between the U.S. and the other countries depends on the countrys development level.

Among the studies dealing with stock markets' interactions which employ Markov Switching Vector Autoregressive (MS-VAR) is the research advanced by Roubaud and Arouri (2018). They analyze interactions between oil prices, exchange rates and stock markets by considering the effects of economic policy uncertainty. Their results evidence important interrelations between exchange rates, oil prices and stock markets, i.e., nonlinear relationships and stronger correlation during high volatility regimes.

Liow and Ye (2018) analyze the relation among the securitized real estate market and stock, money, bond and foreign exchange markets for 10 economies employing a Markov regime-switching approach. Findings evidence that risk exposure increased during high-volatility market conditions. BenSaïda, Litimi and Abdallah (2018) applied a MS-VAR model extension to investigate volatility spillovers across global developed financial markets. Their evidence reveals that total and directional spillovers are more intense during turbulent periods.

Summing up, our paper contributes to the existent and previously mentioned literature analyzing the financial linkages between the US and the main European and Canadian and Latin American markets. First, Network Theory is employed to analyze FPI flows among a selected sample of 19 countries during three periods 2003 (pre-GFC), 2008 (GFC) and 2015 (post-GFC). Second, we analyze the dynamic linkages between US stock market returns and equity markets returns of the main European and American countries using daily data for the period 2003-2015.

3. Methodology

Essentially, a Network is graph representing a set of points known as nodes or vertices, joint by edges or lines based on an association rule which describes the relation among nodes (Mitchell, 2009; Battison 2016a). In our research Direct and Weighted Networks are used. Weighted Networks or Graphs show the links in a valued way; in other words, links associate intensities, represented by a numeric value.

Directed Networks allow us to estimate the degree centrality; it is subdivided into outdegree and indegree. The degree centrality measures the number of connections among one node and other nodes; it is a local and static indicator and only considers direct "neighbors" of each node (Wasserman and Faust, 1994).

The indegree centrality estimates the number of incoming edges that one node has. The outdegree centrality measures the number of outgoing edges that one node has to the other nodes. To estimate these relations an adjacent matrix is taken which is a matrix conformed by 1 and 0 (Newman, 2018). It is defined as follows:

$$D_j^{in} = \sum_{j=1}^{n} x_{ij} \qquad\qquad D_i^{out} = \sum_{i=1}^{n} x_{ji} \tag{1}$$

These centrality measures are used to analyze the relationship between the European and American economies, in terms of the Foreign Portfolio Investment flows. In this sense, the number of incoming and outgoing edges are estimated for each country (node), as well as the strength and size of these financial connections. Thus, Network theory is employed to analyze the linkages among our sample countries and, specifically, between each country and the US.

MS-AR model

We continue examining FPI flows employing, a MS-AR univariate model. It can be described as follows. A time-series variable yt can be modeled by a Markov switching autoregressive of order p (MS-AR), with regime shifts in mean and variance. It is represented as follows (Hamilton, 1989; 1994).

$$y_t = \mu(s_t) + \left[\sum_{i=1}^{p} \emptyset_i \left(y_{t-1} - \mu(s_t)\right)\right] + \sigma(s_t)\,\varepsilon_t \tag{2}$$

where $\emptyset_i$ are the autoregressive coefficients; μ and σ are the mean and standard deviation depending on the regime s_t at the time t. y_t represents the stock market returns of the European and American countries. This MS-AR model detect potential regime shifts in the stock market returns and enable to estimate the impact of crises on stock market volatility (Chkili Nguyen, 2014).

MS-VAR model

The MS-AR model arouse great research interest dealing with macroeconomic fluctuations and lead to several MS-VAR extensions first advanced by Krolzig (1997). However, research by Sims and Zhag (2006) identified moderation in their application, even though MS-VAR models have demonstrated superior data fit; Bognanni and Herbst (2015) attribute this restrain to the complex estimation processes required. Contributing to the literature, one of the essential objectives of this study is to analyze in depth the dynamic relationship between the US stock markets and European and the rest of the Americas equity markets; therefore, we employ the Markov Switching Vector Autoregressive model developed by Krolzig (1997). This model is a generalization of the MS-AR presented above and can be written as follows:

$$e_{us} = \alpha_1 + \sum_{k=1}^{l} \alpha_{2j}\left(s_t\right) e_{us-k} + \sum_{k=1}^{l} \alpha_{3j}\left(s_t\right) e_{t-k} + v\left(s_t\right) u_{r,t} \tag{3}$$

$$e_t = \beta_1 + \sum_{k=1}^{l} \beta_{2j}\left(s_t\right) e_{t-k} + \sum_{k=1}^{l} \beta_{3j}\left(s_t\right) e_{us-k} + v\left(s_t\right) u_{e,t} \tag{4}$$

Where e_{us} and e_t represent the US stock market returns and the stock markets returns for each European countries, and for the Canadian and Latin American countries, u_t is the innovation process with a variance $v\left(s_t\right)$ depending on regime s_t which is assumed to follow an irreducible ergodic two-state Markov process, defined by the transition probabilities p_{ij} between states as follows

$$P_{ij} = P\left[S_t = jS_{t-1}\right] = i \quad with \quad \sum_{j=1}^{2} P_{ij} = 1 \quad for\ all \quad i,j \in \{1,2\} \tag{5}$$

Where,

$$\left\{ \begin{array}{c} P_{11} = P\left(S_t = 1|S_{t-1} = 1\right) \\ P_{12} = 1 - P_{11} = P\left(S_t = 1|S_{t-1} = 2\right) \\ P_{21} = 1 - P_{22} = P\left(S_t = 2|S_{t-1} = 1\right) \\ P_{22} = P\left(S_t = 2|S_{t-1} = 2\right) \end{array} \right.$$

The MS-VAR model provides an accurate estimation of the potential regime shifts in the stock market returns, above all, during the turbulent period analyzed in this study. The inclusion of structural breaks in the financial time-series analysis is crucial to avoid mistaken conclusions related to the dynamic behavior of stock and currency markets as well as their existent relationships.

Data

To analyze the US Foreign Portfolio Investment linkages with the rest of the European and American countries, Directed and Weighted Networks are used. To build up these Networks, we use the "Geographic Breakdown of Total Portfolio Investment Assets: Total Portfolio Investment" from the Coordinated Portfolio Investment Survey (CPIS) of the International Monetary Fund (IMF) for 2003, 2008 and 2015. It includes data for equity and investment fund shares, long term-debt instruments and short-term debt instruments. These statistics are reported in millions of US Dollars.

To test the dynamic relationship between the US stock market return and the rest of the Americas and Europe equity market returns (MS-VAR model), daily closing prices of stock indexes in US dollars are employed (thus, only shares are included). The sample includes nineteen stock indexes from the main European and American stock markets: Ireland (ISEQ), France (CAC 40), Germany (DAX), Portugal (PSI 20), Switzerland (SMI), United Kingdom (FTSE 100), Greece (Athex 20), Spain (IBEX), Sweden (OMX Stockholm 30), Norway (OSEAX) e Italy (FTSE MIB), Argentina (MerVal), Mexico (IPC), Canada (S&P TSX Composite), Brazil (BOVESPA), USA (S&P's 500 Index), Chile (IPSA), Colombia (IGBC-COLCAP) y Peru (IGBVL). Transmission and effects of the global financial crisis are studied for a period including 01/01/2003 to 02/27/2015 Daily returns are estimated by taking the difference in the logarithm of two consecutive prices. Exchange rate series was gathered from Bloomberg; series for PSI 20, IBEX 35 y SMI were drawn from Euroinvestor; IBOVESPA, MERVAL, IPSA, y IPC were obtained from Economatica; COLCAP e IGBVC from Bloomberg; other indexes were gathered from Yahoo finance.

