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Walmir Geraldo da Silva

Essays on financial systemic risk

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Abril, 2018

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Tese apresentada no curso de Doutorado Acadêmico do Programa de Pós-Graduação em Administração, na área de concentração de Finanças e Métodos Quantitativos, da Universidade de Brasília, como requisito para obtenção do grau de Doutor.
Orientador: Prof. Tit. Herbert Kimura
Coorientadora: Prof. Tit. Marcelle Chauvet

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Prof. Tit. Herbert Kimura
Faculdade de Economia, Administração,
Contabilidade e Ciência da Informação e
Documentação
Universidade de Brasília – UnB

Prof. Pedro Henrique Melo Albuquerque
Faculdade de Economia, Administração,
Contabilidade e Ciência da Informação e
Documentação
Universidade de Brasília - UnB

Prof. Fabiano Guasti Lima
Faculdade de Economia, Administração e
Contabilidade de Ribeirão Preto
Universidade de São Paulo - USP

Prof. Marcelle Chauvet
Department of Economics
University of California, Riverside - UCR

Dedico este trabalho à memória de meus pais

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Abstract

This dissertation presented to obtain the Ph.D. degree in Business Administration is composed of two articles. The first one presents an analysis of the literature on systemic financial risk. To that end, we analyze and classify 266 articles that were published no later than September 2016 in the databases Scopus and Web of Knowledge; these articles were identified using the keywords “systemic risk”, “financial stability”,“financial”, “measure”, “indicator”, and “index”. They were evaluated based on 10 categories, namely, type of study, type of approach, object of study, method, spatial scope, temporal scope, context, focus, type of data used, and results. The analysis and classification of this literature made it possible to identify the remaining gaps in the literature on systemic risk; this contributes to a future research agenda on the topic. Moreover, the most influential articles in this field of research and the articles that compose the main stream research on systemic financial risk were identified. In the second article, we model an indicator that aims to identify systemic risk in the financial markets. Using 93 assets from different classes and from both developed and emerging countries, we apply principal components analysis (PCA) to calculate an initial indicator that is then submitted to Markov switching (MS) technique. This procedure advances the use of PCA in systemic risk modelling by preventing the need for arbitrary definitions of normal and stressed regimes. Additionally, applying MS to the indicator extracted by PCA from the correlation matrix of a relevant number of assets of various classes supports the argument that the indicator is indeed systemic. The results show that the probabilities that the indicator is under stress, according to the MS model, can be used as a signal of systemic risk. We also verified that the average risk of assets, calculated by the average value-at-risk (VaR), is affected when the series of these assets are separated in the systemic risk and normal regimes. In addition, we measure the performance of the indicator compared to other metrics built with only an asset class, especially stock indices. The results show that our model adequately depicts periods of high systemic risk, being relatively thorough.

Keywords: Systemic risk; Financial Markets; Financial stability; Bibliometry; Measure; Systemic Risk Indicator; Principal Components Analysis; Markov Switching Models; Value-at-Risk; Asset Risk Classification.

List of Figures

List of Tables

Contents

1 Brief comment

This work is my final dissertation presented to obtain the Ph.D. degree in Business Administration, Finance and Quantitative Methods track, in University of Brasília. I am an employee for the Central Bank of Brazil who works with the foreign reserves investments and whose tasks were focused in providing quantitative analyses to support the staff in charge to make the investment decisions. Thus, I could follow the development of the financial crisis started in 2007 and the huge impact those events had over the financial markets and the real economy, and what followed in terms of loss of confidence of agents. The concerns caused by that crisis mobilized international organisms and central banks around the world in an unprecedented way and many and diverse measures were proposed to rescue financial stability, a precious asset to the economies.

Identifying, managing and mitigating financial systemic risk became crucial for regulators and market agents in general. IMF drew attention to the need for tools that would allow systemic risk to be detected since the ability to identify systemic risk at an early stage (early warning systems) could allow regulators to proactively engage in defining measures to control crisis (IMF, 2009). Moreover, early warning systems would be desirable tools for the portfolio managers as well. More specifically, systemic risk indicators to monitor stress in the markets would be of great value for reserve managers. I started researching the theme and became personally involved with monitoring systemic risk and modelling financial stress indicators. The initial results were of great interest for our teams.

As a consequence, when I decided to apply for a PhD grade, it was natural for me to present a project related to those kinds of issues, given the great interest and usefulness of the theme for central bank both for its impact on the international reserves and for financial stability and regulation concerns.

The work is composed by two articles. The first one, "An analysis of the literature on systemic financial risk: A survey", presents a systematic analysis of the literature on the theme. As identified in the present study, the academic research on systemic risk has grown since the financial crisis that began in 2007, which shows the relevance of the subject. It is not a simple review, since we used a consolidated methodology to analyze and classify a huge number of articles (266) that were published no later than September 2016 in the databases Scopus and Web of Knowledge, identified using specific keywords and evaluated based on 10 categories, namely, type of study, type of approach, object of study, method, spatial scope, temporal scope, context, focus, type of data used, and results.

The analysis and classification of this literature made it possible to identify the remaining gaps in the literature on systemic risk; this contributes to a research agenda on the topic.

Moreover, the most influential articles in this field of research and the articles that compose the mainstream research on systemic financial risk were identified.

In the second article, "A financial systemic risk indicator using PCA and Markov switching", we propose a modelling of an indicator that aims to identify systemic risk in the financial markets. In this study, systemic financial risk is identified with the notion of financial stress, in which there may be strong and generalized variation in asset prices. More particularly, the contribution of the paper involves the combination of principal components analysis (PCA) and Markov switching (MS) to establish an indicator of systemic risk.

Taking into account nearly one hundred publicly traded assets from different classes and from both developed and emerging countries, we apply principal components analysis (PCA) to calculate an initial indicator that is then submitted to Markov switching (MS) technique. This procedure advances the use of PCA in systemic risk modelling by preventing the need for arbitrary definitions of normal and stressed regimes. Additionally, applying MS on the indicator extracted in PCA from the correlation matrix of relevant number of assets of various classes supports the argument that the indicator is indeed systemic.

The study of the variables *vis-à-vi*s the indicator using PCA allowed us to map which assets work as safe havens and which ones are riskier. This indicator can be very useful in helping portfolio managers pick assets and define allocation strategies. The results show that the probabilities that the indicator is under stress, according to the MS model, can be used as a signal of systemic risk. Thus, the systemic risk indicator not only can help regulators establish mechanisms to prevent markets from severe crises, but also can allow managers of financial institutions and fund managers to choose assets when facing different market regimes.

The final indicator generated by PCA and MS was evaluated for the ability to reveal a generalized risk increase among assets as well as by the comparison to other metrics built with only an asset class. Episodes of financial stress in international markets were also identified. Results show that our model adequately depicts periods of high systemic risk, being relatively thorough.

2 An analysis of the literature on systemic financial risk: a survey

2.1 Introduction

Research on systemic risk in financial markets has intensified since the US mortgage crisis started in 2007. The vulnerability of the financial system was exposed in the bankruptcy of the Lehman Brothers investment bank in September 2008 and, subsequently, the sovereign debt crisis of the Eurozone countries. Such events generate panic and chain reactions, undermining the confidence that is necessary for the proper functioning of the financial system. According to the International Monetary Fund (IMF), the lack of effective mechanisms for addressing these situations brings great risks for economies (IMF, 2009).

These events are even more serious because the financial sector has increased its relative weight in economies and has globalized, with new telematic technologies having increased the trading speed. According to Grilli et al. (2014a), in recent decades, a massive transfer of resources from the productive sector to the financial sector has been one of the characteristics of economic systems. According to the same authors, this re–allocative process, known as the financialization of the economy, is one of the factors responsible for the growing financial instability, characterized by recurrent crises of increasing intensity.

Oort (1990) cites the following three possible sources of vulnerability to the international banking system: i) a larger bank failure causing a general banking crisis via an extensive network of interconnections among banks; ii) the systemic risks alleged to be inherent to certain "new" bank products; and iii) the impact of external events, such as debt crises, violent changes in interest or exchange rates, deregulation, and recession. Oort (1990) considers the likelihood of a major banking crisis to be small, mainly because of increased banking oversight and its exercise on a comprehensive and consolidated global basis (OORT, 1990, p.463). Subsequent events, particularly the 2007 crisis, have contradicted this assumption.

Interestingly, certain articles published before the 2007 crisis called attention to the increased systemic financial risk. For example, Nicolo and Kwast (2002) state that the ongoing consolidation of the financial system was one of the most notable features at that time and that the resulting creation of a number of very large and, in some cases, very complex financial institutions increased concerns regarding the growth of systemic risk. Lehar (2005) also notes an increase in systemic risk in the banking sector due to the ongoing rapid integration of financial markets, which brought concerns to regulators and supranational agencies, given that a simultaneous failure of many banks could result in a serious economic crisis, as past experience had already shown.

Daníelsson (2002) warns that macro–prudential regulation focused only on the risks taken by banks and other financial institutions individually was not sufficient to prevent crises. In the opinion of this author, risk measures that consider only the specific risk of the institution do not help in the monitoring of systemic risk; on the contrary, they can aggravate it. Moreover, Danielsson et al. (2016) show that model risk increases with market uncertainty, which has to be taken into account given fundamental role risk models play in the regulatory process.

The IMF in its Global Financial Stability Report of 2009 draws attention to the need for tools that would allow systemic risk to be detected and states that the ability to identify systemic risk at an early stage can allow regulators to proactively engage in defining measures to control crisis (IMF, 2009).

As identified in the present study, the academic research on systemic risk has grown since the financial crisis that began in 2007, which shows the relevance of the subject. Consequently, following the method proposed by Jabbour (2013), Lage-Junior and Godinho-Filho (2010), and Seuring (2013), the objectives of this study are as follows:

- Identify articles in the *Scopus* and *Web of Knowledge* databases related to systemic financial risk to build a sample
- Classify and code the characteristics and scope of the papers
- Generate summary of the contribution of each article and analyze the mainstream research on systemic financial risk
- Identify the strengths and weaknesses of the studies
- Identify the most influential articles in this field of study, building a network of studies
- Provide a framework to address the relevant gaps in the current discussion on systemic financial risk.

Below, are presented the research method (Section 2.2); the classification and coding mechanism for the papers (Section 2.3); a brief review of the concept of systemic financial risk (Section 2.4); the results of the article classification, including perceived gaps, as well as the identification of research networks and analysis of the main research path (Section 2.5); and final considerations (Section 2.6).

2.2 Research methods

This work follows the method of Jabbour (2013), Lage-Junior and Godinho-Filho (2010), and Seuring (2013), who refer to Huisingh (2012). This study is a literature analysis; it is useful for structuring the results of research that addresses emerging themes; it also provides a comprehensive assessment of the cutting edge of the literature. In addition, this approach aims to characterize the research field and identify gaps in the research, providing a basis for further investigation (HUISINGH, 2012). Although many studies follow a review based method, including the works cited, the research on systemic financial risk has not been addressed to a large extent. Jabbour (2013) and Lage-Junior and Godinho-Filho (2010) propose that literature reviews should involve the following stages:

- First Stage: Perform a comprehensive search of the published papers on the theme in relevant databases
- Second Stage: Develop a classification model, coded using a logical structure
- Third Stage: Apply the classification model and elaborate a framework of the current discussion on the theme
- Fourth Stage: Present characteristics of the scientific literature and the main results, taking into account the coding system
- Fifth Stage: Analyze the gaps and suggest opportunities for further study

To map the scientific production on systemic financial risk, the first step was to build a significant sample of the articles produced in the field. Thus, on December 22, 2014, searches were performed in the Scopus database using the keywords "systemic risk" and "financial stability" and further combining "systemic risk" and "financial" and "measure" or "indicator" or "index". These searches were not limited temporally, but the thematic areas were limited to "Social Sciences & Humanities" and "Physical Sciences", excluding the thematic areas of "Life Sciences" and "Health Sciences". In the first search, a sample of 170 articles was obtained, with 86 being available in full for download (only the abstracts were available for the others). The second search produced 134 articles, of which 61 were available in full for download. Eight articles were listed in both searches; therefore, the sample was composed of 139 articles available in the database. Of these articles, two were excluded because they were editorials; three did not correspond to the articles advertised when downloaded, due to errors in the databases; and two were later found to address a subject different from the one intended. Thus, an initial sample of 132 articles of interest and available in full to download was obtained.

In May 2015, an additional 25 articles published until 2014 and not included in the original sample were downloaded from the *Web of Knowledge* database, using the same combinations of keywords used in *Scopus*. In April 2016, it was decided to incorporate articles that were published in 2015 and available for download. Thus, an additional 45 articles were added to the sample. In September 2016, 64 articles published in 2015 and 2016 were added, for a final sample of 266 articles downloaded from the *Scopus* and *Web of Knowledge* databases for classification, as shown in Table 1 below.

Keywords	**Total *Scopus***	***Scopus Download***	***WoK Download***	**General Total**
Systemic risk e *financial stability*.	170	86		
Systemic risk e *measure* ou *indicator* ou *index*.	134	61		
Duplicity inside the database.		-8		
Addition of *Web of Knowledge*.			35	
Exclusions.		–7	–10	
Totals.		**132**	**25**	**157**
Addition of 2015.			35	
Addition of 2015 *Web of Knowledge*.			10	
Addition of 2016.			52	
Addition of 2016 *Web of Knowledge*.			12	
General Total.				**266**

Table 1 – Sample of articles on systemic financial risk.

Regarding the vehicles of publication of the articles, it is observed that 17 journals concentrated 61% of the published articles (162 of 266), as shown in Table 2.

Journal	Number of Articles
Journal of Financial Stability.	41
Journal of Banking & Finance.	35
Journal of Economic Dynamics and Control.	11
Physica A.	11
Journal of International Financial Markets, Institutions and Money.	8
Journal of International Money and Finance.	8
Scientific Reports.	7
Economic Modelling.	5
International Review of of Economics & Finance.	5
International Review of Financial Analysis.	5
Journal of Financial Intermediation.	5
Insurance: Mathematics and Economics.	4
Journal of Financial Services Research.	4
Journal of Econometrics.	4
Journal of Financial Economics.	3
National Institute Economic Review.	3
Review of Financial Studies.	3
Annals of Finance.	2
Annual Review of Financial Economics.	2
Economic Systems.	2
European Economic Review.	2
Financial Markets, Institutions and Instruments.	2
International Economics.	2
International Journal of Finance and Economics.	2
Journal of Central Banking Theory and Practice.	2
Journal of Empirical Finance.	2
Journal of International Economics.	2
Mathematical Finance.	2
Procedia – Social and Behavioral Sciences.	2
Proceedings of the National Academy of Sciences of the United States of America.	2
Research in International Business and Finance.	2
The Spanish Review of Financial Economics.	2
Others.	74

Table 2 – Number of articles published per journal.

A large dispersion of publishing vehicles is observed for the remaining 104 articles. In total, the sample consists of articles published in 106 journals, with the vast majority of journals (74) publishing only one article and 15 journals publishing two articles, as shown in Figure 1.

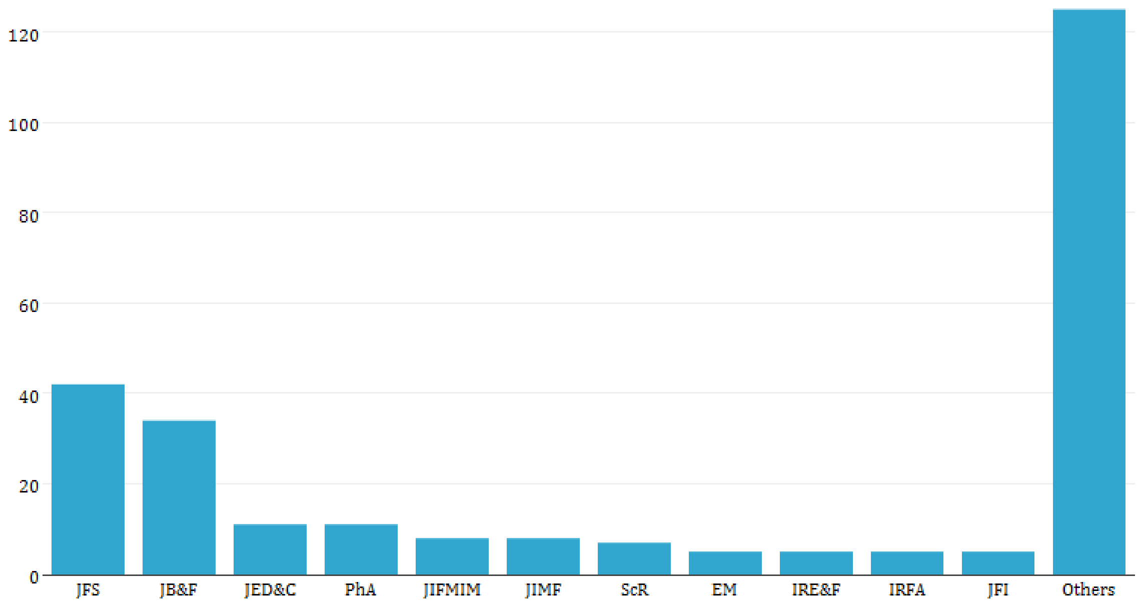

Figure 1 – Number of articles per journal.