4. Results

Foreign Portfolio Investment Flows Analysis

Figure 2 presents total portfolio investment outflows for each country in 2003 (pre-crisis period), 2008 (during the crisis) and 2015 (post-crisis). Latin American countries' portfolio investment outflows are very low in comparison with the other markets. In this group of countries, stands out the high growth of Chilean outflows; it almost doubled from 2008 to 2015. Albeit, Latin American countries have lower investment levels, in comparison with European economies, all of them experienced an increment from 2003 to 2015.

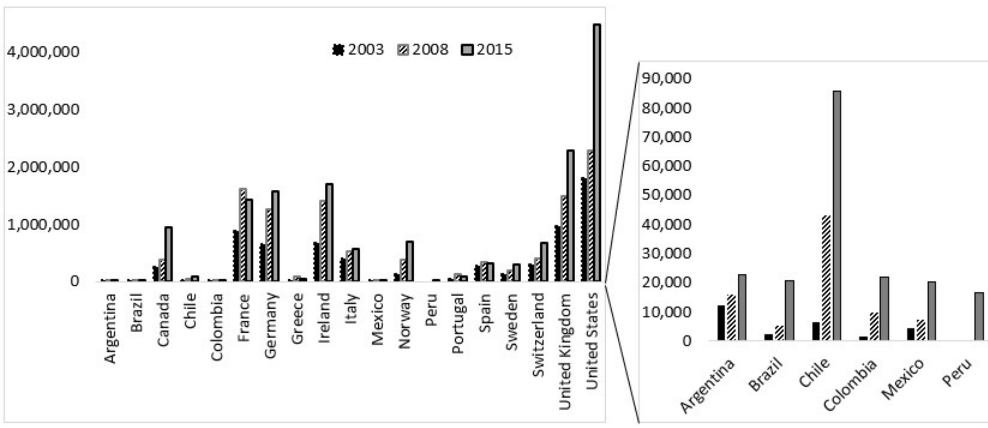

Figure 2. Total Investments: 2003, 2008 and 2015 (mills USD)
Source: own elaboration with "Geographic Breakdown of Total Portfolio Investment Assets: Total Portfolio Investment" CRPI(FMI, 2019).

Table 2. Main Business Partner (FPI flows destinies)
Developed Countries

Investment from:	Country	Percentage	Country	Percentage	Country	Percentage
Canada	United States	70	United States	70	United States	76
	United Kingdom	13	United Kingdom	10	United Kingdom	8
	France	5	France	5	France	3
France	Germany	21	Germany	22	Italy	18
	Italy	20	Italy	17	United States	17
	United States	17	United Kingdom	15	United Kingdom	17
Germany	United States	20	Spain	18	France	23
	France	18	France	17	United States	20
	Italy	16	Italy	14	United Kingdom	13
Greece	United Kingdom	28	United Kingdom	75	United Kingdom	38
	United States	27	United States	13	Italy	26
	France	19	Germany	4	Spain	19
Ireland	United States	34	United States	33	United States	38
	United Kingdom	25	United Kingdom	25	United Kingdom	26
	Germany	12	Italy	11	France	9
Italy	United States	24	France	23	France	25
	Germany	23	Germany	20	Ireland	16
	France	18	United States	20	United States	15
Norway	United States	31	United States	29	United States	44
	Germany	19	United Kingdom	17	United Kingdom	13
	United Kingdom	14	Germany	16	Germany	11

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Portugal	Germany	24	Ireland	28	Spain	22
	France	21	Germany	14	Italy	19
	Ireland	12	Spain	13	Germany	17
Spain	Germany	23	France	22	Italy	31
	Italy	21	Italy	18	France	15
	France	19	Germany	16	United States	11
Sweden	United States	46	United States	35	United States	47
	United Kingdom	19	United Kingdom	19	United Kingdom	15
	Germany	11	Germany	12	Germany	10
Switzerland	United States	32	United States	28	United States	40
	Germany	27	Germany	23	Germany	12
	France	14	France	18	France	12
United Kingdom	United States	42	United States	46	United States	42
	France	12	Ireland	11	France	13
	Germany	12	Germany	11	Germany	13
United States	United Kingdom	37	United Kingdom	28	United Kingdom	28
	Canada	17	Canada	17	Canada	16
	Germany	10	France	12	Ireland	11
Latin American Countries						
Argentina	United States	91	United States	93	United States	97
	Spain	3	Spain	3	Brazil	2
	Brazil	2	Brazil	2	Spain	0
Brazil	United States	65	United States	47	United States	64
	United Kingdom	13	Spain	28	Switzerland	14
	Portugal	6	Norway	8	Spain	9
Chile	United States	52	United States	53	United States	71
	Ireland	25	Germany	15	Germany	6
	United Kingdom	10	Brazil	14	Ireland	5
Colombia	United States	89	United States	85	United States	86
	Ireland	3	Ireland	4	Germany	2
	United Kingdom	3	Germany	4	United Kingdom	2
Mexico	United States	91	United States	86	United States	86
	Ireland	3	United Kingdom	6	Brazil	7
	United Kingdom	2	France	3	Spain	2
Peru					United States	76
					Colombia	6

Source: Own elaboration based on "Geographic Breakdown of Total Portfolio Investment Assets: Total Portfolio Investment" CRPI(FMI, 2019).

Investments from France, Greece, Portugal and Spain bounded from 2003 to 2008, but fell after Global Financial Crisis and had lower level by 2015, in relation to 2008. Canada, Germany, Ireland, Italy, Norway, Sweden, Switzerland, the UK and the US increased their investments during the period from 2003 to 2008 and from 2008 to 2015. It is important to point out that, despite of the fact that, global financial crisis began in the US, portfolio outflows from this market not only increased, but doubled from 2003 to 2015.

Table 2 presents the three main business partners for each country and year under analysis. It is evident the US relevance as the common investment flows destiny. For all countries (except Portugal) the US is one of the three countries with greatest weight as FPI receptor. Not only that, but for 11 of the 18 countries (Canada, Ireland, Norway, Sweden, Switzerland, the UK, Argentina, Brazil, Chile, Colombia and Mexico), the US was the main portfolio investment receptor during the three years under study. In terms of the US investments destiny, the UK is the main receptor of USs FPI. Another country with important share in FPI outflows is Germany which is the main investment destiny from France, Portugal and Spain flows.

Once investment flows were analyzed in general, the indegree centrality measures are estimated; results are presented in Figure 3. The indegree centrality measure estimates the number of incoming links of each node. In this case, the "nodes" are the 19 countries and the links direction show the investment destiny for each one. The node size is related to the number of countries that invest in each country, in other words, each node is as big as the number of countries which invest in a given country.