By organizing articles by publication year, it is observed that, until 2001, there are only two articles in the sample. From 2002 onwards, articles on systemic financial risk occur every year, on a regular but low frequency until 2008. From 2009 onwards, after the bankruptcy of Lehman Brothers and the worsening of the global financial crisis, the number of articles on systemic financial risk grows significantly, as shown in Figure 2.

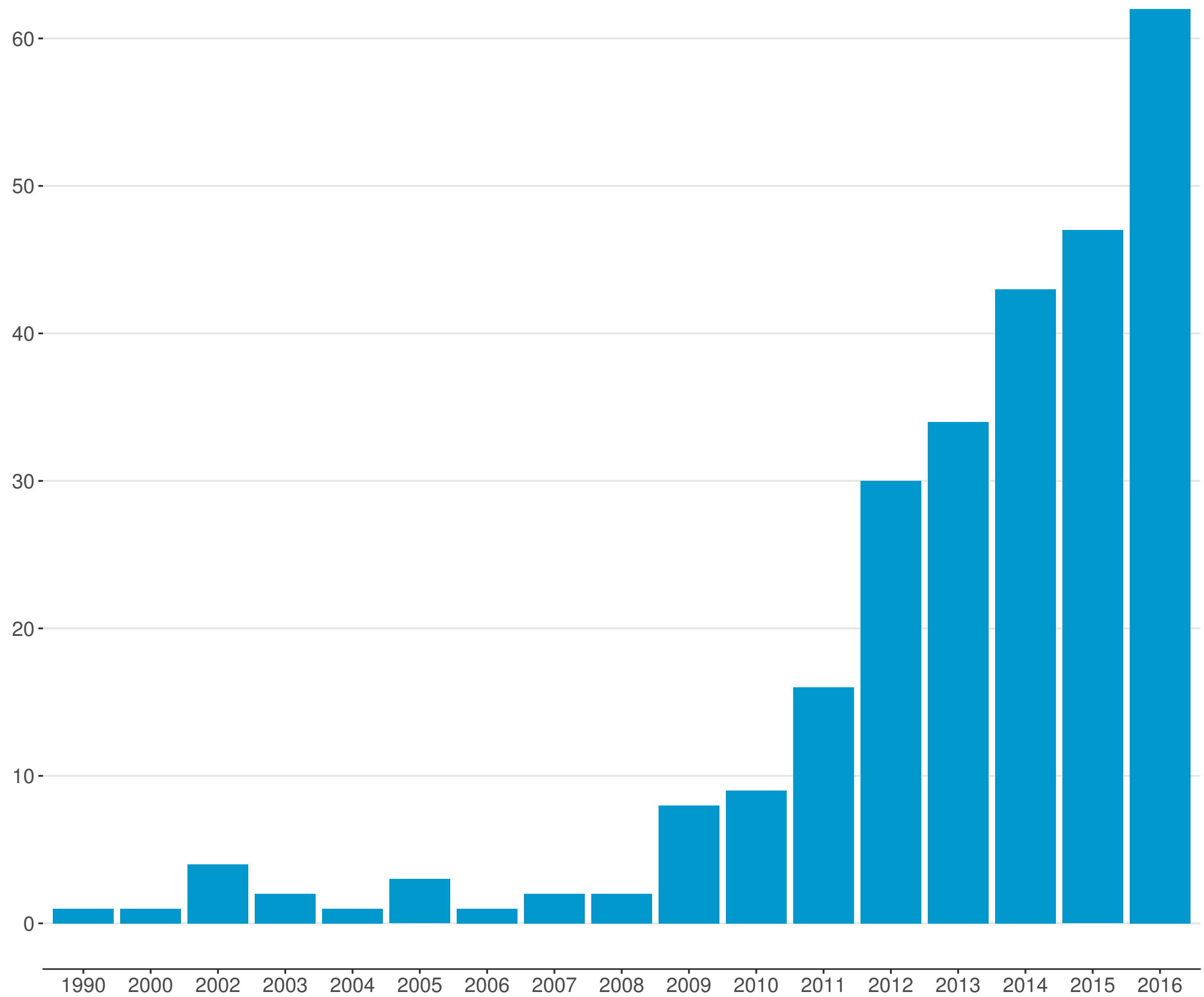

Figure 2 – Number of articles per year.

As the article were read and analyzed, a proposed classification system was built, and it was refined as more articles were analyzed. Ten classes were proposed for analyzing and mapping the scientific production on systemic financial risk; they are presented in the next section together with the classification of the articles.

2.3 Classification and coding

The structure for classification is built following the method proposed by Jabbour (2013), Lage-Junior and Godinho-Filho (2010), and Seuring (2013). The classification scheme includes 10 categories, numbered 1 through 10. Each of the classifications is also coded with letters (A, B, C, etc.). Thus, this classification system involves an aggregation of numbers and letters. It is important to note that an article can be associated with several codes for a given item.

- Classification 1: *Type of study*, coded on a scale from A to C

- Classification 2: *Approach*, coded from A to D
- Classification 3: *Object of study*, coded from A to J
- Classification 4: *Comprehensiveness in geographic terms*, coded from A to E
- Classification 5: *Context*, related to the degree of development of the countries analyzed, coded from A to D
- Classification 6: *Focus*, related to the type of institutions and markets analyzed, coded from A to H
- Classification 7: *Period studied*, coded from A to E
- Classification 8: *Type of data analyzed*, coded from A to E
- Classification 9: *Methods used*, coded from A to D
- Classification 10: *Results*, coded from A to E

Table 3 shows the classification structure and codes used.

Category	Rating	Meaning
Study type.	A	Theoretical.
	B	Empirical.
	C	Both.
Type of approach.	A	Quantitative.
	B	Qualitative.
	C	Quantitative and qualitative.
	D	Review/Survey.
	E	Not applicable.
Object of study.	A	Regulation.
	B	Market risk.
	C	Credit Risk/Default risk/Counterparty risk/Sovereign risk.
	D	Liquidity risk.
	E	Contagion.
	F	Size of institutions.
	G	Interconnectivity/Interdependence.
	H	Concentration/Diversification/Competition.
	I	Others.
	J	Not applicable.

Continue on next page

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Category	Rating	Meaning
Scope.	A	One country.
	B	More than one country.
	C	Region/Block.
	D	World.
	E	Not specified/Not applicable.
Context.	A	Developed country.
	B	Undeveloped country.
	C	Both.
	D	Not applicable.
Focus.	A	Financial institutions in general.
	B	Banks.
	C	Stock market.
	D	Insurance companies.
	E	Investment funds/Hedge funds.
	F	Real Estate/Mortgages.
	G	General market (non–financial).
	H	Countries/Government Bonds.
	I	Other segments.
Studied periods.	A	Up to 2 years.
	B	From 2 to 5 years.
	C	From 5 to 10 years.
	D	More than 10 years.
	E	Not applicable.
Types of data analyzed.	A	From market.
	B	From balance sheets.
	C	Macroeconomic.
	D	From regulators, IMF, and other bodies.
	E	Others.
	F	Not applicable.
Methods used.	A	Econometric/Statistical/Multivariate analysis.
	B	Computational/Simulation.
	C	Mathematical modelling.
	D	Not applicable.
Results.	A	New perspectives.
	B	Consistent with previously published literature.
	C	Replication to a different context or period.

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Category	Rating	Meaning
	D	Comparative study.
	E	Not applicable.

Table 3 – Classification and coding used to analyze the articles.

The full list of articles that comprise the sample and their classification in the various items listed above are shown in Table 4.

Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Aboura and Wagner (2016).	1B	2A	3B	4A	5A	6C	7D	8A	9A	10A
Abreu and Gulamhussen (2013).	1B	2A	3A, 3F	4D	5C	6B, 6C	7A	8A	9A	10B
Adrian et al. (2015).	1A	2C	3A	4A	5A	6A	7D	8A, 8B, 8D	9D	10B
Aglietta and Scialom (2010).	1A	2B	3A	4D	5C	6B	7D	8A, 8C, 8D	9C	10B
Ahrend and Goujard (2015).	1B	2A	3C, 3E	4D	5C	6B	7D	8A, 8B, 8C	9A	10B
Aleksiejuk and Holyst (2002).	1C	2A	3E, 3G	4E	5D	6B	7E	8F	9B, 9C	10B
Alexander (2011).	1A	2B	3A	4C	5A	6A	7D	8D	9D	10A
Allen et al. (2012).	1B	2A	3B, 3D	4D	5C	6B	7D	8A, 8C	9A	10A
Allen and Carletti (2013).	1A	2C	3A, 3B, 3I	4E	5D	6F	7E	8F	9D	10D
Amini et al. (2013).	1A	2A	3A, 3E, 3G	4A	5B	6B	7A	8D	9A, 9C	10A
Amini et al. (2016).	1C	2A	3A, 3C, 3E, 3G	4E	5D	6B	7E	8E	9B, 9C	10B
Andersen et al. (2011).	1B	2A	3B	4D	5C	6C	7C	8A	9A	10A
Anginer et al. (2014a).	1B	2A	3A, 3I	4D	5C	6B	7C	8A, 8B, 8C	9A	10A

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Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Anginer et al. (2014b).	1B	2A	3C, 3H	4D	5C	6B	7D	8A, 8B	9A	10A
Anufriev and Panchenko (2015).	1B	2A	3G, 3E	4A	5A	6A, 6G	7D	8A	9A	10B
Apostolakis and Papadopoulos (2015).	1B	2A	3B, 3G	4B	5A	6B, 6I	7D	8A, 8D	9A	10C
Arinaminpathy et al. (2012).	1B	2A	3F, 3G	4A	5A	6B	7D	8A, 8B	9A	10B
Arnold et al. (2012).	1A	2B	3A	4D	5C	6G	7E	8D	9D	10B
Arora and Rathinam (2011).	1A	2B	3A, 3I	4A	5B	6G, 6I	7D	8D	9D	10B
Ashraf et al. (2016).	1B	2A	3A	4C	5B	6B	7D	8C, 8D	9A	10B
Avramidis and Pasiouras (2015).	1B	2A	3B, 3C, 3G	4D	5C	6B	7D	8A, 8B	9A	10A
Baglioni and Cherubini (2013).	1B	2A	3C, 3I	4C	5A	6B	7B	8A, 8B, 8D	9A	10A
Balbás et al. (2016).	1B	2A	3A, 3C, 3E, 3G	4B	5A	6A, 6H	7B	8A	9A	10B
Balogh (2012).	1B	2A	3A	4C	5A	6B	7C	8C, 8D	9A	10B
Banerjee et al. (2016).	1B	2A	3C, 3G	4C	5A	6B, 6H	7B	8A	9A	10B
Banulescu and Dumitrescu (2014).	1B	2A	3B, 3F, 3G	4A	5A	6B, 6D, 6I	7D	8A	9A	10B
Barnea et al. (2015).	1C	2A	3I	4E	5D	6B	7E	8E	9C	10B

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Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Barnett and Chauvet (2011).	1C	2A	3I	4A	5A	6G	7D	8A, 8C, 8D	9A	10B
Barth and Schnabel (2013).	1B	2A	3B, 3F, 3G	4D	5C	6B	7C	8A, 8B, 8C, 8D	9A	10B
Barth and Wihlborg (2016).	1A	2B	3A, 3F, 3I	4B	5A	6B	7D	8B, 8D	9D	10B
Battaglia and Gallo (2013).	1B	2A	3I	4A	5A	6B	7C	8A, 8B	9A	10C
Battiston et al. (2012).	1A	2A	3E, 3G	4E	5D	6B	7E	8F	9C	10B
Battiston et al. (2012).	1B	2A	3C, 3G	4A	5A	6B	7B	8D	9A	10A
Baur and Schulze (2009).	1B	2A	3E, 3I	4D	5C	6C	7D	8A	9A	10A
Beale et al. (2011).	1A	2A	3A, 3H	4E	5D	6B	7E	8F	9A, 9B	10B
Beck et al. (2013).	1B	2A	3H	4D	5C	6B	7D	8A, 8B, 8D	9A	10A
Bengtsson (2014).	1A	2B	3A, 3C, 3D, 3I	4D	5C	6E, 6I	7B	8D	9D	10B
Benoit (2014).	1B	2A	3A, 3B	4C	5A	6B	7D	8A	9A	10D
Berger and Pukthuanthong (2012).	1B	2A	3B, 3E, 3G	4D	5C	6C	7D	8A	9A	10B
Berger and Pukthuanthong (2016).	1B	2A	3B	4A	5A	6C	7D	8A, 8C	9A	10B

Continue on next page

Continued from previous page

Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Bernal et al. (2014).	1B	2A	3B	4B	5A	6B, 6C, 6D, 6I	7C	8A	9A	10C
Bernal et al. (2016).	1B	2A	3C	4B	5A	6H	7B	8A	9A	10B
Betz et al. (2016).	1B	2A	3B, 3C, 3G	4C	5A	6B, 6H	7C	8A	9A	10B
Bianconi et al. (2015).	1B	2A	3B, 3I	4A	5A	6B, 6C	7D	8A, 8E	9A	10C
Billio et al. (2012).	1B	2A	3D, 3E, 3G	4A	5A	6B, 6D, 6E, 6I	7D	8A	9A	10A
Birch and Aste (2014).	1C	2A	3C, 3E, 3G	4B	5A	6B	7C	8B	9A, 9C	10A
Black et al. (2016).	1B	2A	3B, 3C	4C	5A	6C	7D	8A	9A	10B
Bluhm and Krahnen (2014).	1A	2A	3A, 3E, 3G	4E	5D	6B	7E	8B	9C	10B
Bordo et al. (2014).	1A	2B	3A	4B	5A	6B	7D	8D	9D	10D
Borio (2011).	1A	2B	3A	4A	5A	6A	7B	8D	9A, 9C	10B
Bosma (2016).	1A	2A	3A, 3I	4E	5D	6B	7E	8F	9C	10A
Bowden and Posch (2011).	1A	2B	3A, 3I	4E	5D	6A	7E	8F	9D	10B
Breitenfellner and Wagner (2012).	1B	2A	3B	4C	5A	6C, 6I	7C	8A	9A	10B
Burkholz et al. (2016).	1A	2A	3G, 3I	4E	5D	6G	7E	8F	9B, 9C	10B
Buti and Carnot (2012).	1A	2C	3C	4C	5A	6H	7D	8A, 8C, 8D	9D	10B

Continue on next page

Continued from previous page

Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Rodríguez et al. (2014).	1B	2A	3E	4A	5B	6A 6G	7C	8C, 8D	9A	10C
Caccioli et al. (2009).	1A	2A	3I	4E	5D	6A, 6G	7E	8F	9C	10A
Caccioli et al. (2012).	1A	2A	3E, 3F, 3G	4E	5D	6B	7E	8F	9A, 9B	10C
Caccioli et al. (2015).	1B	2A	3C, 3E, 3I	4A	5A	6B	7B	8B	9A	10B
Caetano and Yoneyama (2011).	1B	2A	3B, 3E	4B	5C	6C	7D	8A	9B, 9C	10A
Calice et al. (2011).	1B	2A	3B, 3C	4B	5A	6B	7C	8A	9A	10B
Calice and Ioannidis (2012).	1B	2A	3B, 3C	4B	5A	6B	7B	8A	9A	10B
Calistru (2012).	1A	2B	3A, 3C	4D	5C	6A, 6I	7D	8D	9D	10B
Calmès and Théoret (2013).	1B	2A	3A, 3D, 3I	4A	5A	6A	7D	8B, 8D	9A	10A
Calmès and Théoret (2014).	1B	2A	3A, 3I	4B	5A	6A	7D	8C, 8D	9A	10A
Cao and Illing (2010).	1A	2A	3A, 3D	4E	5D	6A	7E	8F	9C	10A
Cambón and Estévez (2016).	1B	2A	3B	4A	5A	6A, 6C, 6G, 6H, 6I	7D	8A	9A	10C
Carmassi and Herring (2016)	1B	2A	3A, 3F, 3H	4B	5A	6B	7D	8B	9A	10B