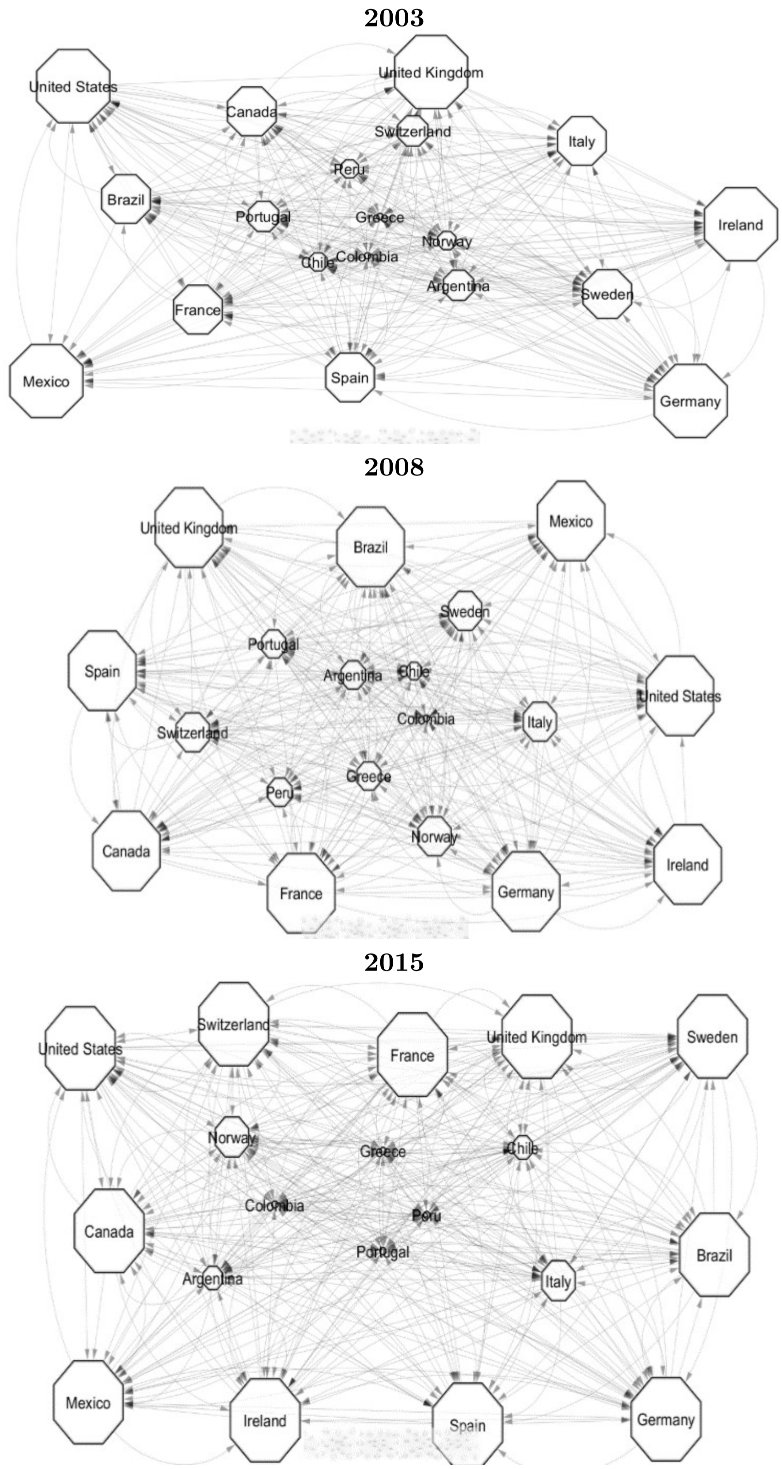


Figure 3. Indegree Analysis
Source: Own elaboration based on "Geographic Breakdown of Total Portfolio Investment Assets: Total Portfolio Investment" CRPI(FMI, 2019).

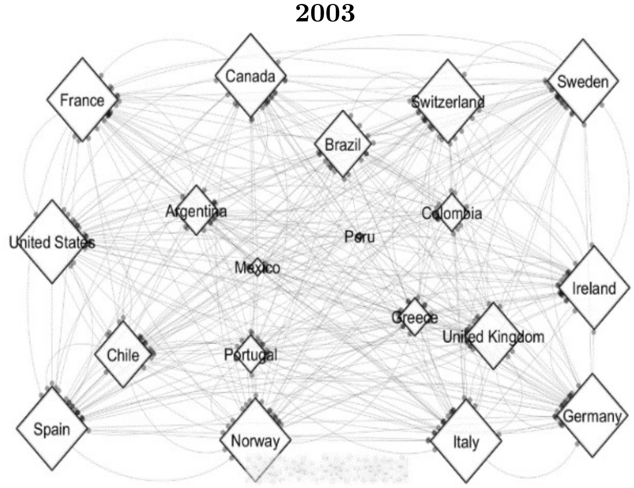
Indegree centrality measure shows that the main investment destinies in 2003 were five countries (the US, the UK, Ireland, Germany and Mexico); it means that 17 from the 19 countries invested in these economies. The second most important FPI destinies were Brazil, France, Italy, Spain, Canada and Sweden. Countries with the lowest number of incoming links were Greece and Colombia, only 13 of the other 18 countries invested in there.

Results for 2008 evidence that the list of the main FPI receptors widened and the main destinies of FPI were Spain, the US, the UK, Ireland, Germany, Brazil, Canada, Switzerland, Sweden, France and Mexico; these 11 countries had 18 incoming links each one. Countries with lowest link number were Portugal, Colombia, Greece and Peru, they had only 15 links. Thus, 2008 financial landscape was very different in comparison to the 2003 scenery. Linkages among different European and American countries developed in five years, increasing the complexity of international financial structure. This picture allows us to explain the Global Financial Crisis transmission magnitude and the number of implied and affected countries.

Changes from 2008 to 2015 were not as significant as from 2003 to 2015. However, the amount of main receptor countries and links among them diminished. Brazil, Ireland, Mexico, Canada, Spain, France, Germany, the UK and the US had 17 links. The country with the lowest number of links was Colombia, with only 13 links. Summarizing, the main destinies in 2003 were the same, despite of the global financial crisis, and their importance remained similar in 2015.

Once the incoming links were analyzed, the outdegree centrality measure is also estimated; it measures the number of outcoming links that each node has. In this context, this analysis allows to know how concentrated outward investments are from each country. The size of each node represents how diversified are its FPI flows.

2003



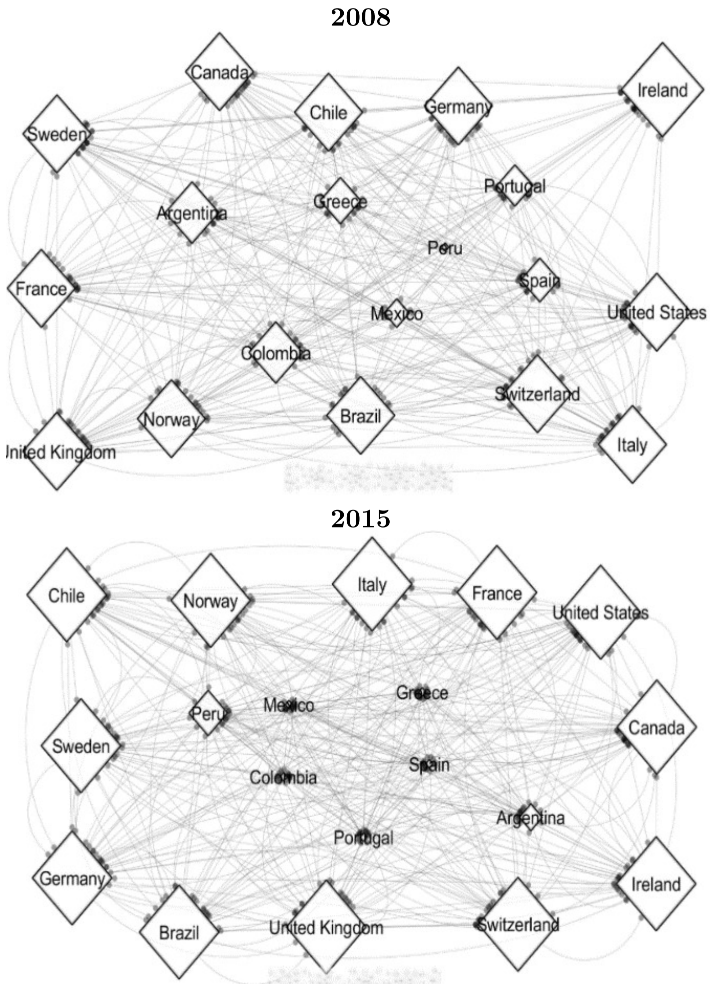


Figure 4. Outdegree Analysis
Source: Own elaboration based on "Geographic Breakdown of Total Portfolio Investment Assets: Total Portfolio Investment" CRPI(FMI, 2019).

Outdegree analysis for 2003 reveals that the developed countries were the main investment source. It is observed that Brazil and Chile became very important because they invested in 17 of the 19 markets, in contrast with Mexico which received FPI from several countries (see indegree analysis), but only invested in 5 economies.

In 2008, Ireland was the country with the greatest FPI outflows diversification, investing in 18 countries. The country with the lowest number of outgoing links, without considering Peru, was Mexico (10).

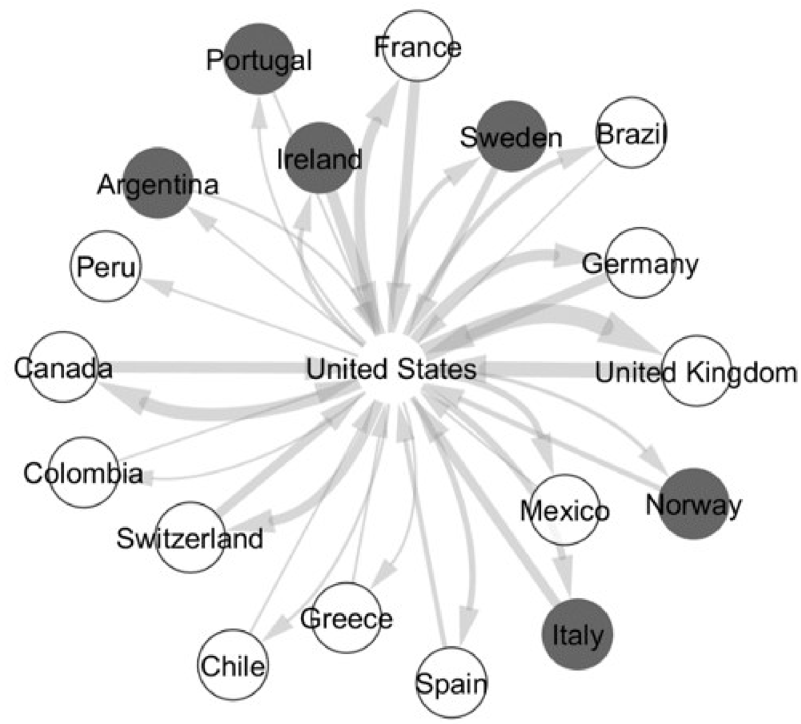
In 2015, the number of outgoing links increased. Countries with greatest number of outgoing links have 18 connections and countries with the lowest number of links had 15 (Colombia, Greece, Spain, Portugal and Mexico). In the case of Mexico, it tripled the number of outgoing links from 2003 to 2015.

In terms of this research, the importance of US flows is confirmed. It is one of the main destinies and origins of FPI during the whole period of study; not only has an important number of outgoing and incoming links, but, in terms of volume, is one of the main FPI receptors and investors.

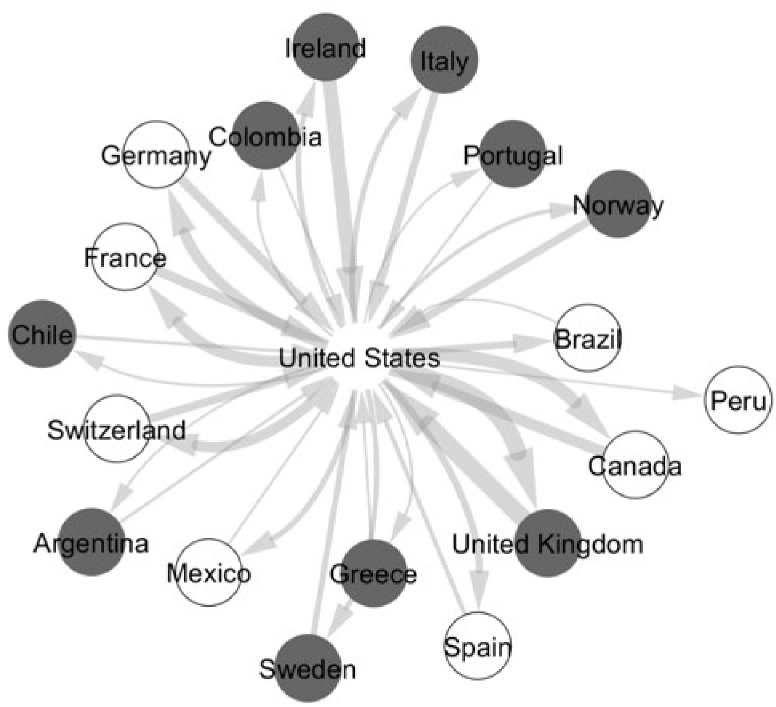
The following network (Figure 5) allows observing in detail the US linkages with the rest of the countries. The links thickness represents the FPI volume from and towards the

US. Dark nodes represent countries with higher outgoing than incoming flows to the US. In contrast, white nodes are countries with positive incoming net flows (incoming flows are higher than outgoing flows to the US).

2003



2008



2015

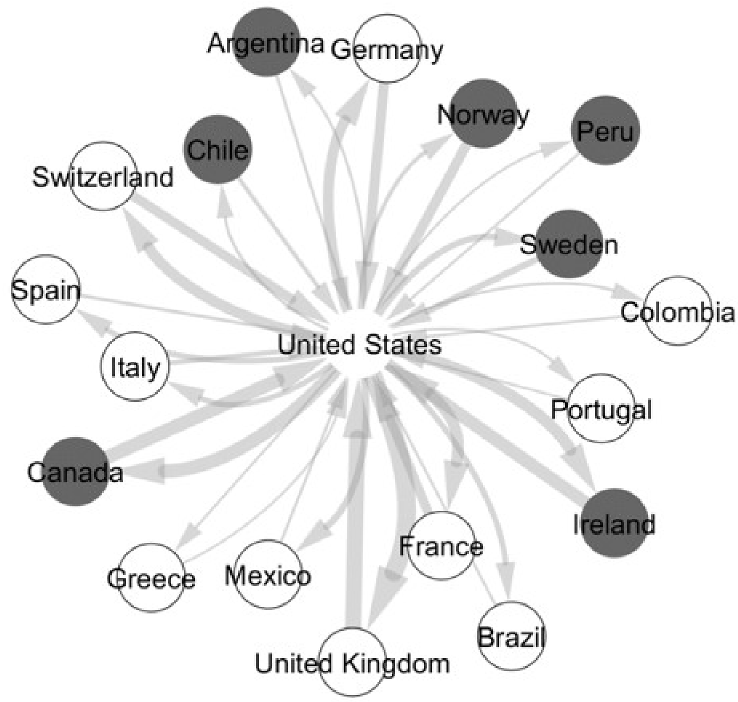


Figure 5. FPI flows from and for the US
Source: Own elaboration based on "Geographic Breakdown of Total Portfolio Investment Assets: Total Portfolio Investment" CRPI(FMI, 2019).

Figure 5 shows the investment from and to the US. In 2003 year, the main countries with FPI flows to the US were: the UK, France, Ireland, Canada, Germany, Italy and Switzerland. The main receptors of US FPI were the UK, France and Canada. In 2008, investments from Ireland and the UK to the US increased significantly (it can be observed by the thickness of each link). By 2015, FPI flows seemingly became be more balanced; linkages between the US and the UK, Canada, Ireland, Switzerland, Germany and Norway remained strong.

It can be observed that, during the three years studied, certain countries invested more in the US, than the US in them: Argentina, Portugal, Ireland, Sweden and Norway. In 2003 there was only six countries with positive net FPI flows (outgoing to the US - incoming from the US >0). In 2008, the number of countries with positive net FPI increased to 10, it means that the FPI flows from the US to other countries diminished or increased in a lower proportion than FPI flows from other countries to the US.

For 2015 and 2003 the situation remained very similar. In 2015 the number of countries with positive outgoing FPI flows was seven. During this year, Canada's situation changed, it registered a positive outgoing investment to the US, in contrast with previous years. These changes evidence dynamic linkages between the US and other countries. It also reveals that US FPI outflows diminished due to Global Financial Crisis, but in the long-run the US influence in the rest of the countries is significant.

Moving on to test whether the US stock market influences the rest of the equity markets under analysis we employ the MS-AR and MS-VAR models. The data, as previously mentioned, is limited to 19 representative stock market indexes from countries included in the study.

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MS-AR Results

Table 3 summarizes descriptive statistics for all stock return series. SP, SMI and TSE are the markets with less risk (low standard deviation), ATHEX, FTSEMIB and PSI registered a negative average return in the whole period. More profitable markets during the period of study are IPC, COLCAP and IGBVL. All series exhibit leptokurtosis and most of the stock market returns are negatively skewed, except for CAC 40, DAX and IPC. Return series are not normal and, in all cases at levels and first differences the null hypothesis that the series present unit root is rejected; the series are stationary.