Continue on next page

Continued from previous page

Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Cerchiello and Giudici (2015).	1B	2A	3C, 3I	4B	5A	6B, 6G	7A	8F	9A, 9B	10A
Chatterjee (2015).	1B	2A	3I	4A	5A	6B, 6C, 6H	7D	8C, 8D	9A, 9C	10B
Civitarese (2016).	1B	2A	3B	4A	5A	6C	7D	8A	9A	10D
Castellacci and Choi (2015).	1A	2B	3E	4C	5A	6G	7E	8B	9C	10C
Castro and Ferrari (2014).	1B	2A	3B, 3F, 3G	4C	5A	6B	7D	8A	9A, 9B	10C
Chang et al. (2008).	1B	2A	3A, 3C, 3H	4A	5B	6B	7C	8B, 8C	9A	10C
Chan-Lau et al. (2012).	1B	2A	3C, 3E	4B	5A	6B, 6C, 6G	7D	8A, 8B, 8C	9A	10B
Chinazzi et al. (2013).	1B	2A	3C, 3G	4D	5C	6C, 6H	7C	8D	9A	10B
Choi et al. (2012).	1B	2A	3B	4A	5A	6B, 6C	7B	8A	9A, 9B	10D
Choi (2014).	1A	2A	3A, 3D, 3E	4E	5D	6A	7E	8A, 8B	9C	10B
Chu (2015).	1C	2C	3H	4A	5A	6B	7D	8C, 8D	9A	10A
Chuang and Ho (2013).	1B	2A	3C, 3G, 3I	4C	5A	6H	7C	8C, 8D	9A	10A
Chung et al. (2012).	1A	2B	3A, 3E, 3I	4A	5A	6G, 6I	7D	8D	9D	10A

Continue on next page

Continued from previous page

Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Claessens et al. (2013).	1B	2A	3A	4D	5C	6B	7D	8D	9A	10C
Clark and Jokung (2015).	1A	2A	3A	4E	5D	6B	7E	8D	9C	10A
Conciarelli (2014).	1B	2A	3A, 3B, 3C	4B	5A	6B, 6C, 6H	7C	8A	9A	10A
Cox and Wang (2014).	1B	2A	3A, 3C, 3I	4A	5A	6B	7B	8D	9A	10C
Cruz and Lind (2012).	1B	2A	3A, 3C, 3E	4E	5D	6B	7E	8F	9B, 9C	10B
Dabrowski et al. (2016).	1B	2A	3C	4C	5A	6B, 6H	7D	8C, 8D	9A	10D
Daníelsson (2002).	1C	2A	3A, 3B, 3I	4B	5A	6C, 6G, 6I	7D	8A	9A	10A
Danielsson et al. (2016).	1B	2A	3B, 3I	4A	5A	6B, 6D, 6F, 6I	7D	8A	9A	10D
De-Jonghe (2010).	1B	2A	3B, 3F, 3H	4C	5A	6B	7D	8A, 8B	9A	10A
Nicolo and Kwast (2002).	1B	2A	3G, 3H	4A	5A	6B	7D	8A	9A	10A
Derbali and Hallara (2016a).	1B	2A	3B	4C	5A	6B	7C	8A	9A	10C
Derbali and Hallara (2016b).	1C	2A	3C, 3E	4A	5A	6H	7C	8A	9A, 9C	10A
Dermine and Schoenmaker (2010).	1A	2B	3A, 3F	4B	5A	6B, 6H	7A	8D	9D	10B

Continue on next page

Continued from previous page

Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Devriese and Mitchell (2006).	1A	2B	3D, 3E	4E	5D	6B, 6I	7E	8F	9B	10B
Bernardino et al. (2015).	1C	2A	3B	4E	5D	6D	7E	8B	9C	10A
Diebold and Yilmaz (2014).	1C	2A	3B, 3C, 3G	4A	5A	6B, 6C, 6D, 6F, 6I	7D	8A	9A	10A
Dimsdale (2009).	1A	2B	3I	4A	5A	6A, 6B, 6G	7B	8A, 8C, 8D	9D	10B
Donadelli and Paradiso (2014).	1B	2A	3B, 3H, 3I	4D	5C	6C, 6H	7D	8A	9A	10B
Duca and Peltonen (2013).	1B	2A	3A, 3B, 3I	4D	5C	6A, 6G	7D	8A	9A	10A
Dumičić (2016).	1B	2A	3A, 3C	4A	5A	6H	7D	8C, 8D	9A	10B
Drakos and Kouretas (2015).	1B	2A	3B	4B	5A	6B, 6D, 6I	7D	8A	9A	10C
Ellis et al. (2014b).	1A	2B	3A, 3I	4D	5C	6B	7E	8F	9D	10B
Farruggio et al. (2013).	1B	2A	3A, 3I	4A	5A	6B	7B	8A, 8D	9A	10B
Fazio et al. (2015).	1B	2A	3A, 3I	4D	5C	6B	7D	8B	9A	10A
Fecht et al. (2012).	1A	2A	3E, 3H, 3I	4D	5C	6B, 6H	7D	8F	9C	10A
Félix et al. (2016).	1B	2A	3B, 3E	4B	5A	6C	7B	8A	9A	10B
Fernández et al. (2016).	1B	2A	3A, 3H	4D	5C	6B	7D	8C, 8D	9A	10B

Continue on next page

Continued from previous page

Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Fernández-Rodríguez et al. (2016).	1B	2A	3C, 3E, 3G	4C	5A	6H	7B	8A	9A	10C
Fink et al. (2016).	1C	2A	3C, 3E, 3G	4A	5A	6B	7A	8D	9A	10B
Framstad (2004).	1A	2A	3B, 3I	4E	5D	6B, 6G	7E	8A	9C	10A
Freixas et al. (2000).	1A	2B	3A, 3D, 3E	4D	5C	6B	7E	8F	9D	10B
Gabbi et al. (2014).	1A	2A	3A, 3C, 3G, 3I	4E	5D	6B, 6G, 6I	7E	8B, 8D	9A, 9C	10A
Gaffeo and Molinari (2015)	1A	2B	3G, 3H	4E	5D	6B	7E	8E	9C	10B
Gao et al. (2015).	1A	2A	3G	4E	5D	6C	7E	8F	9B, 10C	10B
Garicano and Lastra (2010).	1A	2B	3A	4B	5A	6A	7E	8F	9D	10D
Gauthier et al. (2012).	1B	2A	3A, 3C, 3G, 3I	4A	5A	6B	7B	8A, 8B, 8D	9A, 9C	10B
Georgescu (2015).	1C	2A	3A, 3D	4C	5A	6B	7A	8B	9B, 9C	10B
Ghosh (2016).	1B	2A	3I	4D	5B	6B, 6H	7D	8C, 8D	9A	10B
Giglio et al. (2016).	1A	2B	3C, 3I	4B	5A	6B, 6C, 6D, 6F	7D	8A, 8C	9A	10D
Glasserman and Young (2014).	1C	2A	3E, 3G, 3I	4E	5D	6B	7E	8B, 8D	9C	10B

Continue on next page

Continued from previous page

Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Gómez (2015).	1A	2A	3I	4E	5D	6B	7E	8E	9C	10A
Goodhart (2010).	1A	2B	3A, 3D, 3I	4E	5D	6B	7E	8F	9D	10B
Gravelle and Li (2013).	1B	2A	3B, 3E	4B	5A	6B, 6D, 6I	7D	8A	9A	10C
Grilli et al. (2014b).	1A	2A	3E, 3F, 3G	4E	5D	6B	7E	8A, 8B, 8D	9A	10B
Grilli et al. (2014a).	1A	2A	3E, 3G	4E	5D	6A, 6B	7E	8A, 8D	9B, 9C	10B
Grira et al. (2016).	1B	2A	3A, 3C	4D	5C	6B	7B	8A, 8B	9A	10B
Guerra et al. (2016).	1B	2A	3C	4A	5B	6B	7D	8D	9A, 9C	10C
Haldane and May (2011).	1A	2A	3A, 3E, 3G, 3I	4E	5D	6B	7E	8D	9C	10A
Hammoudeh and McAleer (2015).	1A	2D	3B	4B	5C	6B, 6G, 6H	7E	8F	9D	10D
Han et al. (2016)	1B	2A	3B	4A	5A	6B, 6C, 6D	7D	8A	9A, 9B, 9C	10B
Hardle et al. (2016).	1B	2A	3B, 3G	4A	5A	6B, 6D, 6I	7C	8A, 8B	9A	10C
Hasan et al. (2015).	1B	2A	3B, 3C	4A	5A	6B	7D	8A, 8B	9A	10A
Hasman (2013).	1A	2D	3E	4D	5C	6B	7E	8F	9D	10D
Hausenblas et al. (2015).	1B	2A	3B, 3D, 3E, 3G	4A	5A	6B	7C	8B, 8D	9B, 9C	10B

Continue on next page

Continued from previous page

Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Hautsch et al. (2015).	1C	2A	3B	4A	5A	6A	7C	8A, 8B	9A, 9C	10B
Hawkins (2011).	1A	2A	3C, 3I	4E	5D	6F	7E	8A, 8D	9A, 9C	10B
He and Chen (2016).	1B	2A	3C, 3F, 3G	4A	5B	6B	7A	8B	9C	10C
Hippler and Hassan (2015).	1B	2A	3A, 3B	4A	5A	6B, 6F, 6G	7D	8A, 8B, 8C, 8D	9A	10B
Hirtle et al. (2016).	1B	2A	3B, 3C	4A	5A	6D	7D	8A, 8B, 8D	9A	10B
Horváth and Vaško (2016).	1B	2A	3A, 3I	4D	5C	6G	7D	8C, 8D	9A	10A
Hu et al. (2016).	1B	2A	3B, 3C	4B	5A	6A, 6C, 6G	7C	8A	9A	10B
Huang et al. (2009).	1B	2A	3C	4A	5A	6B	7C	8A	9A, 9B	10B
Huang et al. (2012b).	1B	2A	3A, 3B, 3C	4C	5C	6B	7B	8A, 8B	9A	10C
Huang et al. (2012a).	1B	2A	3C, 3F, 3G	4A	5A	6B	7C	8A	9A	10B
Huang et al. (2016).	1B	2A	3B	4A	5B	6B, 6D, 6I	7B	8A	9A	10C
Hutchison (2002).	1B	2A	3A, 3I	4D	5C	6B, 6I	7D	8C, 8D	9A	10B
Iachini and Nobili (2016).	1B	2A	3D	4A	5A	6C, 6H, 6I	7C	8A, 8D	9A	10B
Idier et al. (2014).	1B	2A	3B	4A	5A	6B	7D	8A, 8B	9A	10D

Continue on next page

Continued from previous page

Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Iori et al. (2008).	1B	2A	3G	4A	5A	6B, 6I	7D	8D	9A	10B
Iori et al. (2015).	1B	2A	3G	4A	5A	6B	7D	8A	9B, 9C	10A
Jacobs and Vuuren (2014).	1B	2A	3A, 3D	4D	5C	6B	7B	8D	9A, 9C	10C
Jin and Zeng (2014).	1A	2A	3C, 3E, 3I	4E	5D	6B	7E	8B, 8C	9C	10C
Jin and Simone (2014b).	1B	2A	3C, 3E	4A	5A	6E	7B	8A, 8C, 8D	9A	10B
Jin and Simone (2014a).	1B	2A	3A, 3C	4D	5A	6B	7D	8A, 8C, 8D	9A	10A
Jinjarak and Zheng (2014).	1B	2A	3B, 3E, 3G	4D	5C	6E	7C	8A	9A	10C
Jobst (2013).	1B	2A	3G, 3H	4B	5A	6B, 6D	7B	8A	9A	10A
Jobst (2014).	1C	2A	3D, 3E	4A	5A	6B	7C	8B	9A, 9C	10A
Joseph et al. (2014).	1B	2A	3G	4D	5C	6G	7D	8D	9A, 9C	10A
Kalemli-Ozcan et al. (2013).	1B	2A	3E, 3G	4D	5C	6H	7D	8C, 8D	9A	10A
Kanno (2015b).	1B	2A	3C, 3E, 3G	4D	5C	6B	7C	8B, 8D	9A, 9C	10B
Kanno (2015a).	1B	2A	3G	4A	5A	6B	7B	8D	9C	10B
Kanno (2016).	1B	2A	3C, 3E, 3G	4D	5C	6D	7D	8B	9C	10A
Kara (2016).	1A	2A	3A, 3D	4B	5D	6B	7E	8F	9C	10B

Continue on next page

Continued from previous page

Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Kerste et al. (2015).	1B	2A	3C, 3G	4A	5A	6C	7D	8A	9A	10A
Khashanah and Yang (2016).	1B	2A	3B	4A	5A	6C	7D	8A, 8D	9A, 9C	10B
King and Maier (2009).	1A	2B	3A	4E	5D	6E	7E	8F	9D	10B
Krainer (2012).	1A	2B	3A	4A	5A	6A	7E	8F	9D	10D
Kroeger (2015).	1A	2B	3A	4E	5D	6G	7E	8F 8	9D	10A
Kupiec (2016).	1C	2A	3A, 3C	4E	5D	6B	7E	8B	9C	10B
Kupiec and Güntay (2016).	1B	2A	3B, 3C	4A	5A	6B, 6C	7A	8A	9A, 9B	10D
Ladley (2013).	1B	2A	3A, 3E, 3G	4E	5D	6B	7E	8D	9B, 9C	10B
Lee et al. (2013).	1B	2A	3B, 3C, 3D	4A	5A	6B	7C	8A, 8C	9A	10D
Lee et al. (2016).	1B	2A	3C	4D	5C	6B, 6D	7D	8C, 8D	9A	10B
Lehar (2005).	1B	2A	3B, 3C, 3D	4D	5A	6B	7D	8A, 8B	9A, 9B, 9C	10A
Levy-Carciente et al. (2015).	1B	2A	3B, 3E	4A	5B	6B	7D	8D	9C	10C
Li et al. (2013).	1B	2A	3A, 3G	4A	5B	6B	7C	8A, 8C, 8D	9A	10A
Liang (2013).	1A	2B	3A	4A	5A	6A	7E	8F	9D	10B
Liang (2016).	1A	2B	3A	4A	5B	6B, 6I	7D	8D	9D	10B

Continue on next page

Continued from previous page

Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Liao et al. (2015).	1B	2A	3A, 3B, 3C	4A	5A	6B	7C	8A, 8B	9A	10B
Liu et al. (2015).	1C	2A	3A	4A	5A	6D	7D	8D	9A, 9B, 9C	10B
Lombardi and Moschella (2016).	1A	2B	3A	4B	5A	6A	7E	8F	9D	10B
López-Espinosa et al. (2013).	1B	2A	3A, 3D, 3E, 3I	4B	5A	6B	7C	8B	9A	10A
López-Espinosa et al. (2015).	1B	2A	3B, 3G	4A	5A	6B	7D	8A, 8B	9A	10C
Lu and Hu (2014).	1A	2A	3F	4E	5D	6A	7E	8F	9A, 9C	10B
Lupu (2015).	1A	2B	3A, 3I	4B	5A	6G	7E	8F	9D	10B
MacDonald et al. (2015).	1B	2A	3B, 3E	4C	5A	6B, 6G, 6H	7C	8A, 8B	9A	10B
Madan and Schoutens (2013).	1B	2A	3H	4A	5A	6B, 6C, 6D	7B	8A	9A	10D
Marinc (2013).	1A	2B	3I	4B	5A	6B	7E	8F	9D	10A
Martínez and León (2016).	1B	2A	3G	4A	5B	6B	7A	8B, 8D	9A	10B
Martinez-Jaramillo et al. (2010).	1B	2A	3E	4A	5B	6B	7A	8B, 8D	9A, 9B, 9C	10C
Martinez-Jaramillo et al. (2014).	1B	2A	3G	4A	5B	6B	7C	8D	9A	10C

Continue on next page

Continued from previous page

Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Mastromatteo et al. (2012).	1A	2A	3G	4E	5D	6B	7E	8B	9C	10A
May (2013).	1A	2B	3G	4E	5D	6B	7E	8B, 8D	9C	10A
Mayordomo et al. (2014).	1B	2A	3F, 3G, 3I	4A	5A	6B	7C	8A, 8B	9A	10D
Mezei and Sarlin (2016).	1B	2A	3G	4B	5A	6A, 6H	7E	8F	9B, 9C	10B
Milne (2009).	1A	2C	3A	4B	5A	6A	7B	8A, 8D	9D	10B
Milne (2014).	1B	2A	3C	4D	5C	6B, 6D, 6F, 6I	7C	8A, 8B	9A	10C
Mühlnickel and Weiß (2015).	1B	2A	3H, 3I	4D	5C	6B, 6D	7D	8A, 8B	9A	10B
Nier et al. (2007).	1A	2A	3D, 3E, 3G, 3H	4E	5D	6B	7E	8B, 8D	9B, 9C	10C
Nobi et al. (2014).	1B	2A	3B, 3G	4D	5C	6C	7D	8A	9A, 9C	10B
Oh et al. (2015).	1B	2A	3B	4B	5A	6C	7C	8A	9A	10A
Oort (1990).	1A	2B	3A	4E	5D	6B	7E	8F	9D	10B
Oosterloo and Haan (2005).	1A	2D	3A	4D	5C	6A, 6B	7E	8F	9D	10B
Pagano and Sedunov (2016).	1B	2A	3C	4C	5A	6H	7C	8A, 8D	9A	10B
Paltalidis et al. (2015).	1B	2A	3E	4C	5A	6B, 6H	7C	8B, 8D	9C	10B