Table 3. Descriptive statistics

Stock Index	Standard Deviation	Mean	Kurtosis	Skewness	Jarque Bera	ADF	
						Levels	First Differences
IGBVL	0.019877	0.000863	20.45452	0.287205	28948.64*	-30.38332*	-20.09397*
COLCAP	0.019873	0.000831	25.42949	-0.812689	48001.63*	-12.17957*	-20.81075*
IPC	0.018733	0.000593	10.96107	0.137819	6022.898*	-43.53714*	-20.4358*
OSEAX	0.021771	0.000567	9.840972	-0.265539	4468.766*	-48.7752	-20.53803*
MERVAL	0.023123	0.000519	9.273355	-0.561148	3854.996*	-46.80414*	-21.46929*
DAX	0.018158	0.000472	9.942444	0.081423	4577.265*	-48.23232*	-17.83258*
IPSA	0.015994	0.000452	16.60219	-0.051205	17562.44*	-43.99138*	-18.02817*
IBOVESPA	0.026801	0.000449	12.59942	0.205738	8762.535*	-47.82695*	-24.2548*
OMX	0.020414	0.000409	7.999202	-0.079779	2374.576*	-49.9205*	-20.71205*
SMI	0.013848	0.000389	10.92545	-0.055278	5963.139*	-51.17723*	-20.84654*
TSE	0.014596	0.000322	10.70884	-0.546732	5754.027*	-43.66195*	-20.93575*
S&P 500	0.013306	0.000304	12.50273	-0.494002	8663.802*	-17.02868*	-18.21612*
IBEX 35	0.019698	0.000176	9.280194	-0.083797	3746.259*	-47.19067*	-21.13664*
FTSE 100	0.015668	0.000167	13.55427	-0.026444	10573.28*	-50.4442*	-18.12235*
CAC 40	0.018533	0.000145	10.18607	0.084284	4904.155*	-50.46032*	-20.07091*
ISEQ	0.018955	0.000086	10.15605	-0.912025	5176.402*	-47.22169*	-21.36509*
PSI 20	0.017119	-0.000065	12.42037	-0.151353	8431.928*	-46.50178*	-21.17337*
FTSEMIB	0.020117	-0.000091	9.044954	-0.040127	3469.006*	-48.44845*	-20.36449*
ATHEX 20	0.027165	-0.000649	7.012534	-0.13576	1535.197*	-46.95777*	-22.98261*

Source: own elaboration. *Indicates 1 % significance level

Stock markets relationships

Testing for volatility regime switch behavior

To examine the dynamic relationship between the US stock market and the rest of the European and American equity markets, it is essential to confirm that all stock markets present regime-switching behavior. The log likelihood test (LR) is employed to test the null hypothesis of homoscedasticity, this means that a linear model could be more suitable, against the alternative hypothesis that the regime switching model (MS-AR) depict better the stock markets behavior (Garcia and Perron, 1996). This test is estimated as follows:

$$LR = 2 \times |\ln L_{MS-AR} - lnL_{AR}| \tag{6}$$

where lnL is the log likelihood of the contrasting models. The best-fitted model is selected through Davies (1987) critical values. This test has been used previously in several studies (Kanas, 2005; Wang Theobald, 2008; Chkili Nguyen, 2014) to prove that other stock markets exhibit a time-varying behavior, which responds to local circumstances and to the effects of crises transmission. To reinforce the tests results, it is also introduced the Akaike Information Criteria (AIC). Table 4 shows the results of both tests.

Table 4. LR and AIC Tests

	LnL(AR)	LnL(MS-AR)	LR	AIC (AR)	AIC(MS-AR)
IGBVL	5701.2	6252.1	550.9*	-5.0028	-5.4830
COLCAP	5838.3	6202.7	364.4*	-4.9982	-5.4396
IPC	5695.9	6197.4	501.5*	-5.1232	-5.4349
OSEAX	5487.0	5902.5	415.5*	-4.8147	-5.1760
MERVAL	5349.6	5643.0	293.5*	-4.6941	-4.9482
DAX	5900.0	6298.7	398.7*	-5.1773	-5.5239
IPSA	6196.5	6587.2	390.8*	-5.4376	-5.7772
IBOVESPA	5013.0	5298.6	285.6*	-4.3986	-4.6458
OMX	5635.4	6061.9	426.4*	-4.9451	-5.3159
SMI	6522.8	6863.5	340.7*	-5.7241	-6.0197
TSE	6406.2	6869.0	462.8*	-5.6218	-6.0246
S&P 500	6619.3	7161.3	542.0	-5.8088	-6.2812
IBEX 35	5714.6	6138.0	423.4	-5.0146	-5.3827
FTSE 100	6239.4	6718.2	478.8	-5.4753	-5.8922
CAC 40	5856.9	6284.9	428.0	-5.1395	-5.5117
ISEQ	5802.1	6256.7	454.5	-5.0914	-5.4870
PSI 20	6034.8	6415.8	381.0	-5.2957	-5.6267
FTSEMIB	5666.8	6110.2	443.5	-4.9726	-5.3584
ATHEX 20	4982.5	5358.1	375.5	-4.3718	-4.6980

Reported values are statistical significance levels of * 1 %

MS-AR Results

Finally, following the proof about regime-switching behavior in stock markets returns, the MS-AR models are estimated; their results are described in Tables 5 and 6.

For all markets (European and from the Americas) the variance (12 and 22) are statistically significant at 1 % and their values suggest the presence of two regimes. The first regime is a low volatility level and the second regime presents a high volatility level.

The stock markets from Brazil, Argentina, Greece and Norway (IBOVESPA, MERVAL, ATHEX and OSEAX, respectively) exhibit the highest volatility level in the low volatility regime. The Colombian (COLCAP), Brazilian, Argentinean and Norwegian markets present the highest volatility in the high volatility regime.

Table 5. MS-AR model results- American Countries

	Const(1)	Const(2)	AR1	σ_1^2	σ_2^2	P_{11}	P_{22}	d1	d2
IGBVL	0.00133*	-0.00076*	0.1428*	-4.5317*	-3.3647*	0.9782	0.9364	45.9448	15.7160
	(0.00033)	(0.00171)	(0.0221)	(0.0260)	(0.0381)				
COLCAP	0.00166*	-0.0070**	0.1238*	-4.3404*	-3.0442*	0.9813	0.8414	53.4207	6.3056
	(0.00036)	(0.00377)	(0.0224)	(0.0337)	(0.0790)				
IPC	0.00136*	-0.00283	0.0875*	-4.3718*	-3.3913*	0.9884	0.9500	85.8950	19.9890
	(0.00034)	(0.00182)	(0.0215)	(0.0204)	(0.0408)				
MERVAL	0.00183*	-0.0036**	0.0434*	-4.2008*	-3.2567*	0.9649	0.8900	28.5058	9.0946
	(0.00043)	(0.00190)	(0.0223)	(0.0291)	(0.0448)				
IPSA	0.00112*	-0.00320*	0.1149*	-4.5251*	-3.4663*	0.9857	0.9251	70.1103	13.3536
	(0.00030)	(0.00198)	(0.0218)	(0.0258)	(0.0551)				
IBOVESPA	0.00165	-0.0046***	0.0258*	-3.9673*	-3.0568*	0.9832	0.9281	59.4631	13.9171
	(0.00050)	(0.00250)	(0.0220)	(0.0272)	(0.0606)				
TSE	0.00102*	-0.00291**	0.0874*	-4.6769*	-3.5950*	0.9894	0.9523	94.5723	20.9613
	(0.00025)	(0.00151)	(0.0214)	(0.0211)	(0.0431)				
S&P 500	0.00087*	-0.0015	-0.050**	-4.8631*	-3.7484*	0.9901	0.9664	100.9817	29.7537
	(0.00018)	(0.00099)	(0.0210)	(0.0218)	(0.0387)				

*,** and*** indicates statistical significance at 1 %, 5 % and 10 %, respectively. Standard deviations are reported in parentheses

Tables 5 and 6 also present the probability of being in each regime. As expected, the probability to be in a high volatility regime (P22) is lower than the probability to be in the low volatility regime (P11), in all cases. This evidence means that the low volatility regime is more persistent than the high volatility regime. The US has the stock market with the highest level of persistence in both low (0.9664) and high volatility regime (0.99) followed by the Swedish (0.9768 and 0.9898), Swiss (0.9512 and 0.9895) and Canadian (0.9523 and 0.9894) markets.

In terms of the average duration, low volatility periods last more than the high volatility ones. The US market has the largest average duration in low volatility periods (102 days), followed by the markets from Sweden (98 days) and Switzerland (95 days). Markets with the highest duration in high volatility periods are the Swedish (43 days), English (39 days), the US (29 days) and Irish (29 days) markets.

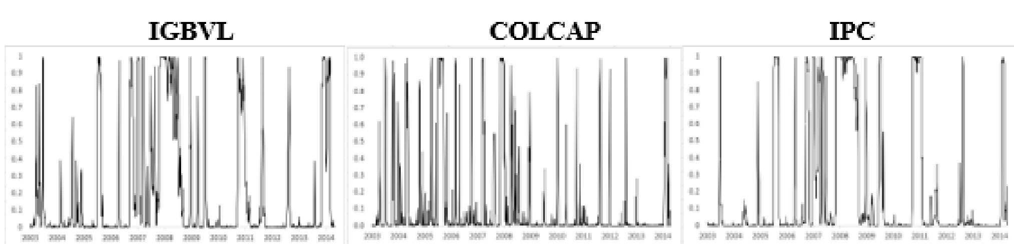
Table 6. MS-AR model results- European Countries

	Const(1)	**Const(2)**	**AR1**	σ_1^2	σ_2^2	P_{11}	P_{22}	**d1**	**d2**
OSEAX	0.00173	-0.00406*	0.00744	-4.257*	-3.241*	0.9886	0.9539	87.3901	21.6895
	(0.00037)	(0.00195)	(0.02223)	(0.032)	(0.060)				
DAX	0.00135	-0.00247*	0.00300	-4.455*	-3.468*	0.9878	0.9584	82.2958	24.0186
	(0.00030)	(0.00141)	(0.02188)	(0.025)	(0.038)				
OMX	0.00129	-0.00151*	-0.03913	-4.422*	-3.450*	0.9898	0.9768	98.2718	43.1236
	(0.00031)	(0.00117)	(0.02158)	(0.024)	(0.031)				
SMI	0.00094***	-0.00210*	-0.03360	-4.644*	-3.682*	0.9895	0.9512	95.2563	20.4800
	(0.00022)	(0.00127)	(0.02159)	(0.023)	(0.047)				
IBEX 35	0.00136**	-0.00300*	0.02736	-4.451*	-3.433*	0.9812	0.9494	53.1541	19.7547
	(0.00032)	(0.00139)	(0.02143)	(0.025)	(0.038)				
FTSE 100	0.00100***	-0.00158*	-0.03302	-4.754*	-3.710*	0.9849	0.9673	66.0602	30.5543
	(0.00023)	(0.00090)	(0.02196)	(0.029)	(0.034)				
CAC 40	0.00124**	-0.00237*	-0.04302	-4.544*	-3.524*	0.9797	0.9517	49.2916	20.7074
	(0.00028)	(0.00113)	(0.02200)	(0.027)	(0.035)				
ISEQ	0.00157*	-0.00280*	-0.00715	-4.564*	-3.544*	0.9832	0.9665	59.4328	29.8098
	(0.00029)	(0.00107)	(0.02197)	(0.027)	(0.032)				
PSI 20	0.00155*	-0.00552*	0.01360	-4.536*	-3.532*	0.9738	0.9111	38.2345	11.2425
	(0.00029)	(0.00142)	(0.02181)	(0.024)	(0.039)				
FTSEMIB	0.00117*	-0.00370*	-0.01527	-4.413*	-3.394*	0.9861	0.9593	72.0267	24.5738
	(0.00032)	(0.00141)	(0.02188)	(0.026)	(0.036)				
ATHEX 20	0.00148*	-0.00364*	0.05508	-4.238*	-3.264*	0.9755	0.9661	40.8143	29.5232
	(0.00052)	(0.00135)	(0.02243)	(0.050)	(0.036)				

*,** and*** indicates statistical significance at 1 %, 5 % and 10 %, respectively. Standard deviations are reported in parentheses.

Graphic Analysis Smooth Probabilities Regime 2 (High volatility)

Regime switching approach offers additional information through a graphic resource about what regime market is in a specific date t based on observation obtained through a later date T. These are referred to as "smoothed" probabilities; according to Nalewaik (2012) is an efficient algorithm whose calculation was developed by Kim and Park (1994).



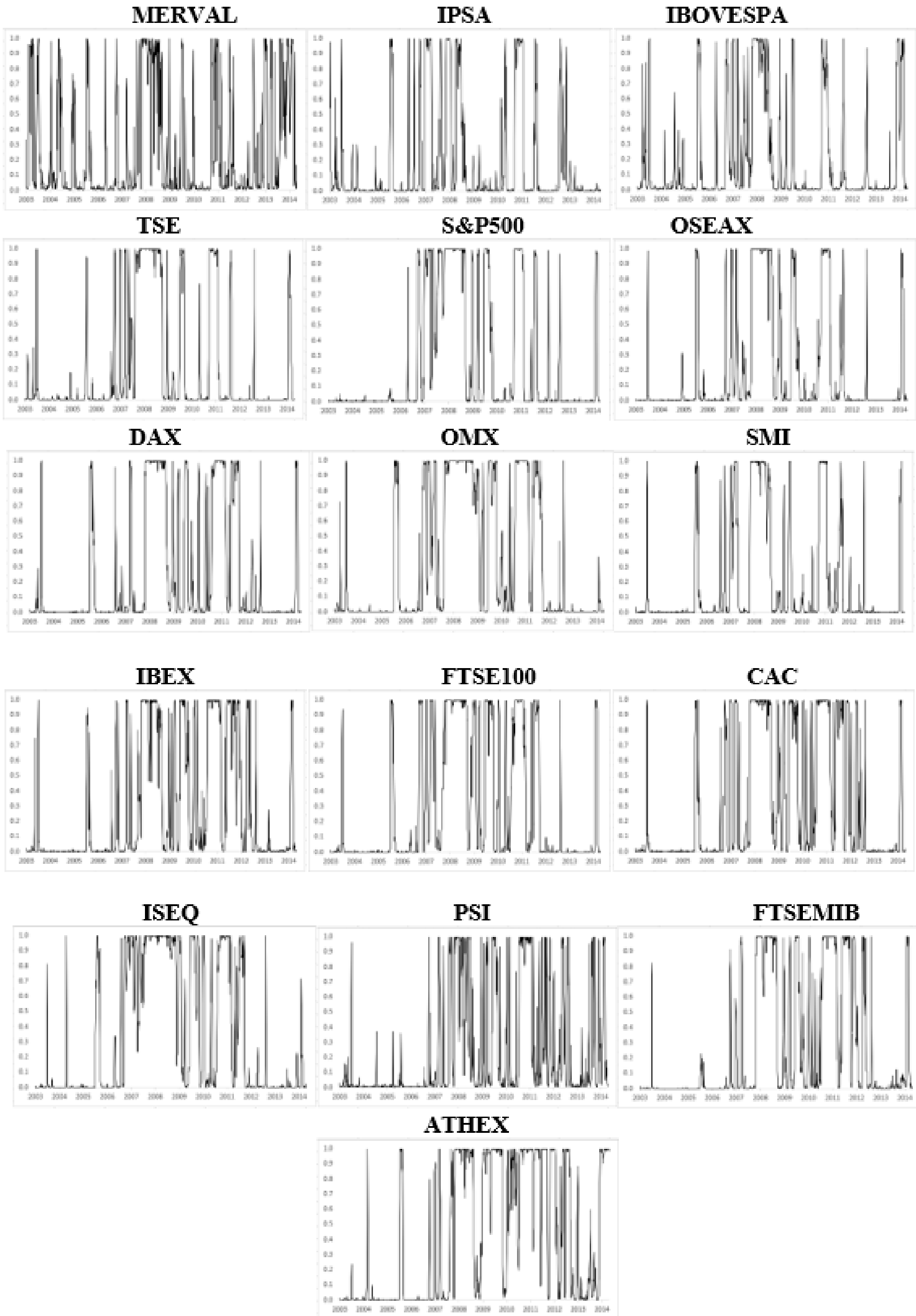


Figure 6. Smooth Probabilities High Volatility Regime
Source: own elaboration based on estimated results.