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Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Papanikolaou and Wolff (2014).	1B	2A	3B, 3I	4A	5A	6B	7D	8A, 8B, 8C	9A	10A
Patro et al. (2013).	1B	2A	3B, 3C	4A	5A	6B, 6C	7D	8A	9A	10A
Petersen et al. (2011).	1A	2A	3I	4E	5D	6F, 6I	7E	8F	9C	10A
Piskorec et al. (2014).	1B	2A	3B	4D	5C	6A, 6C, 6I	7A	8A, 8E	9A	10A
Poledna et al. (2015).	1B	2A	3E	4A	5B	6B	7C	8D	9A, 9C	10A
Poon et al. (2003).	1C	2A	3I	4B	5A	6C	7D	8A	9A	10A
Pourkhanali et al. (2016).	1B	2A	3C, 3G	4D	5C	6B, 6D	7D	8A	9A	10B
Puliga et al. (2014).	1B	2A	3B, 3C	4B	5A	6B, 6F	7C	8A, 8D	9A, 9C	10A
Quax et al. (2013).	1B	2A	3B	4B	5A	6I	7D	8A	9A	10B
Reboredo and Ugolini (2015a).	1B	2A	3C	4C	5A	6H	7D	8A	9A	10C
Reboredo and Ugolini (2015b).	1B	2A	3C	4C	5B	6H	7B	8A	9A	10C
Rodríguez-Moreno and Peña (2013).	1B	2A	3B	4B	5A	6B, 6C, 6I	7C	8A, 8B	9A	10D
Rösch and Scheule (2016).	1B	2A	3B, 3C, 3H	4C	5C	6B	7D	8A, 8B	9A	10B
Roukny et al. (2013).	1B	2A	3D, 3E, 3G, 3I	4C	5A	6B	7D	8B, 8D	9A, 9B, 9C	10B

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Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Saldías (2013).	1B	2A	3C, 3E, 3G	4C	5A	6B, 6C, 6D	7C	8A	9A	10A
Sandhu et al. (2016).	1C	2A	3B	4A	5A	6C	7D	8A	9C	10A
Sarlin and Peltonen (2013).	1B	2A	3I	4D	5C	6B, 6C, 6I	7C	8C, 8D	9A	10A
Schoenmaker and Siegmann (2014).	1B	2A	3A, 3I	4C	5A	6B	7A	8B, 8C	9C	10A
Schwaab et al. (2014).	1B	2A	3C, 3E	4D	5C	6B, 6C, 6D, 6G, 6I	7D	8A, 8C	9A, 9B	10A
Sedunov (2016).	1B	2A	3B	4A	5A	6B, 6D, 6I	7D	8A, 8B, 8D	9A	10D
Shiller et al. (2013).	1C	2A	3B	4E	5D	6F	7E	8F	9C	10B
Silva et al. (2016).	1B	2A	3D, 3E, 3G	4A	5B	6A	7B	8D	9C	10B
Simpson and Evans (2005).	1B	2A	3B, 3E, 3G	4B	5A	6B	7D	8A	9A	10A
Singh et al. (2015).	1B	2A	3C	4C	5A	6B	7C	8A	9C	10B
Solorzano-Margain et al. (2013).	1B	2A	3E, 3G	4A	5B	6B, 6I	7D	8A, 8C, 8D	9A	10C
Souza et al. (2015).	1B	2A	3C, 3E	4A	5B	6B	7D	8D	9C	10B
Souza (2016).	1B	2A	3A, 3D	4D	5B	6A	7B	8D	9C	10C

Continue on next page

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Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Souza et al. (2016).	1B	2A	3C, 3E, 3G	4B	5B	6B	7B	8D	9C	10C
Stein (2011).	1C	2A	3A, 3I	4A	5A	6B, 6F, 6G	7D	8B, 8D	9A, 9C	10A
Stolbov (2016).	1B	2A	3C	4A	5B	6H	7B	8A	9A	10C
Straetmans and Chaudhry (2015).	1B	2A	3E	4B	5A	6B	7D	8A	9A	10D
Suh (2012).	1B	2A	3C	4A	5A	6B, 6D, 6I	7D	8A	9A	10C
Summer (2003).	1A	2D	3A	4E	5D	6B	7E	8F	9D	10B
Summer (2013).	1A	2D	3E, 3G	4B	5C	6B	7E	8B	9D	10D
Tabak and Staub (2007).	1B	2A	3B, 3I	4A	5B	6B	7B	8A, 8C	9A, 9C	10C
Terzi and Ulucay (2011).	1A	2B	3C	4E	5D	6I	7C	8D	9D	10B
Tian et al. (2015).	1B	2A	3C	4A	5B	6B, 6I	7C	8B, 8C	9C	10A
Tsenova (2014).	1C	2A	3A, 3D, 3I	4A	5B	6B	7A	8B, 8C, 8D	9B, 9C	10C
Uechi et al. (2015).	1B	2A	3I	4B	5A	6C	7D	8A	9A	10A
Upper (2011).	1A	2A	3E, 3G	4B	5C	6B	7E	8B, 8D	9C	10D
Vallascas and Keasey (2012).	1B	2A	3A, 3E, 3F, 3I	4B	5A	6B, 6H	7D	8A, 8B, 8C	9A	10B
Bekkum (2016).	1B	2A	3B, 3C	4A	5A	6B, 6H	7A	8A	9A	10B
End (2009).	1B	2A	3D	4A	5A	6B	7A	8D	9A, 9B	10B

Continue on next page

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Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
End and Tabbae (2012).	1B	2A	3D, 3E	4A	5A	6B	7C	8B	9A	10B
Vitali et al. (2016).	1C	2A	3C, 3E, 3G	4E	5D	6B	7E	8E	9B, 9C	10B
Vlahović (2014).	1A	2D	3A	4C	5C	6A	7E	8F	9D	10D
Vodenska et al. (2016).	1B	2A	3B	4D	5C	6C, 6I	7D	8A	9A, 9C	10B
Walter (2009).	1A	2B	3A, 3F, 3I	4D	5C	6B, 6D, 6I	7D	8D	9D	10B
Walter (2012).	1A	2B	3A, 3I	4B	5A	6B, 6E, 6I	7E	8F	9D	10B
Weiss and Mühlnickel (2014).	1B	2A	3F, 3I	4A	5A	6D	7B	8B	9A	10C
Weiss et al. (2014).	1B	2A	3H	4D	5C	6B	7D	8A, 8B, 8C, 8D	9A	10A
Wilson et al. (2010).	1A	2D	3D, 3H, 3I	4E	5D	6B	7E	8F	9D	10D
Wymeersch (2010).	1A	2B	3A	4C	5A	6A, 6I	7B	8F	9D	10B
Xie et al. (2016).	1B	2A	3E, 3G	4A	5B	6B	7C	8B	9C	10B
Yao et al. (2015).	1B	2A	3E, 3I	4A	5B	6B	7A	8B	9C	10B
Yaqoob and Khan (2011).	1A	2D	3A	4E	5D	6A	7E	8F	9D	10B
Zheng et al. (2012).	1B	2A	3B, 3I	4A	5A	6C	7D	8A	9A	10B
Zhou (2013).	1A	2A	3A, 3G, 3I	4E	5D	6B	7E	8D	9A	10A

Continue on next page

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Study	Type	Approach	Object	Scope	Context	Focus	Period	Data	Method	Results
Zhu et al. (2012).	1B	2A	3B, 3I	4A	5B	6A, 6G	7C	8A, 8C, 8D	9A	10B
Zigraiova and Jakubik (2015).	1B	2A	3B	4B	5C	6G, 6H	7D	8A, 8C	9A	10B

Table 4 – Articles that compose the sample.

2.4 A brief conceptual foundation of financial systemic risk

As noted by Jorion (1997), companies are exposed to the following three types of risk:

- Business risks are those that companies voluntarily take to create a competitive advantage and add value for shareholders;
- Strategic risks are those that result from fundamental changes in the economic or political environment; and
- Financial risks relate to potential losses in the financial markets and are the focus of this article.

In general, financial risks are classified into the categories of market risks, credit risks, liquidity risks, operational risks, and legal risks. Yet according Jorion (1997), such risks can be briefly defined as follows:

- Market risks arise from changes (volatilities) in the prices of financial assets and liabilities;
- Credit risks arise when counterparties are unwilling or unable to honour their contractual obligations. They may also arise from the possibility of the company's rating being downgraded by a credit agency and also include sovereign risk;
- Liquidity risks occur due to the possibility that a transaction cannot be conducted in the prevailing market prices due to insufficient market activity (market/product liquidity) or the inability to honour cash flow obligations (cash/funding flow), which may force early liquidation;
- Operational risks involve the potential losses resulting from inadequate systems, management failures, faulty controls, fraud, or human error. They also include model risk, which is the risk that the model used to price positions is flawed; and
- Legal risks occur when a counterparty does not have the legal or regulatory authority to engage in a transaction, which can lead to lawsuits.

When systemic financial risks are discussed, these financial risks are not analyzed from the perspective of the individual firm but from the perspective of the financial system.

2.4.1 Definition of systemic financial risk

According to Summer (2003), there is no universal definition of systemic financial risk. For De-Bandt and Hartmann (2000), any concept of systemic financial risk should include widespread events in the banking and financial segments as well as in the related payment and settlement systems. The effects of contagion are at the core of the concept, which would also include simultaneous instances of financial instability following aggregate shocks. According to these authors, several rigorous models of contagion within the banking and payment system have been suggested, but there is no general theoretical framework. More specifically, it is difficult to stablish empirical tests that allow a distinction between the contagion itself and joint crises caused by common shocks (DE-BANDT; HARTMANN, 2000).

The European Central Bank (ECB, 2009) characterizes systemic risk as the possibility of an institution failing to honor its obligations, prompting the same failure on the part of other participants and causing wider effects due to liquidity and credit constraints; ultimately, the stability of the financial system is jeopardized. For the ECB, *"one perspective is to describe it as the risk of experiencing a strong systemic event. Such an event adversely affects a number of systemically important intermediaries or markets (including potentially related infrastructures)"* (ECB, 2009, 134). In the same vein, Lehar (2005) defines systemic financial risk as the potential of occurrence of an event that implies the simultaneous bankruptcy of a certain number of financial institutions.

For Adrian and Brunnermeier (2010), systemic financial risk is related to the malfunction of an institution spreading extensively and disorganizing the supply of credit and capital to the real economy. This definition is similar to that presented by Acharya and Richardson (2009), who defines systemic risk as the possibility of joint failure of financial institutions or of freezing of capital markets that can considerably shorten the supply of capital to the real economy.

Billio et al. (2012) suggest that an important symptom of systemic risk is related to the existence of abrupt shifts in regime, as the economy typically fluctuates between a state of low volatility during economic growth and a state of high volatility during economic contraction.

In the words of Abdymomunov (2013, 455), *"In general, systemic risk is perceived as the risk of a negative shock, severely affecting the entire financial system and the real economy. This shock can have different causes and triggers, such as a macroeconomic shock, a shock caused by the failure of an individual market participant that affects the entire system due to tight interconnections in the system, or a shock caused by information disruption in financial markets"*. In his work, this author limits the definition to systemic financial stress, which occurs when market participants experience growing uncertainty and modify their expectations of the economic environment, defining other estimates for potential losses and assets value.

From a a more current and comprehensive perspective, Patro et al. (2013) describe systemic risk as a situation in which the entire financial system is simultaneously stressed, with an ensuing credit and liquidity crisis. Systemic risk can have a significant influence not only on financial markets and institutions but also on the real economy due to decreased supply of capital and increased capital losses. Furthermore, Patro et al. (2013) conceptualize systemic risk as the probability of a severe decline in the financial system, caused by a strong and broad event, such as the breakdown of a financial institution.

2.4.2 Factors present in the discussion on systemic financial risk

An important task is to identify which characteristics of financial institutions and of the functioning of the market in general have a greater impact on systemic risk and the amplifying or dampening of shocks. Some common points identified in the literature are highlighted next.

Caccioli et al. (2009) identify the uncontrolled proliferation of financial instruments with the potential to cause large fluctuations and instability in the financial system, which may lead the market to a state in which trading volumes quickly expand and saturate the demand of investors. This situation makes the market seem arbitrage-free, efficient, and complete, but it occurs at the expense of stability.

In Dimsdale (2009)'s analysis, financial innovation also appears as one of the causes of the global financial crisis that started in 2007, inserted in a framework of excessive risk–taking, following a prolonged period of macroeconomic stability. For this author, problems initially arise with the increase in defaults in the subprime mortgage market in the United States, leading to a drop in the Asset Backed Securities (ABS) market in mid–2007. Liquidity problems then arose in the interbank market, affecting banks around the world. The bankruptcy of Lehman Brothers in September 2008 was the turning point, confirming that the world was facing a systemic financial crisis (DIMSDALE, 2009). Petersen et al. (2011) argue that the subprime mortgage crisis was mainly caused by the intricate and complex securitization design of these mortgages, which led to information asymmetry, contagion, inefficiency and loss issues, pricing opacity, and inefficient risk mitigation.

In the assessment of Battiston et al. (2012), the diversification of individual credit risk has the potential to generate ambiguous effects at the systemic level, especially in the presence of credit runs. The benefit of mitigating results from defaults would be offset by a situation in which agents are are more exposed to credit runs due to the high number of counterparties. In particular, these authors argue that the structure of interrelationships and the differences in financial robustness levels should be considered when establishing policies that aim to strengthen the resilience of the financial markets.

Addressing the regulatory framework, Vallascas and Keasey (2012) argue that restrictions on leverage and imposing liquidity requirements, as in the Basel III Accord, can enhance the resilience of financial entities to systemic events. In turn, the results also demonstrate that the size of the bank, the share of non–interest income, and asset growth are key determinants of the risk exposure of a bank and that these elements are not at the centre of the new regulation. More specifically, the requirement of a cap on absolute bank size can be, in these authors' view, a more effective tool for reducing a bank's risk of default, given the occurrence of systemic events (VALLASCAS; KEASEY, 2012).

For Battaglia and Gallo (2013), securitization increases the likelihood of banks becoming systemically more risky. Thus, in severe scenarios, banks that securitize would have higher expected losses on average, which would suggest that the risk transfer by securitization is relatively insignificant compared to the risk retained by the originating bank (BATTAGLIA; GALLO, 2013). Critics of securitization (SIMKOVIC, 2013) suggest that the complexity inherent in the process ends up limiting the ability of the investor to monitor risk. Furthermore, according to Simkovic (2013), the very dynamics of competition in a market with many securitization agents would have lowered the safety standards in the pre–crisis period.

Carbo-Valverde et al. (2015, p.36) state the following: *"a securitization instrument that retains risk (covered bond) may induce a more prudent risk behavior of bank than an instrument that provides risk transferring (ABS)"*.

Securitization and leverage are constituted as related problems because, as Acharya and Richardson (2009) argue, financial institutions were allowed to keep the assets securitized off–balance–sheet to avoid needing to hold capital buffers to guarantee them; in addition, they were able to hold a reduced amount of capital against the AAA–rated tranches of the securitized mortgages remaining on the balance sheets, all of which led to risky capital structures and an underassessment of credit risk, thereby increasing systemic risk. In turn, Adrian and Shin (2009) study the relationship between leverage and liquidity. For them, in an environment where balance sheets are continuously marked–to–market, adjustments in asset prices are immediately reflected in changes to net worth and lead institutions to adjust the size of their balance sheets. Thus, they conclude that in a mark-to-market context, leverage is strongly pro–cyclical, which also enhances systemic risk.

Leverage increases the individual risk of banking firms, implying higher vulnerability to financial shocks (PAPANIKOLAOU; WOLFF, 2014). Reversing the level of leverage, on the other hand, is beneficial to the health of banks individually but detrimental to financial stability. For these authors, banks that focus on traditional lines of business are less risky than those involved with modern financial instruments; additionally, the literature would identify the high leverage of financial institutions, on a global scale, as a key factor in the severe structural weakness and the adverse market dynamics during the pre–crisis period. For Papanikolaou and Wolff (2014), regulatory changes and technological advances have largely changed the banking systems; in response, banks reacted to the challenges posed by the new environment by creating new products and expanding their activities to areas of business that were previously not explored.

According to Anginer et al. (2014a), bank competition also affects systemic risk in a robust negative relationship. Increased competition would encourage banks to take more diversified risks, making the system less vulnerable to shocks. Banking systems would be more fragile in countries with weak private supervision and monitoring, more state-owned banks, and policies that restrict competition. These researchers conclude that the negative effect of the lack of competition may be mitigated by an institutional environment that enables both public and private efficient monitoring (ANGINER et al., 2014a). Consistent with this finding, Cubillas and González (2014) states that financial liberalization increases bank risk-taking. In developed countries, strong competition among banks increases risk taking, whereas in developing countries, new opportunities to take risks drive risk-taking behavior.

Ghosh (2016) examines the impact of financial services liberalization on banking crisis and finds that greater banking sector globalization diminishes their occurrence, while bank asset concentration increases their likelihood. The results of the study show that foreign bank presence implies stronger financial stability in the banking industry of host nations. This is coherent with Nicolò and Juvenal (2014), who analyze the relevance of measures of financial integration and globalization for real activity.

Exploring another aspect, Glasserman and Young (2014) consider the interconnectivity of the modern financial system as a key factor in understanding the recent financial crisis: due to the complex network of connections among financial institutions, critical changes in a part of the system can spread to others, representing a threat to the financial instability of the entire system. According to these authors, examples include the effects of the Lehman Brothers bankruptcy, the failure of AIG, and the exposure of European banks to sovereign default risks.

Regarding the systemic importance of institutions, there is a rich literature that analyzes the impact of size, complexity, and interconnectivity, in particular on banks, for the composition of systemic risk. For Arinaminpathy et al. (2012), large and well–connected banks are critical for financial stability since collapses are not only large and widespread but also threaten trust in the market. Therefore, placing tougher capital requirements on big banks can improve the resilience of the system. Furthermore, these effects would be more pronounced in more concentrated systems (ARINAMINPATHY et al., 2012).

Systemically important financial institutions (SIFIs) are defined by Banulescu and Dumitrescu (2014) as institutions whose disorderly failure due to their size, complexity, and interconnectivity would significantly disrupt the financial system, harming economic activity. The Basel Committee on Banking Supervision classifies useful factors for determining whether a financial institution is systemically relevant and the exact factors used to identify systemically important global banks (G–SIBs). In addition to the three factors noted above and their global activity (cross–jurisdiction), the Basel Committee includes banks in this category if there are no readily available substitutes for the financial infrastructure that they provide (BANULESCU; DUMITRESCU, 2014).

Another concept, “Too Big To Fail” institutions (TBTF), has become a major public policy debate that, according to Kaufman (2014), has not been concluded due to disagreements about definitions and thereby the estimates of the benefits and costs. In banking, this definition varies widely and *"differ according to which counterparties of insolvent covered firms may need to be protected to minimize collateral damage, caused directly or indirectly by the failure, which third parties fund the protection, and for what reason"* (KAUFMAN, 2014, 221).

2.4.3 Measuring systemic risk

Even without a precise definition, given that it is a field of study in ongoing development, there are several elements that are present in the various definitions that complement and make it possible to understand what systemic risk is. However, how can systemic risk be measured? Once there are different starting points for systemic shocks, there are also different approaches to defining and measuring systemic risks (ABDYMOMUNOV, 2013).

According to Daníelsson (2002), a growing body of evidence exposes the limitations of risk-modelling technology and imperfect regulatory design; these models therefore act more as placebos than as a scientific means of preventing crashes. For this author, because market data are endogenous to market behaviour, statistical analysis performed at times of stability would not be useful at times of crisis. Daníelsson (2002) views Value-at-Risk (VaR) modelling as not robust and excessively volatile. Moreover, he states that, for regulatory use, this type of analysis may provide misleading information about risk and even increase both idiosyncratic and systemic risks, imposing significant and unnecessary costs on financial institutions arising from inadequacy in the allocation of capital and frequent portfolio rebalancing (DANíELSSON, 2002).

In the view of Huang et al. (2009), traditional regulatory measures have focused on information from bank balance sheets, such as the proportion of non–performing loans, profitability, liquidity, and capital adequacy ratios. However, because the balance information is available only at a relatively low frequency (typically quarterly) and significant lag, there have been increased efforts to measure the health of the financial system based on information from the financial markets (HUANG et al., 2009).

The joint 2009 report by the IMF, Bank for International Settlements (BIS), and Financial Stability Board (FSB) proposes the use of indicators for size, interconnectedness, and substitutability to measure the systemic importance of an enterprise (IMF–BIS–FSB, 2009). Thomson (2009) proposes the use of the four Cs (Contagion, Concentration, Correlation, and Conditions) as criteria for determining the systemic importance of a firm.

Regulators generally focus on indicators related to the financial health of banks, such as balance sheets and liquidity indicators. There are still many indices of more comprehensive financial conditions, typically constructed using a weighted sum of indicators or a principal components method, for example, Bloomberg FCI, Goldman FCI, and the Kansas Fed Financial Stress Index.

The European Central Bank publishes the Composite Indicator of Systemic Stress (CISS), which uses both market and supervision data. According to Holló et al. (2012), systemic financial stress occurs when market participants experience great uncertainty and change their expectations on future losses, asset values, and economic activity. Because these stress measures depend on the choice of specific criteria and methods of combining financial variables, their performance is sensitive to their causes. The CISS aggregates five sub–indices that represent the most important segments of the financial system, namely, the banking and non–banking intermediaries sector, the money market, and the stock, securities, and currencies markets, taking into account the cross–correlations between the sub–indices over time. The CISS places relatively more weight on situations in which stress prevails in many markets simultaneously, thus being more systemic (HOLLó et al., 2012).

Many other forms of systemic risk measurement are found in the literature. Bisias et al. (2012) designate 31 quantitative measures of systemic risk; Segoviano and Goodhart (2009) make use of the multivariate density of the adjusted portfolio tail of companies in the financial sector; Khandani and Lo (2008) and Hu et al. (2013), by their turn, use liquidity measures; Adrian and Brunnermeier (2010) measure the Value–at–Risk (VaR) of the financial sector conditioned by the VaR of a single bank in the system, called CoVaR, using quantile regressions; De-Jonghe (2010) uses extreme value analysis; Acharya et al. (2010) use the Systemic Expected Shortfall (SES) to measure the contribution of each individual institution to systemic risk; Brownlees and Engle (2010) measure systemic risk focusing on the Marginal Expected Shortfall (MES); Kritzman and Li (2010) use the Mahalanobis distance metric; and Kritzman et al. (2011) use the absorption ratio. Zheng et al. (2012) use the growth rate of the principal components of the correlation matrix of assets returns. Patro et al. (2013) use the correlations of stocks returns of financial institutions as a systemic risk indicator.

Several authors, such as Patro et al. (2013) and Kritzman et al. (2011), seek information only on asset prices to assess systemic risk. These prices have the advantage of being easily accessible compared to others related to the balance sheets and financial indicators of companies. In addition, the information reflected in asset prices is always forward looking. According to Patro et al. (2013), if the primary purpose is to monitor the ongoing systemic risk level to prevent systemic failures and the associated costs, forward–looking indicators, such as stock prices, offer relevant information, have the advantage of being widely traded between market participants over a long history, and are easily available in almost every work day.

For Gropp et al. (2002), from a supervisory perspective, assets issued by banks are interesting to monitor because the market prices of debts and equity can increase the funding cost of banks. The market can play a particularly useful role in disciplining the risk of large, complex, and internationalized organizations. Market information is available at a very high frequency and can complement the traditional balance sheet data when checking for possible bank weaknesses. Therefore, market information can provide early signs to identify banks that must be

Study type	Type of approach	Number of articles
Theoretical.	Quantitative.	29
Theoretical.	Qualitative.	35
Theoretical.	Mixed.	4
Theoretical.	Survey/Review.	8
Empirical.	Quantitative.	167
Theoretical and Empirical.	Quantitative.	22
Theoretical and Empirical.	Mixed.	1

Table 5 – Classification according to items 1 and 2.

better scrutinized.

According to Rodríguez-Moreno and Peña (2013), periods of general turmoil in the financial system can have multiple causes, and therefore, a single systemic risk measure may be neither appropriate nor desirable. Ellis et al. (2014a) follow this same line; for them, the diversity within the financial system also supports the fact that it is unlikely that a single systemic risk measure or a single financial stability policy instrument can be universally applicable.

2.5 Results of the literature analysis

The results of the classification according to items 1 and 2 are summarized in Table 5, which shows the predominance of empirical studies and the massive presence of studies with a quantitative approach. There are a low number of survey–type studies (questionnaires) and literature reviews, which together add up to only eight.

The results for each category analyzed are presented next.

- ***Object***: Table 6 shows the classification of the sample according to item 3 (*Object of Study*). It was attempted to isolate the most relevant object(s) in each article. Only one object was assigned to 103 articles, two objects to 96 articles, three objects to 57 articles, and 10 objects to only nine articles. There were a large number of articles that address aspects of regulation, which is not surprising, given the nature of the subject and the search criteria, which also used the expression "financial stability". The objects "market risk", "credit risk together with default, counterparty and sovereign risks", "contagion" and "interconnectivity/interdependence" were also numerically noteworthy. A total of 33 articles simultaneously addressed "contagion" and "interconnectivity/interdependence", which indicates a strong link between these objects. The item regarding the "size of the institutions" appeared with a lower weight. The lower presence of the concept of "too big to fail", compared to the concept of "too interconnected to fail", reveals the greater weight given by researchers to the latter as a systemic risk factor. The item "concentration" and the related items "diversification" and "competition" were addressed in only 19 articles and may deserve greater attention from researchers in future studies.

Object	Number of Articles
Regulation.	71
Market Risk.	53
Credit Risk/Default/Counterparty/Sovereign.	46
Liquidity risk.	23
Contagion.	55
Size of institutions.	14
Interconnectivity/Interdependence.	54
Concentration/Diversification/Competition.	15
Others.	56

Table 6 – Classification according to item 3.

The item "Others" includes topics such as leverage/derivatives (addressed in 10 articles); securitization and proliferation/complexity of financial instruments (six articles); bank governance, including executive compensation and performance strategies (five articles); conglomeration/consolidation (five articles); confidence/sentiment (five articles); monetary policy (five articles); mark–to–market/valuation (three articles); deregulation (two articles); international financial integration (three articles); and modelling risk (three articles); in addition, further topics include bubbles, market efficiency, complexity, taxation, corporate governance, overlapping portfolios, prepayment risk, bank liquidity creation, shadow banking, and the impact of information technology (IT), among others.

It is important to note that the object "regulation" encompassed a range of issues related to the actions of regulatory bodies and supervisory practices, including the following: actions by central banks, central banks transparency, Basel accords, coordination mechanisms, capital allocation, limits to the performance of financial institutions, NSFR (Net Stable Funding Ratio), debt ratios, regulation credibility, regulatory ratio, accountability, deposit insurance, mark–to–market, and funding, among others.

- ***Scope***: This item is summarized in the graph below (Figure 3). It is noted that studies related to only one country are greater in number. The blocks and regions have been less studied.

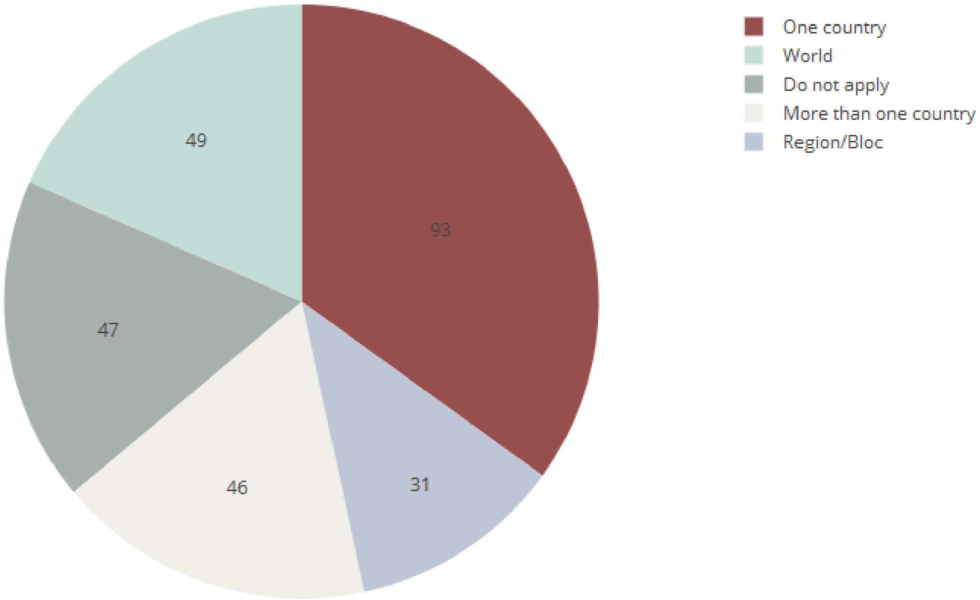

Figure 3 – Scope of the articles.

- ***Context***: This item is summarized in the graph below (Figure 4). The great predominance of research on developed countries is observed; this finding is to be expected, given the high concentration of researchers in these countries. Even if also considering the greater systemic importance of financial institutions in developed countries, instabilities in the financial systems of emerging countries also have important impacts, not only in their own economies and markets but also internationally. This fact reveals the opportunity to perform a larger number of studies that address countries that are considered undeveloped.

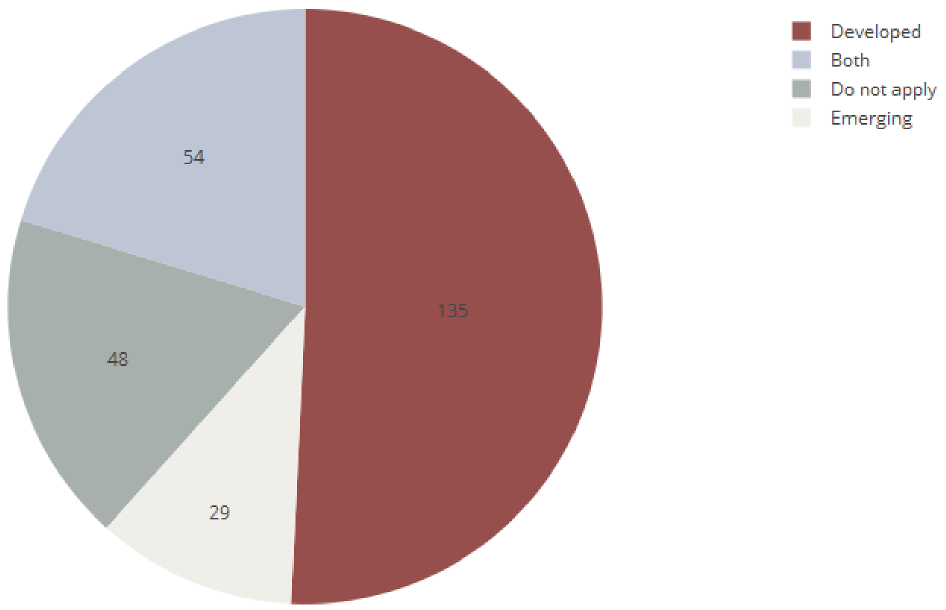

Figure 4 – Context of the articles.

- ***Focus***: The various focuses of the articles (item 6) and their frequency are shown in Figure 5. A total of 33 articles addressed the financial system and financial institutions in a generic manner – in general, studies classified in this classification discussed aspects of regulation or were theoretical articles, even if they had a quantitative approach. Of those that focused only on specific institutions, 165 articles analyzed only one type of institution/market segment and 68 more than one type. Banks had ample prominence and were studied in 174 of the 266 articles. The stock market was also the focus of study in 44 articles. Articles that focused on countries also add up to 31. The impact of systemic financial risk on non-financial institutions (or vice versa) was studied in 29 articles, generally in conjunction with the financial institutions themselves. Next were the insurers, which were studied in 27 articles. These were followed by mortgages/real estate markets, which were analyzed in 11 articles, and investment funds/hedge funds in six articles. The item "Others" gathered the remaining institutions, such as exchange brokers, money market, clearing houses, and credit card companies. Although the emphasis on banks is easily understandable, due to the impact that they have on systemic financial risk, there may also be opportunities for greater diversification of the focus of studies to focus more intensively on other types of institutions.