Figure 6 presents the smooth probabilities of being in regime 2 (high volatility regime). In this study, we use it as a graphic test to identify common high volatility periods in the stock markets. The smooth probability of being in the high dependence regime

(S(P2)) indicates the presence of several common high dependence episode; stands out some periods: 2008-2009 (subprime crisis), 2011-2012 (sovereign debt crisis) and 2013-2014 (global financial crisis residual effects).

MS-AR Results

As, previously, analyzed the US is the most important country in terms of Foreign Portfolio Investments, both as investor and as receptor. As a result of its size and share, the US financial and economic indicators are used as international references and basis to examine their impact on local factors (interest rates, exchange rates, indexes, etc.). Similarly, because the US stock market is the largest one in the world[3] its dynamics has influenced the rest of the international equity indexes. To evidence that returns from the main European and Canadian and Latin American are influenced by US equity market returns we apply the MS-VAR model. Results are presented in Tables 7 and 8.

The variance of the stock markets is lower in regime one (low volatility regime) than in regime two (high volatility regime), for all the markets. This indicates the presence of two different volatility regimes.

Tables 7 and 8 report the correlation coefficient between the US stock index and the other American and European indexes, in low and high volatility regimes. In all cases, the correlation level is higher during turmoil episodes (high volatility periods). This finding is similar to evidence obtained by Kanas (2005), Lin (2012) and Chkili and Nguyen (2014). Results signal that linkages between the US market and the other markets are stronger during high volatility periods. This phenomenon is commonly known as asymmetric correlation.

Equity markets with highest correlation during high volatility regime with the US are Mexico (0.78), Canada (0.762), Brazil (0.756), Germany (0.706) and France (0.704). Stock markets more related with the US market during low volatility periods are Mexico (0.66), Ireland (0.654), Canada (0.607).

[3]The New York Stock Exchange (NYSE) market is the largest stock market in the world (WFE, 2019). "Standard Poor's 500 Index (known commonly as the SP 500) is a larger and more diverse index than the DJIA. Made up of 500 of the most widely traded stocks in the US, it represents about 80 % of the total value of US stock markets" (Investopedia, 2018) 15/01/2019.
`https://www.investopedia.com/insights/introduction-to-stock-market-indices/`

Table 7. MS-VAR Results American Stock Markets

	IGBVL		COLCAP		IPC		MERVAL		IPSA		IBOVESPA		TSE	
	Coef	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**
α_1	0.0009*	0.0002	0.0009*	0.0002	-0.001***	0.0010	0.009*	0.0002	0.009*	0.0002	0.009*	0.0002	0.009*	0.0002
α_{21}	-0.0183	0.0727	-0.0167	0.0677	-0.0013	0.0666	-0.0104	0.0639	-0.0175	0.0697	-0.0188	0.0679	-0.0092	0.0725
α_{22}	-0.0761**	0.0837	-0.1041	0.0812	-0.2436	0.0852	-0.0706	0.0874	-0.1051	0.0854	-0.1405	0.0893	-0.0672	0.0911
α_{31}	-0.0217	0.0140	0.0021	0.0107	0.1441**	0.0572	-0.0024	0.0105	0.0072	0.0189	0.0058	0.0113	-0.0133	0.0253
α_{31}	-0.0858	0.0429	-0.0437	0.0542	0.0152*	0.0185	-0.0591	0.0481	-0.0291	0.0545	0.0121	0.0413	-0.0819	0.0642
β_1	0.0010*	0.0003	0.001*	0.0004	-0.0027	0.0018	-0.04**	0.0022	0.001*	0.0003	0.001*	0.0005	0.007*	0.002
β_{21}	0.2313*	0.0796	-0.0037	0.0842	-0.0554	0.1020	-0.22**	0.1053	0.1094	0.1063	-0.0146	0.0795	0.171*	0.0401
β_{22}	0.0877	0.0978	-0.269*	0.1040	-0.0013	0.0659	-0.0425	0.1074	-0.1436	0.1206	-0.22**	0.1074	0.1052	0.0760
β_{31}	0.1183*	0.0323	0.095*	0.0306	0.1172	0.1047	0.2223	0.1026	0.0609*	0.0325	0.0655	0.0679	0.246*	0.0331
β_{32}	0.1712**	0.0858	0.310**	0.1405	0.0505	0.0483	-0.0055	0.0498	0.309**	0.1013	0.31**	0.1503	0.265*	0.0833
Average duration														
Regime 1	102.376	44.740	86.686	27.895	68.446	60.412	93.930							
Regime 2	31.116	6.165	20.181	8.956	13.168	13.877	22.616							
Std deviation US market														
Regime 1	-4.868	-4.864	-4.865	-4.864	-4.863	-4.864	-4.865							
Regime 2	-3.765	-3.754	-3.763	-3.756	-3.754	-3.753	-3.757							
Std deviation t market														
Regime 1	-4.532	-4.367	-4.372	-4.203	-4.530	-3.965	-4.703							
Regime 2	-3.373	-3.122	-3.393	-3.265	-3.492	-3.061	-3.629							
Correlation coeficient														
Regime 1	0.371	0.396	0.660	0.511	0.486	0.599	0.607							
Regime 2	0.560	0.502	0.782	0.611	0.704	0.756	0.762							

*,** and*** indicates statistical significance at 1 %, 5 % and 10 %, respectively

Table 8. (Part 1) MS-VAR Results European stock markets

	OSEAX		**DAX**		**OMX**		**SMI**		**IBEX 35**		**FTSE 100**	
	Coef	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**
α_1	0.0009*	0.0002	0.0009*	0.0002	0.0009*	0.0002	0.0009*	0.0002	0.0009*	0.0002	0.0009*	0.0002
α_{21}	-0.0108	0.0660	-0.0452*	0.0305	-0.0271	0.0684	-0.0262	0.0674	0.0004	0.0731	-0.0290	0.0709
α_{22}	-0.1030	0.0824	-0.1610	0.0606	-0.1229	0.0801	-0.0897	0.0845	-0.1043	0.0840	-0.0860	0.0862
α_{31}	-0.0039	0.0146	0.0216	0.0189	0.0192	0.0164	0.0264	0.0220	0.0018	0.0181	0.0138	0.0240
α_{32}	-0.0266	0.0372	0.0266	0.0490	-0.0004	0.0445	-0.0607	0.0609	-0.0108	0.0452	-0.0610	0.0542
β_1	0.0013*	0.0003	0.0013*	0.0003	0.0009*	0.0003	0.0007*	0.0002	0.0012*	0.0004	0.0006*	0.0002
β_{21}	0.0008	0.0602	-0.1419*	0.0295	-0.0069	0.0563	0.0258	0.0461	-0.1067	0.1210	-0.0302	0.0498
β_{22}	-0.2425*	0.0802	-0.2463*	0.0616	-0.1276**	0.0674	-0.2618*	0.0718	-0.1885	0.1208	-0.2698*	0.0638
β_{31}	0.4017*	0.0455	0.4071*	0.0834	0.4506*	0.0475	0.3366*	0.0297	0.3093*	0.0427	0.3903*	0.0365
β_{32}	0.6022*	0.1016	0.3762*	0.0395	0.4979*	0.0816	0.4175*	0.0638	0.3217*	0.0795	0.5527*	0.0662
Average duration												
Regime 1	97.173	77.091	73.731	74.171	18.206	67.205						
Regime 2	22.398	23.024	33.221	17.731	47.828	26.682						
Std deviation US market												
Regime 1	-4.864	-4.863	-4.862	-4.861	-4.863	-4.862						
Regime 2	-3.756	-3.752	-3.752	-3.751	-3.754	-3.753						
Std deviation t market												
Regime 1	-4.265	-4.488	-4.469	-4.699	-4.479	-4.758						
Regime 2	-3.267	-3.496	-3.477	-3.761	-3.451	-3.725						
Correlation coeficient												
Regime 1	-0.004	0.557	0.473	0.413	-0.021	-0.038						
Regime 2	0.637	0.706	0.682	0.647	0.017	0.054						