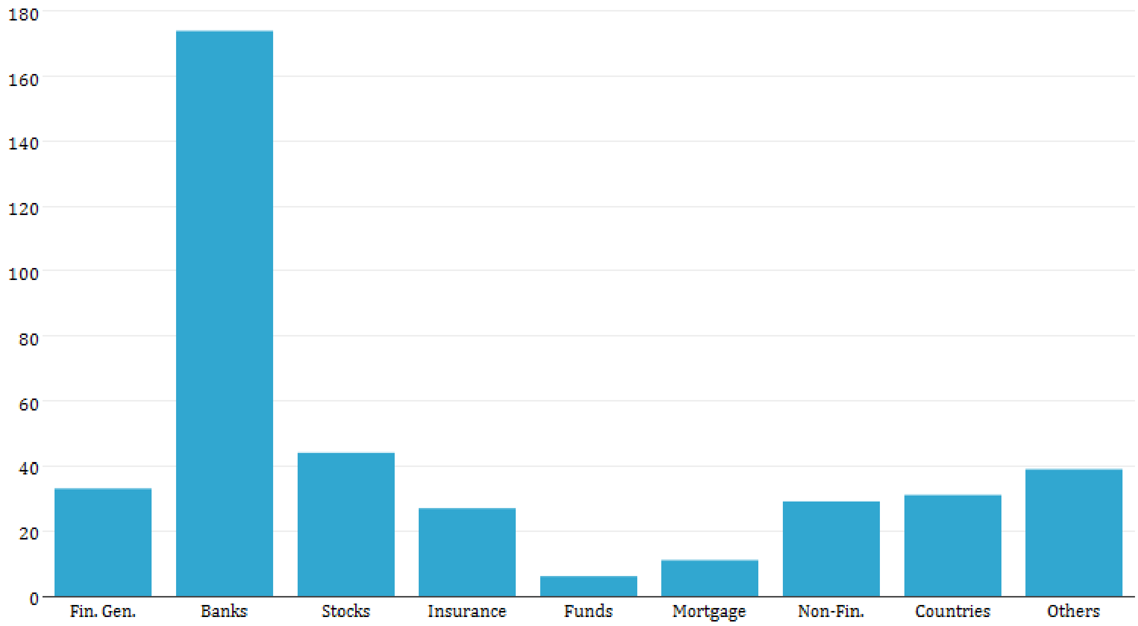

Figure 5 – Focus of the articles.

There is room for a greater number of articles that focus on investment funds and mortgages, given the importance that they have for systemic stability. It is important to remember that it was the bursting of a mortgage bubble that precipitated the financial crisis of 2007. Articles that analyze risk from the perspective of countries totaled 31, including here those that analyze banks and other institutions in a cross–country approach, i.e., a comparison of what occurs in each country. Articles that study sovereign risk numbered only 11, suggesting a large research gap in the analyzed sample of the literature, given that problems related to sovereign debt significantly affect financial stability. An example is the recent events related to sovereign debt in the eurozone and their strong impacts on regional and global economic and financial stability.

- ***Period studied***: Item 7 (Period studied) is shown in the graph below (Figure 6). It is very interesting that the researchers chose to study longer periods, with 152 studying five years or more and only 16 studying less than 2 years. A longer perspective for theoretical studies may be necessary to compare the consecutive occurrence of crisis periods and periods of stability.

Type of data	Articles – One type	Articles – Multiple types
From market.	46	50
From balance sheet.	14	46
Macroeconomic.	-	34
From regulators.	31	44
Not applicable.	35	-

Table 7 – Classification according to item 8.

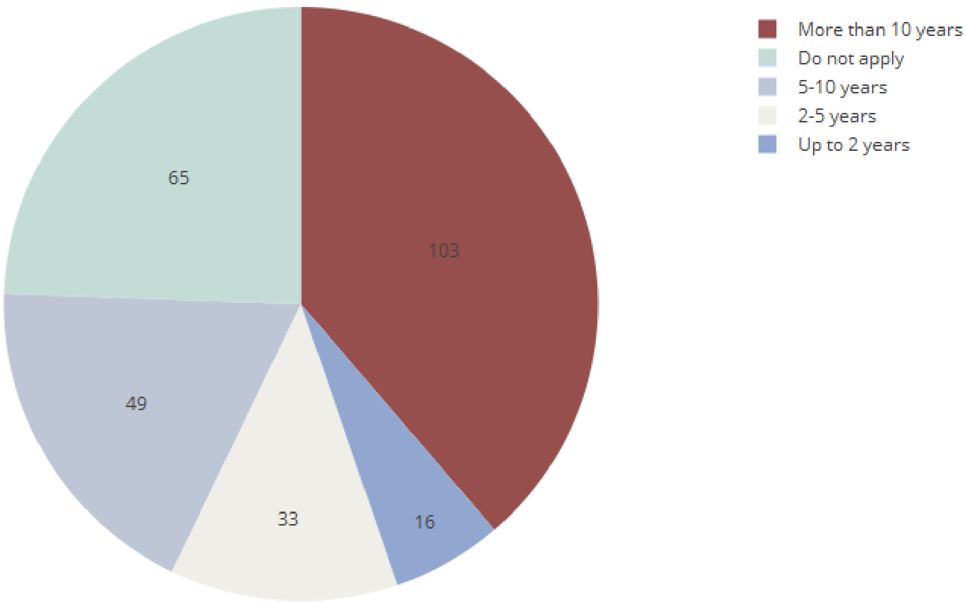

Figure 6 – Period studied in the articles.

- ***Types of Data Analyzed***: Item 8 (Types of Data Analyzed) is summarized in Table 7, which shows that market and regulator data prevail when the articles use only one type of data; however, there is a greater balance when data types are used in combination, with less emphasis on macroeconomic-type data.

- ***Methods Used***: Item 9 (Methods Used) is summarized in Table 8. Emphasis is given to econometric, statistical, and multivariate analytical methods, which were used in 170 articles (alone or in conjunction with other types of methods considered). It can be observed that other methods have been used much less frequently, particularly simulation methods, which were used in only 30 articles and often in conjunction with other methods.

  A variety of methods were used. Emphasis was given to the following: regression – including multiple, quantile, logit, and probit regressions, used in 60 articles; network models, considered in the item "mathematical modelling" (34 articles); correlation analysis (13 articles); extreme value theory (EVT) (12 articles); factor models (principal component analysis (PCA), discriminant and cluster analyses) (12 articles); GARCH models

Methods used	Number of Articles
Econometric/Statistical/Multivariate Analysis.	134
Computational/Simulation.	1
Mathematical Modelling.	40
Econom./Stat./ Multivariate An. & Comput./Simulation	9
Econom./Stat./ Multivariate An. & Mathematical Model.	22
Comput./Simulation & Mathematical Model.	15
Econom./Stat./ Multivariate An. & Comput./Simulation & Mathematical Model.	5
Not applicable.	40

Table 8 – Classification according to item 9.

(15 articles); vector autoregression (VAR) (11 articles); the Shapley value (five articles); Monte Carlo simulation (four articles); copulas (five articles); consistent information multivariate density optimizing (CIMDO) (three articles); vector error correction (three articles); agent-based models (two articles); entropy models (two articles); group debt rank (GDR) (two articles); and the Jaccard index matrix (three articles), among others.

Other models were also used, including from other fields of study; these include the following: the Kalman filter, game theory, particle physics, Ricci curvature, partial equilibrium models, catalytic reaction models, epidemic model, stochastic optimal control, message–passing algorithms, asymmetric dynamic covariance (ADC) models, the self–organizing financial stability map (SOFSM), the support vector machine (SVM), and random matrix theory. Some auxiliary models used included the Merton credit risk model (nine articles), Kealhofer, McQuown and Vasicek model (KMV) (2 articles), distance to default (four articles), and portfolio analysis (four articles), among others.

The systemic risk measures used included the following: CoVaR, proposed by Adrian and Brunnermeier (2010), used or discussed in 23 articles; Marginal Expected Shortfall (MES), proposed by Brownlees and Engle (2010), used or discussed in 12 articles; credit default swap (CDS) spreads (10 articles); VaR – including quantile VaR, component VaR, incremental VaR, and systemic VaR (five articles); coherent measures (three articles); and tail dependence (three articles). The following measures were also found: the Lerner index, catastrophic risk in the financial sector (CATFIN), Collateralized Debt Obligations (CDOs), tail beta, financial index stress, LIBOR spreads, volatility, VoV (volatility of volatility), the contagion index for each node (on a network), balance sheet ratios, the measure of joint default, the house price index, the China Financial Stress Index (CFSI), the News Cohesiveness Index (NCI), the number of bank failures, the Degree of To-

Results	Number of articles
New perspectives.	75
Consistent with previously published literature.	127
Replication to a different context or period.	40
Comparative study.	24

Table 9 – Classification according to item 10.

tal Leverage (DTL), the Information Dissipation Length (IDL), the systemic risk index based on the value of assets (SIV), Loss Given Default (LGD), the Distress Insurance Premium (DIP) (two articles), the Joint Probability of Default (JpoD), the Sector Diversity Index (SDI), the Correlation Response Index (CRI), the Implied Systemic Cost of Risk (I–SCOR), Credit Risk Deviation (CRD), extreme downside risk, the sector dominance ratio, expected systemic losses, Hirsch index, absorption ratio and the systemic importance score, among others.

Several articles analyzed the contribution of individual institutions to systemic risk, and some of them proposed stress tests for institutions. However, it is remarkable that in the literature analyzed, no article proposed using the systemic risk indices built for stress tests in asset portfolios.

- ***R*esults**: Item 10 (Results) is presented in Table 9. Articles strongly based on the literature already published or replicating studies in other contexts are dominant. Comparative studies, in which two or more other studies and/or methods are compared, are fewer.

In general, when analysing the results of the classification of the literature on systemic financial risk into the proposed categories, it is possible to highlight some aspects that may reveal gaps and opportunities for future studies. There seem to still be relatively few studies that involve bank concentration and its impact on systemic financial risk, and the same can be said for emerging markets. It is also noted that the literature on the subject is very focused on banking institutions, which is easy to understand, given the nature of the subject, but this finding may also reveal an opportunity for further studies of other types of financial institutions and their relationship with systemic risk.

Diverse methods are used; however, studies using computer simulations are far fewer compared to studies using econometric methods or other statistical techniques or multivariate analysis. Some works compare estimates of two or more systemic risk measures over a data basis (Li et al. (2013), Madan and Schoutens (2013), Mayordomo et al. (2014), Weiss and Mühlnickel (2014)). Kupiec and Güntay (2016), using daily stock returns, define a statistic to evaluate systemic risk using CoVaR and MES. Given the profusion of systemic risk measures appeared in literature in recent years, there is still large room for conducting studies that compare the effectiveness of the indicators and methods proposed in the studies.

2.5.1 Research networks

To supplement the results presented above, an analysis of the citations of each article in the sample was performed to identify the mainstream, i.e., the major research networks and the evolution of the discussion on systemic financial risk over time. Thus, within the initial sample, relationships between articles were sought by analysing the citations between these articles and the other studies that they citeonlined. It was possible to confirm that a large number of important articles were not included in the sample, whose composition criteria was already explained at the beginning of Section 2.4. . In this sense, when analysing this new set of articles, the articles already citeonlined and those that citeonlined them were identified. More specifically, articles not citeonlined by other articles in the sample itself were excluded, and the articles not yet present in the sample and that had at least five citations in *Scopus* and *Web of Knowledge* were included. After this round of recording the citations of the selected articles, the articles citeonlined at least four times by their listed peers and that were still not in the list were included, proceeding again to the scrutiny of the bibliographies of those included. In a final round of refinement, articles that were citeonlined by at least seven articles listed and that were not yet on the list were included. The reference lists of articles from 2015 and 2016 that were available for download on *Scopus* and *Web of Science* were also reviewed. A final round of analysis of the articles that were citeonlined eight or more times was performed. Some articles from 2012 onwards were included even without reaching the total of eight citations because the period in which they had to be citeonlined was relatively smaller. Ultimately, the references of 398 articles were analyzed, and citations were checked for a total of 3925 articles.

This process made it possible to measure the importance of each article not only by a number of easily verifiable citations on a research basis but also by the references of the researchers of the area themselves. It also made possible to construct the citations networks. Thus, maintaining the criterion of a minimum number of citations between pairs of the list of 398 scrutinized articles, the final list of 132 articles was reached, from which an additional 18 articles were removed for demonstrating reduced importance in relation to the other articles in the first construction of the figures (point vertices), as is described below. The 102 selected articles are listed in Table 10, in which they appear numbered according to the chronological order of publication. This selection criterion enabled the list of studies to be representative but not so extensive as to make it difficult to analyze the data and/or dilute the "reference" character of the articles.

#	Reference	Article's Title
1	Kindleberger and Aliber (1978).	Manias, panics and crashes: a history of financial crises.
2	Bryant (1980).	A model of reserves, bank runs and deposit insurance.

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#	Reference	Article's Title
3	Stiglitz and Weiss (1981).	Credit rationing in markets with imperfect information.
4	Bernanke (1983).	Non-monetary effects of the financial crisis in the propagation of the great depression.
5	Diamond and Dybvig (1983).	Bank runs, deposit insurance and liquidity.
6	Diamond (1984).	Financial intermediation and delegated monitoring.
7	Bhattacharya and Gale (1987).	Preference shocks, liquidity and central bank policy.
8	Gorton (1988).	Banking panics and business cycles.
9	Bernanke and Gertler (1989).	Agency costs, net worth and business fluctuations.
10	Calomiris and Gorton (1991).	The origins of banking panics: models, facts, and bank regulation.
11	Calomiris and Kahn (1991).	The role of demandable debt in structuring optimal banking arrangements.
12	Shleifer and Vishny (1992).	Liquidation values and debt capacity: a market equilibrium approach.
13	Kaufman (1994).	Bank contagion: a review of the theory and evidence.
14	Rochet and Tirole (1996).	Interbank lending and systemic risk.
15	Calomiris and Mason (1997).	Contagion and bank failures during the Great Depression: the June 1932 Chicago banking panic.
16	Holmstrom and Tirole (1997).	Financial intermediation, loanable funds, and the real sector.
17	Allen and Gale (1998).	Optimal financial crisis.

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#	Reference	Article's Title
18	Freixas and Parigi (1998).	Contagion and efficiency in gross and net interbank payments system.
19	Holmström and Tirole (1998).	Private and public supply of liquidity.
20	Sheldon and Maurer (1998).	Interbank lending and systemic risk: an empirical analysis for Switzerland.
21	Diamond and Rajan (1999).	Liquidity risk, liquidity creation, and financial fragility.
22	Kaminsky and Reinhart (1999).	The twin crises: the causes of banking and balance of payments problems.
23	Allen and Gale (2000b).	Bubbles and crises.
24	Allen and Gale (2000a).	Financial contagion.
25	De-Bandt and Hartmann (2000).	Systemic risk: a survey.
26	Freixas et al. (2000a).	Systemic risk, interbank relations, and liquidity provision by the central bank.
27	Acharya (2001).	A theory of systemic risk and design of prudential regulation.
28	Borio et al. (2001).	Procyclicality of the financial system and financial stability.
29	Borio and Lowe (2002).	Asset prices, financial and monetary stability.
30	Nicolo and Kwast (2002).	Systemic risk and financial consolidation, are they related?
31	Borio (2003).	Towards a macroprudencial framework for financial supervision and regulation?
32	Furfine (2003).	Interbank exposures: quantifying the risk of contagion.
33	Upper and Worms (2004).	Estimating bilateral exposures in the German interbank market: is there a danger of contagion?

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#	Reference	Article's Title
34	Wells (2004).	Financial interlinkages in the United Kingdom's interbank market and the risk of contagion.
35	Cifuentes et al. (2005).	Liquidity risk and contagion.
36	Diamond and Rajan (2005).	Liquidity shortages and banking crises.
37	Lehar (2005).	Measuring systemic risk: a risk management approach.
38	Leitner (2005).	Financial networks: contagion, commitment, and private sector bailouts.
39	Mistrulli (2005).	Interbank lending patterns and financial contagion.
40	Elsinger et al. (2006).	Risk assessment for banking systems.
41	Allen and Gale (2007).	Understanding financial crises.
42	Degryse and Nguyen (2007).	Interbank exposures: an empirical examination of contagion risk in the Belgian banking system.
43	Mistrulli (2007).	Assessing financial contagion in the interbank market: maximum entropy versus observed interbank leading patterns.
44	Nier et al. (2007).	Network models and financial stability.
45	Upper (2007).	Using counterfactual simulations to assess the danger of contagion in interbank markets.
46	Adrian and Shin (2009).	Liquidity and leverage.
47	Battiston et al. (2009).	Liasons dangereuses: increasing connectivity, risk sharing, and systemic risk.
48	Segoviano and Goodhart (2009).	Banking stability measures.
49	Allen and Babus (2009).	Networks in finance.

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#	Reference	Article's Title
50	Brunnermeier (2009).	Deciphering the liquidity and credit crunch 2007—2008.
51	Brunnermeier and Pedersen (2009).	Market liquidity and funding liquidity.
52	Brunnermeier et al. (2009).	The fundamental principles of financial regulation.
53	Haldane (2009).	Rethinking the financial network.
54	Acharya et al. (2010).	Measuring systemic risk.
55	Adrian and Brunnermeier (2010).	CoVaR.
56	Brownlees and Engle (2010).	Volatility, correlation and tails for systemic risk measurement.
57	Craig and Peter (2010).	Interbank tiering and money center banks.
58	Gai and Kapadia (2010).	Contagion in financial networks.
59	May and Arinaminpathy (2010).	Systemic risk: the dynamics of model banking systems.
60	Tarashev et al. (2010).	Attributing systemic risk to individual institutions.
61	Zhou (2010).	Are banks too big too fail? Measuring systemic importance of financial institutions.
62	Brunnermeier et al. (2011).	Banks' non–interest income and systemic risk.
63	Drehmann and Tarashev (2011).	Systemic importance: some simple indicators.
64	Gai et al. (2011).	Complexity, concentration and contagion.
65	Haldane and May (2011).	Systemic risk in banking ecosystems.
66	Huang et al. (2011).	Systemic risk contributions.
67	Mistrulli (2011).	Assessing financial contagion in the interbank market: maximum entropy versus observed interbank lending patterns.

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#	Reference	Article's Title
68	Upper (2011).	Simulation methods to assess the danger of contagion in interbank markets.
69	Acharya et al. (2012).	Capital shortfall: a new approach to ranking and regulating systemic risks.
70	Arinaminpathy et al. (2012).	Size and complexity in model financial systems.
71	Billio et al. (2012).	Econometric measures of connectedness and systemic risk in the finance and insurance sectors.
72	Bisias et al. (2012).	A survey of systemic risk analytics.
73	Caccioli et al. (2012).	Heterogeneity, correlation and financial contagion.
74	Cont et al. (2012).	Network structure and systemic risk in banking systems.
75	Fricke and Lux (2014).	Core–periphery structure in the overnight money market: evidence from the e–MID trading platform.
76	Gauthier et al. (2012).	Macroprudential capital requirementes and systemic risk.
77	Lelyveld and Veld (2012).	Finding the core: network structure in interbank markets.
78	Zheng et al. (2012).	Changes in cross-correlations as an indicator for systemic risk.
79	Battiston et al. (2012).	Default cascades: When does risk diversification increase stability?
80	Battiston et al. (2012).	DebtRank: too central too fail? Financial networks, the FED and systemic risk.

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#	Reference	Article's Title
81	Huang et al. (2012a).	Assessing the systemic risk of a heterogeneous portfolio of banks during the recent financial crisis.
82	Acemoglu et al. (2013).	Systemic risk and stability in financial networks.
83	Girardi and Ergun (2013).	Systemic risk measurement: multivariate Garch estimation of CoVaR.
84	Huang et al. (2013).	Cascading failures in bi-partite Graphs: model for systemic risk propagation.
85	Rodríguez-Moreno and Peña (2013).	Systemic risk measures: the simpler the better?
86	Roukny et al. (2013).	Default cascades in complex networks: topology and systemic risk.
87	Bargigli et al. (2014).	The multiplex structure of interbank networks.
88	Bernal et al. (2014).	Assessing the contribution of banks, insurance and other financial services to systemic risk.
89	Diebold and Yilmaz (2014).	On the network topology of variance decompositions: measuring the connectedness of financial firms.
90	Elliott et al. (2014).	Financial networks and contagion.
91	Glasserman and Young (2014).	How likely is contagion in financial networks?
92	Langfield et al. (2014).	Mapping the UK interbank system.
93	Martinez-Jaramillo et al. (2014).	An empirical study of the Mexican banking system's network and its implications for systemic risk.

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#	Reference	Article's Title
94	Chinazzi and Fagiolo (2015).	Systemic risk, contagion and financial networks: a survey.
95	Hautsch et al. (2015).	Financial network systemic risk contributions.
96	Civitarese (2016).	Volatility and correlation-based systemic risk measures in the US market.
97	Fink et al. (2016).	The credit quality channel: modeling contagion in the interbank market.
98	Hardle et al. (2016).	TENET: Tail-Event driven NETwork risk.
99	He and Chen (2016).	Credit networks and systemic risk of Chinese local financing platforms: Too central or too big to fail?
100	Huang et al. (2016).	A financial network perspective of financial institutions' systemic risk contributions.
101	Sandhu et al. (2016).	Ricci curvature: An economic indicator for market fragility and systemic risk.
102	Souza et al. (2016).	Evaluating systemic risk using bank default probabilities in financial networks.

Table 10 – Articles considered in the research on systemic financial risk.

The list of items and the table of articles citeonlined versus the respective articles that citeonline them served as inputs to the free software *Pajek*. Chronological ordering is required to use the software, which also requires that the generated network of citations be acyclic, i.e., reciprocal citations or citations in a closed chain are not allowed for the construction of figures (i.e., Figures 9 and 10). Figures built with the help of this software are shown below. For details on *Pajek*, see Mrvar and Batagelj (2014) and DeNooy et al. (2005). Figure 7 presents the network of citations of the articles.

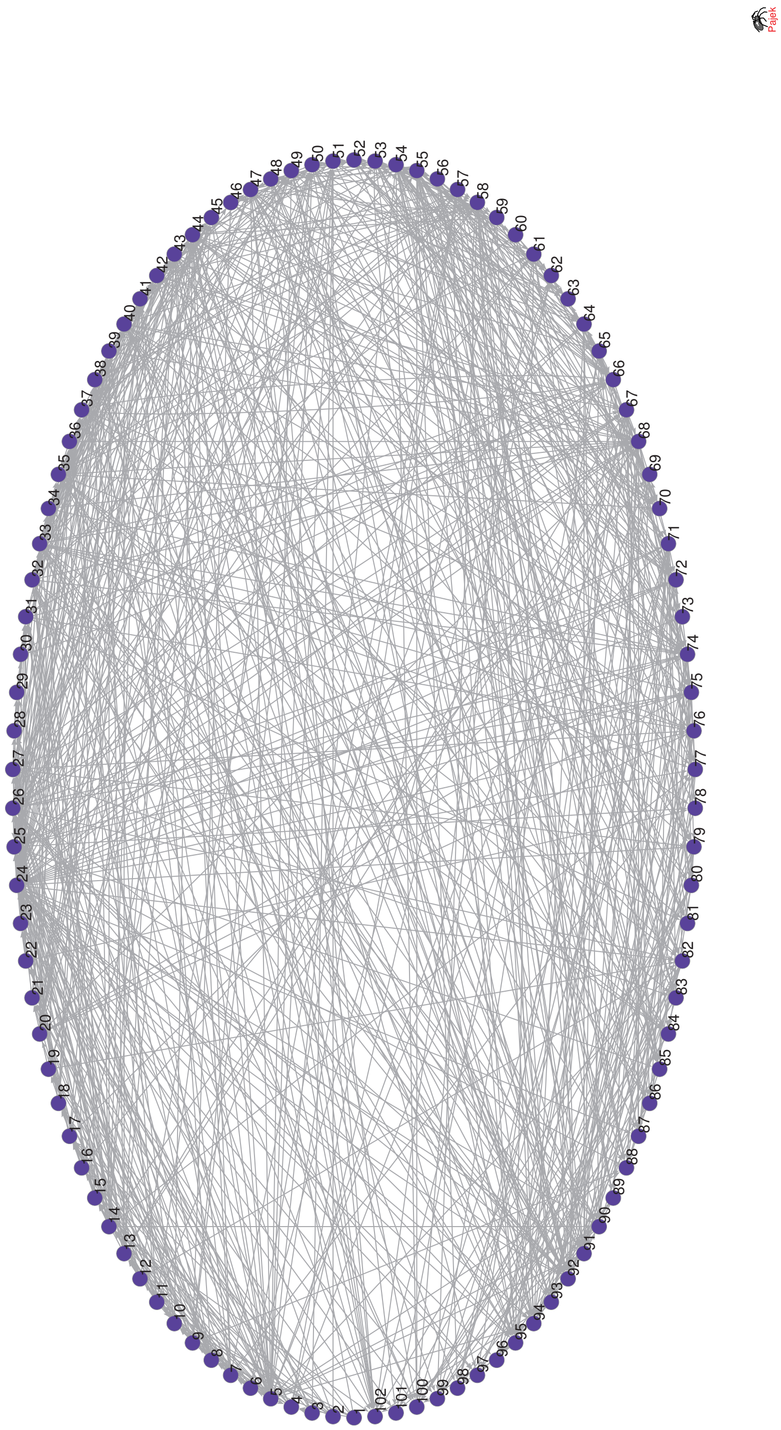

Figure 7 – Network of links (General).

Figure 8 shows the most citeonlined articles between the pairs in the list, which correspond to the major vertices. In addition, the articles are divided into two research networks, yellow (main) and blue (secondary). Darker lines represent a greater link between the research studies.

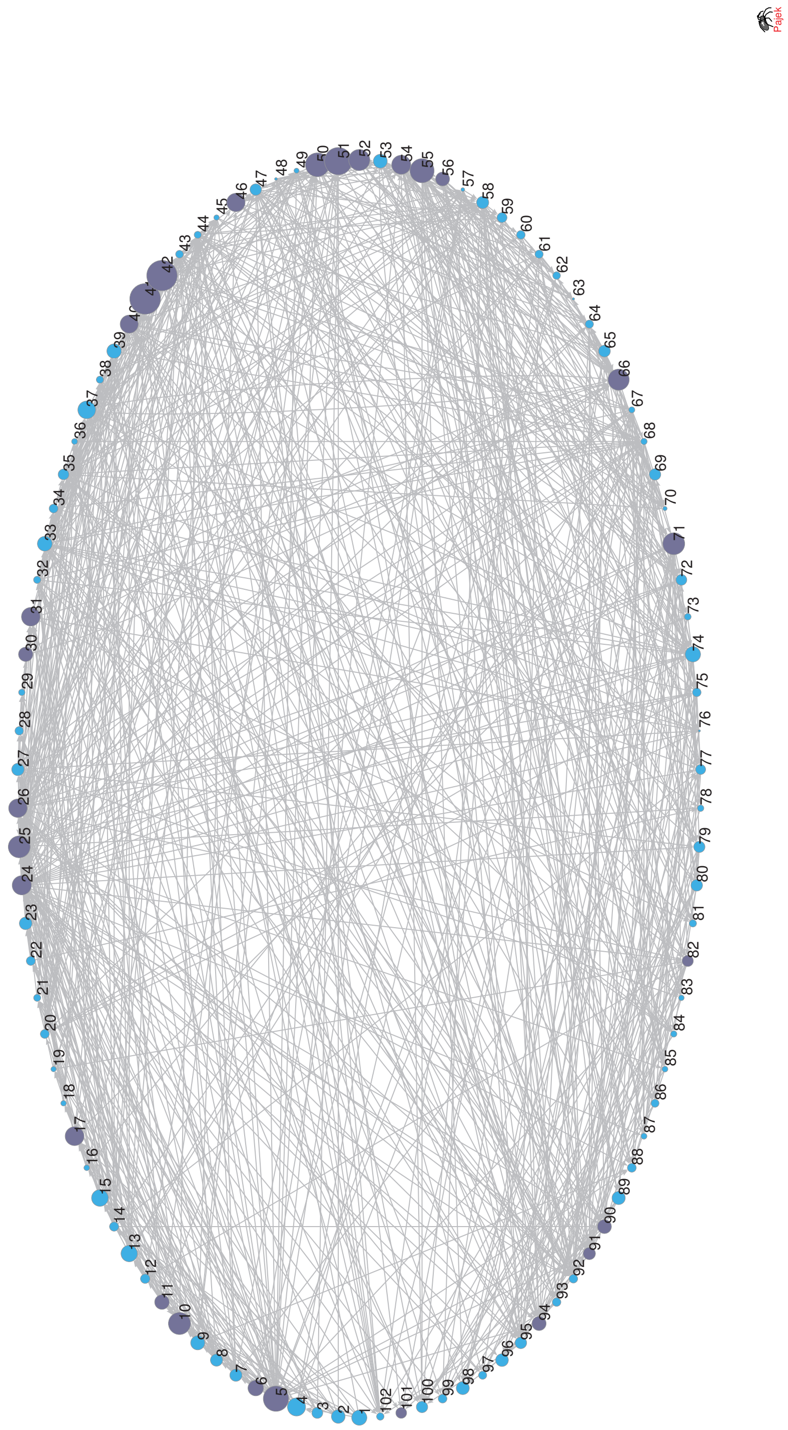

Figure 8 – Network links.

In Figure 9, these networks are separated.

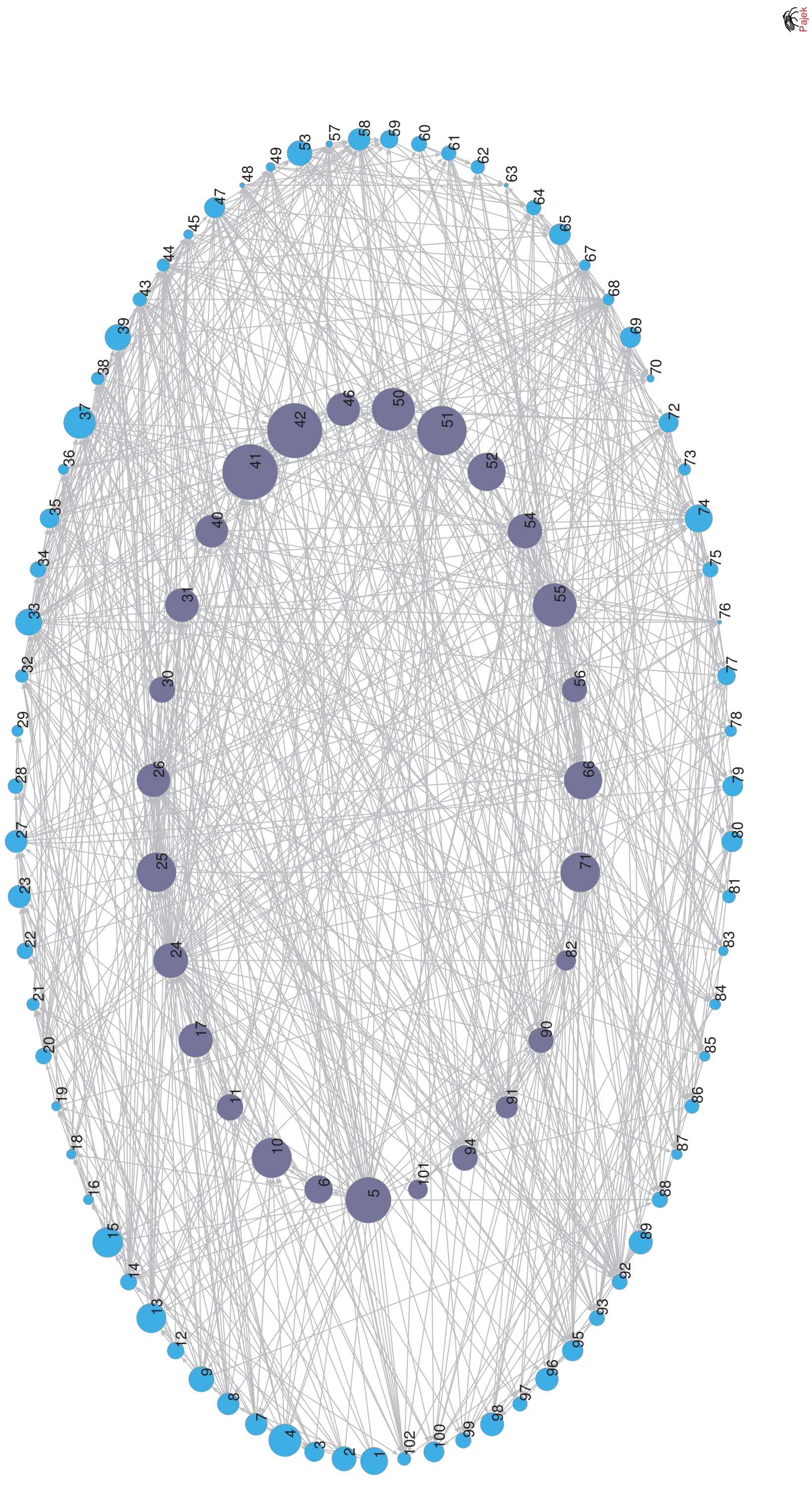

Figure 9 – Main and secondary networks.