*,** and*** indicates statistical significance at 1 %, 5 % and 10 %, respectively

Table 8. (Part 2) MS- VAR Results European Stock Markets

	CAC 40		**ISEQ**		**PSI 20**		**FTSEMIB**		**ATHEX 20**	
	Coef	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**
α_1	0.0009*	0.0002	0.0009*	0.0002	0.0009*	0.0002	0.0009*	0.0002	0.0009*	0.0002
α_{21}	0.0010	0.0667	-0.0041	0.0856	-0.0170	0.0684	-0.0127	0.0709	0.0019*	0.0657
α_{22}	-0.1029	0.0876	-0.1257	0.0864	-0.1112	0.0794	-0.1243	0.1101	-0.1438	0.0749
α_{31}	0.0098	0.0189	-0.0079	0.0180	-0.0033	0.0163	0.0027*	0.0176	0.0030	0.0087
α_{32}	-0.0018	0.0484	0.0016	0.0447	-0.0347	0.0495	0.0003*	0.0536	0.0483	0.0320
β_1	0.0009*	0.0003	0.0012*	0.0003	0.0016*	0.0003	0.0009*	0.0003	0.0008**	0.0004
β_{21}	-0.0572	0.0658	-0.0170	0.0689	-0.1433	0.0936	0.0571	0.0595	0.1801	0.0546
β_{22}	-0.2160*	0.0764	-0.1007	0.0753	-0.2390**	0.1004	-0.0649	0.0737	0.0477	0.0651
β_{31}	0.4215*	0.0419	0.3769*	0.0435	0.1944*	0.0322	0.3241*	0.0425	0.3979*	0.0545
β_{32}	0.5133*	0.0782	0.4418*	0.0668	0.3009*	0.0736	0.4522*	0.0898	0.3036*	0.0788
Average duration										
Regime 1	47.645	62.016	34.245	69.021	50.903					
Regime 2	20.241	29.866	10.367	23.363	34.278					
Std deviation US market										
Regime 1	-4.863	-4.865	-4.864	-4.864	-4.865					
Regime 2	-3.754	-3.755	-3.755	-3.754	-3.758					
Std deviation t market										
Regime 1	-4.582	-4.577	-4.559	-4.432	-4.227					
Regime 2	-3.557	-3.565	-3.555	-3.412	-3.264					
Correlation coeficient										
Regime 1	0.561	0.654	0.370	0.517	0.261					
Regime 2	0.704	0.692	0.612	0.664	0.405					

*,** and*** indicates statistical significance at 1 %, 5 % and 10 %, respectively

The estimated coefficients capturing the impact of stock market returns (European and American) on the US stock market returns (α_{31} and α_{32}) are not significant in most of the cases, except for the Italian and Mexican market. This suggests that, in the major part of the sample, the equity markets under study do not have an important effect on the US stock market.

On the other hand, the coefficients (β_{31} and β_{32}) capture t effects of the US stock market returns on t stock market returns (European, Canadian and Latin American markets). They are statistically significant, for most of the stock markets in the sample, but insignificant for the Mexican, Argentinean and Brazilian markets. It means that, most of the stock markets are influenced by the US equity market. These results are consistent with those of Tabak and Lima (2013) who find that Latin American stock markets and the US equity market do not present a long-term relationship and that the Mexican market seems to have an impact on the US stock market. The relation is negative in both regimes, high and low level of volatility, suggesting that an increase in the US stock market inflows leads to diminish investments in other international stock markets. This finding is consistent with practice, in international asset allocation, short-run investments look for higher returns and lower risk. Thus, when the US market exhibits positive trends, international flows are directed to this market, reducing investments in other international markets.

5. Conclusions

This research analyzes the US dynamic linkages with the 18 most important economies of Europe and the Americas from 2003 to 2015. To achieve this goal, first, Network Theory is used to analyze Foreign Portfolio Investment (FPI) flows among countries in the sample. Second, the MS-AR and MS-VAR models are used to test whether the US equity market influenced European and other American stock markets or vice versa.

Our hypothesis states that US financial markets keep a close financial relationship with the most important European and American countries' stock markets, both by receiving and delivering FPI, and in addition influencing the behavior of stock indexes.

Centrality measure analysis reveals, as expected, the importance of U.S. regarding international portfolio flows; it is one of the main destinies and origin of FPI during the whole period of study; not only presents an important number of outcoming and incoming links, but also, in terms of volume, is one of the main FPI receptors and investors.

Analysis of FPI flows from and towards the US acknowledges dynamic linkages between the US and other countries in the sample. It also reveals that US FPI outflows weaken due to the Global Financial Crisis; however, in the long-run its powerful influence remained significant over the other 18 countries.

Empirical results offer evidence favoring the presence of regime-switching properties in all returns series. These findings provide strong evidence in favor of nonlinear relations between the US stock market returns and the rest of the European and Canadian and Latin American equity market returns. High and low volatility correlation results signal that linkages between the US market and the other markets are stronger during high volatility periods, phenomenon also known as asymmetric correlation.

MS-VAR model findings suggest that, for the major part of the sample, equity markets under study do not have an important impact on the US stock market. On the contrary, most of the stock markets under study are influenced by the US equity market. The relation is negative in both regimes of high and low level of volatility, revealing that an increase in the US stock market inflows leads to diminish investments in other international stock markets. When the US market exhibits positive trends, international flows are directed to this market, reducing investments in other international markets.

The empirical evidence on the direction and quantity of international flows suggests the need to strengthen local productive and financial institutions in order to anchor

FPI. Productivity and innovation, both in the private and public sectors must gear development, particularly in emerging markets to increase their competitiveness and share in world wide business activities. Moreover, corruption and security problems must be eradicated, and property rights must be legally guaranteed both for foreign direct and portfolio investments. Essentially, all these actions mean enhancing social trust, locally and for international relationships.

Additionally, some local regulation policies to stabilize the economy and flows are required, mainly in developing markets such as the Latin American countries included in our study. Impacts of the GFC on the behavior of stock markets imply the need to enhance the development and resilience of these markets to respond effectively to unfavorable world economic conditions; since dependence (correlations) increase under those circumstances preventive policies must be a permanent preoccupation of both private and public decision makers. Finally, since speculative flows have always increased and destabilized the world economy; international financial governance needs to evolve to control those ill investment impacts. Particularly, speculation both in the short-term and long-term assets should be discouraged enforcing taxes on large international outflow transactions as suggested by Tobin (1974; 1978). Like he suggested to make this tax effective and avoid restrains on capital inflows and simultaneously promote international financial stability, this tax should be adopted internationally, and the proceedings donated to developing countries experiencing foreign debt and currency problems. This global taxation policy would deter financial crisis which have led to large changes and instabilities in the direction and volume of financial flows needed to promote economic development.

Future research agenda must include studies about dynamic linkages between stock markets and exchange rate, oil prices or other commodity prices. It also should include other emerging markets and different study periods. Finally, future research should also deal with causality factors, such as international rate spreads, inflation, monetary policy, economic growth, and others, on capital flows movements.

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