Figure 10 provides a view of the importance of each study within the field of research on systemic financial risk

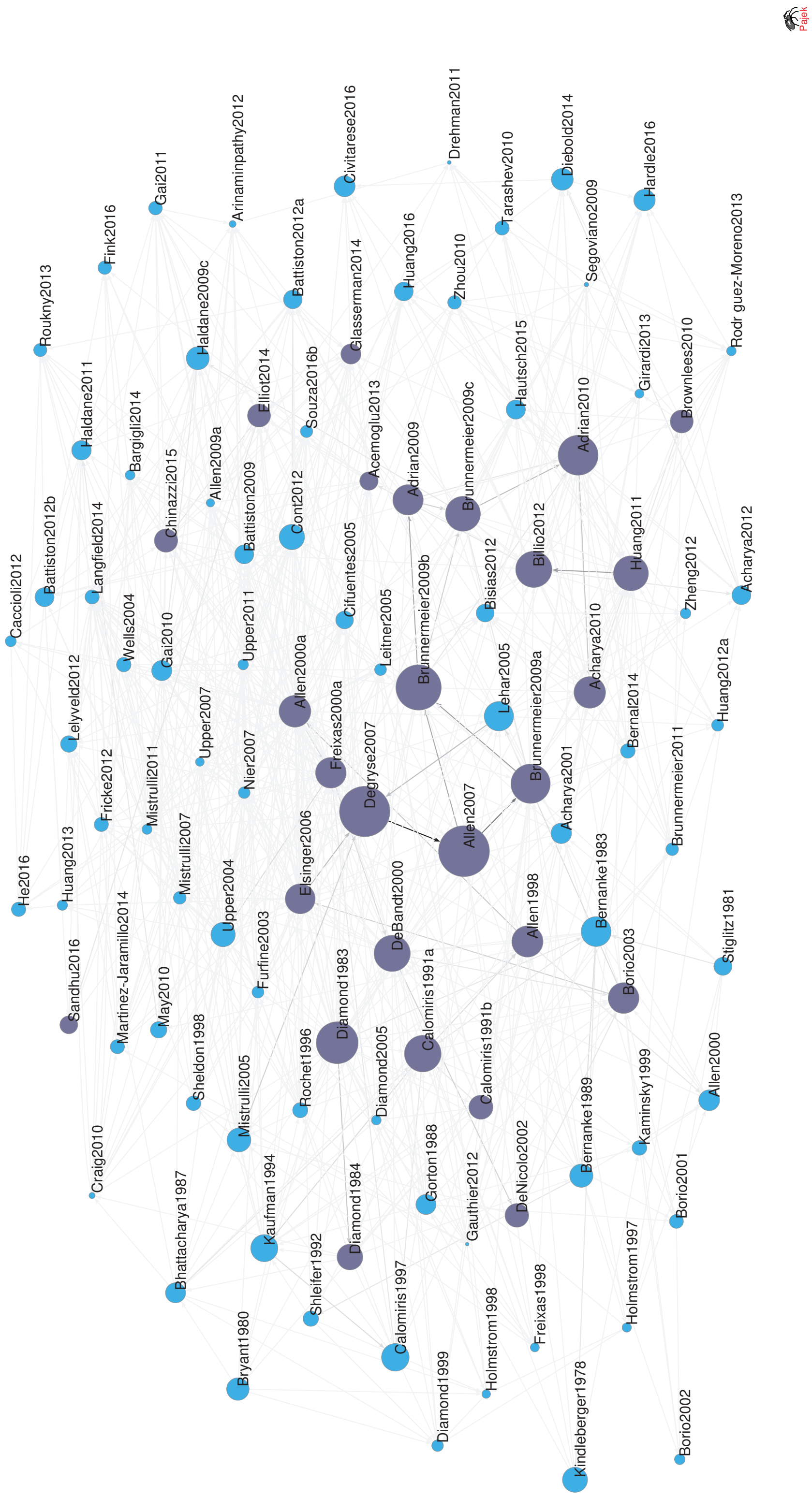

Figure 10 – Research network.

Figure 11 shows the evolutionary path of the main research network.

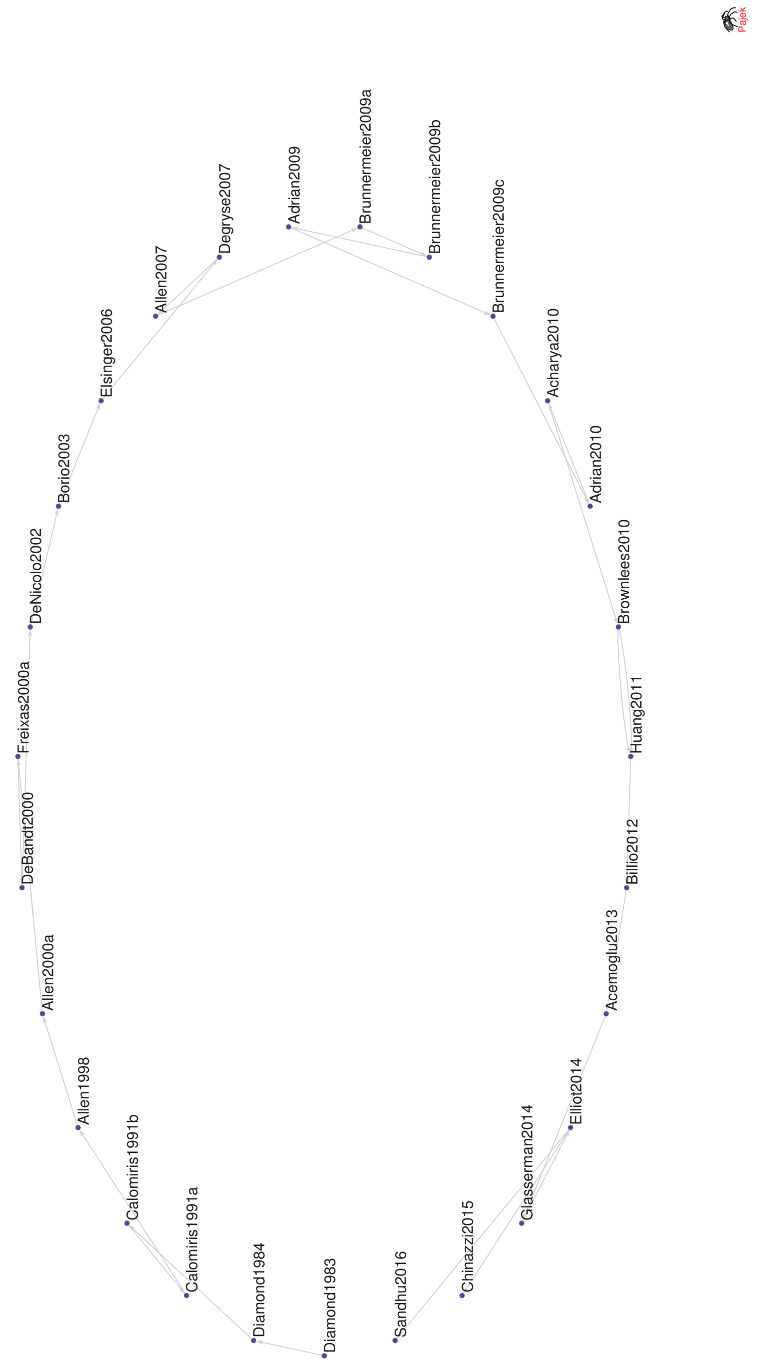

Figure 11 – Main research path.

2.5.2 Analysis of the main research path

Table 11 lists the articles that compose the main research path, considered thus by the researchers of the area themselves, a result found according to the method described above.

#	Reference	Article's Title
1	Diamond and Dybvig (1983).	Bank runs, deposit insurance and liquidity.
2	Diamond (1984).	Financial intermediation and delegated monitoring.
3	Calomiris and Kahn (1991).	The role of demandable debt in tructuring optimal banking arrangements.
4	Calomiris and Gorton (1991).	The origins of banking panics: models, facts, and bank regulation.
5	Allen and Gale (1998).	Optimal financial crisis.
6	Allen and Gale (2000a).	Financial contagion.
7	Freixas et al. (2000a).	Systemic risk, interbank relations, and liquidity provision by the central bank.
8	De-Bandt and Hartmann (2000).	Systemic risk: a survey.
9	Nicolo and Kwast (2002).	Systemic risk and financial consolidation, are they related?
10	Borio (2003).	Towards a macroprudencial framework for financial supervision and regulation?
11	Elsinger et al. (2006).	Risk assessment for banking systems.
12	Degryse and Nguyen (2007).	Interbank exposures: an empirical examination of contagion risk in the Belgian banking system.
13	Allen and Gale (2007).	Understanding financial crises.
14	Brunnermeier (2009).	Deciphering the liquidity and credit crunch 2007–2008.
15	Brunnermeier and Pedersen (2009).	Market liquidity and funding liquidity.
16	Adrian and Shin (2009).	Liquidity and leverage.
17	Brunnermeier et al. (2009).	The fundamental principles of financial regulation.
18	Adrian and Brunnermeier (2010).	CoVaR.

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#	Reference	Article's Title
19	Acharya et al. (2010).	Measuring systemic risk.
20	Brownlees and Engle (2010).	Volatility, correlation and tails for systemic risk measurement.
21	Huang et al. (2011).	Systemic risk contributions.
22	Billio et al. (2012).	Econometric measures of connectedness and systemic risk in the finance and insurance sectors.
23	Acemoglu et al. (2013).	Systemic risk and stability in financial networks.
24	Glasserman and Young (2014).	How likely is contagion in financial networks?
25	Elliott et al. (2014).	Financial networks and contagion.
26	Chinazzi and Fagiolo (2015).	Systemic risk, contagion and financial networks: a survey.
27	Sandhu et al. (2016).	Ricci curvature: an economic indicator for market fragility and systemic risk.

Table 11 – Reference articles in the research on systemic financial risk (Main network).

Table 12 shows a classification that allows aspects of the studied articles to be compared.

#	Article	Type	Theme/Main object	Method	Scope	Period
1	Diamond and Dybvig (1983).	Theoretical.	Banking panics.	Mathematical modelling.	Not applicable.	Not applicable.
2	Diamond (1984).	Theoretical.	Financial intermediation and diversification.	Mathematical modelling.	Not applicable.	Not applicable.
3	Calomiris and Gorton (1991).	Theoretical.	Banking panics.	Review.	USA.	Secs. XIX e XX.
4	Calomiris and Kahn (1991).	Theoretical.	Callable debt, optimal contract.	Mathematical modelling.	Not applicable.	Not applicable.
5	Allen and Gale (1998).	Theoretical.	Banking panics.	Economic modelling.	Not applicable.	Not applicable.
6	Allen and Gale (2000a).	Theoretical.	Contagion.	Mathematical modelling.	Not applicable.	Not applicable.
7	Freixas et al. (2000a).	Theoretical.	Liquidity and contagion in the interbank system.	Mathematical modelling.	Not applicable.	Not applicable.
8	De-Bandt and Hartmann (2000).	Theoretical.	Concepts and models of systemic risk.	Review.	Not applicable.	Not applicable.
9	Nicolo and Kwast (2002).	Empirical.	Bank consolidation.	Econometric	USA	1988–1999.
10	Borio (2003).	Theoretical.	Micro x macro–regulation.	Descriptive–analytical.	Not applicable.	Not applicable.

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#	Article	Type	Theme/Main object	Method	Scope	Period
11	Elsinger et al. (2006).	Empirical.	Contagion.	Network models.	Austria.	1989–2002.
12	Degryse and Nguyen (2007).	Empirical.	Contagion.	Simulation.	Belgium.	1993–2002.
13	Allen and Gale (2007).	Theoretical.	Financial crisis.	Comparative analysis.	World.	Secs. XIX a XXI.
14	Brunnermeier (2009).	Theoretical.	2007 crisis.	Descriptive–analytical.	USA	2007–2009.
15	Brunnermeier and Pedersen (2009).	Theoretical.	Liquidity and funding.	Statistical and mathematical modelling.	Not applicable.	Not applicable.
16	Adrian and Shin (2009).	Empirical.	Liquidity and leverage.	Econometric.	USA.	1992–2008.
17	Brunnermeier et al. (2009).	Theoretical.	Regulation.	Descriptive–analytical.	Not applicable.	Not applicable.
18	Adrian and Brunnermeier (2010).	Empirical.	Systemic risk of a given bank.	Econometric.	USA, Europe.	1971–2013.
19	Acharya et al. (2010).	Empirical.	Systemic risk of a given bank.	Econometric.	USA.	2006–2009.
20	Brownlees and Engle (2010).	Empirical.	Systemic risk of a given bank.	Econometric.	USA.	2000–2010.
21	Huang et al. (2011).	Empirical.	Systemic risk of a given bank.	Econometric.	USA.	2004–2010.

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#	Article	Type	Theme/Main object	Method	Scope	Period
22	Billio et al. (2012).	Empirical.	Contagion.	Econometric.	USA.	1994–2008.
23	Acemoglu et al. (2013).	Theoretical.	Contagion and counterparty risk.	Mathematical and network modelling.	Not applicable.	Not applicable.
24	Glasserman and Young (2014).	Empirical.	Contagion.	Network models.	Europe.	2010.
25	Elliott et al. (2014).	Empirical.	Contagion.	Network models.	Europe.	2011.
26	Chinazzi and Fagiolo (2015).	Theoretical.	Contagion.	*Review*.	Not applicable.	Not applicable.
27	Sandhu et al. (2016).	Theoretical and empirical.	Systemic risk in a specific market.	Mathematical.	USA.	1998–2013.

Table 12 – Comparative classification of articles.

The oldest articles in this sample of 27 articles date from the 1970s–1980s, and they mainly address bank runs and panics and related subjects, such as liquidity problems. From there, other striking elements of financial stability begin to be incorporated, and the articles start to also focus on methods of measuring systemic financial risk. Starting in 2000, the vast majority of the articles address some method of measuring systemic risk.

Interestingly, eight articles (see Table 12) study the systemic importance or the systemic risk attributed to a specific institution. From this similarity, each article opts for a method to make attributions to the institutions concerning their weight on the risk to the system. The measures and methods that are used for this purpose are varied. In other direction, seven articles propose aggregate risk indicators for the financial system as a whole. Only Elsinger et al. (2005) use stress tests.

The focus of these articles is mostly banks; three articles classified as reviews are more generic in this regard. No article analyzes emerging markets; two articles analyze global data, nine data from the United States, and five data from European countries. Regarding the study period, Calomiris and Gorton (1991) review bank panics since the nineteenth century, and Allen and Gale (2007) analyze financial crises, also since the nineteenth century. Of the other studies, three focus only on the pre–2008 crisis period, and ten analyze data that include the 2008 crisis.

Fifteen articles are theoretical and one is both theoretical and empirical. Three of these are classified as reviews or comparative analyses, four are analytical, six use mathematical models, one mathematical and networks modelling, one statistical and mathematical modelling, and one economic modelling. The other 11 studies are empirical and use econometric methods (seven articles), network models (three articles) or simulation (one article).

The "too central to fail" phenomenon is a prominent factor in several articles, considered more impactful on systemic risk than "too big to fail". Nine articles specifically analyze the effects of interconnectivity and the consequent potential for contagion and spread of financial problems for the detection and measurement of systemic risk.

Many of the articles of this main research path propose systemic risk indicators: Allen and Gale (2000a) propose a measure of preference for liquidity; Freixas et al. (2000a) an indicator of risk of contagion; Nicolo and Kwast (2002) the correlation of bank shares; Degryse and Nguyen (2007) the intersection of loss given the default (LGD) between banks. Other works focus on the systemic importance and the systemic risk due to a specific institution, for which Adrian and Shin (2009) propose the variation of leverage and the VaR/assets relationship of the institution as a measure; Adrian and Brunnermeier (2010) propose the popular CoVaR, which measures the VaR of the entire financial system, conditional on a particular institution being in a given state; Acharya et al. (2010) the Systemic Expected Shortfall (SES); Brownlees and Engle (2010) the Marginal Expected Shortfall (MES); Huang et al. (2011) the Distress Insurance Premium (DIP); Billio et al. (2012) the degree of connectivity of the institution; Glasserman and

Young (2014) the fraction of the institution's debts held by other financial institutions. Sandhu et al. (2016) use a mathematical concept from Topology, the Ricci curvature, as an economic indicator for market fragility and systemic risk and apply it to analyze a set of stocks comprising S&P500.

Correlation between assets and markets is always an important element in the analysis of systemic financial risk because it seems that, empirically, in falling markets, volatility increases and assets move in a more coupled manner, increasing systemic risk. Several articles use correlations as a direct or indirect measure. Nicolo and Kwast (2002) propose the correlation of bank stock returns as a systemic risk indicator; Lehar (2005) the correlation between bank investment portfolios; Elsinger et al. (2005) the correlation of risk exposures and mutual credit between banks. The three articles use econometric modelling.

Regarding the origin of the data, some articles in the main research path use balance sheet data. Elsinger et al. (2006) use data from portfolios owned by banks, and Degryse and Nguyen (2007) use data from aggregate interbank exposures. According to Drehmann and Tarashev (2011), it is unlikely that a regulatory authority directly uses a more sophisticated measure to measure systemic risk; on the contrary, it must observe these measures only to bring them closer to simpler and more reliable indicators specific to banks. According to Elsinger et al. (2005), although in highly developed financial systems stock market data most likely incorporate all relevant public information on the risk exposure of the bank, the data do not necessarily incorporate private information that is often contained in supervisory bank microdata and loan registers. The values of bank assets are often opaque. Thus, the private information that is contained in statements monitored by regulatory authorities is of paramount importance (ELSINGER et al., 2005).

However, still according to Elsinger et al. (2005), methods that use market data can be more easily applied than those that are heavily based on proprietary information, such as loan registers and supervisory data. Although such data sources are very rich and allow a more detailed analysis of risk factors, their disadvantage is that they are not widely available and generally are under the strict control of national supervisory bodies. Market prices have the advantage of being easily accessible compared to data related to the balance sheets and financial indicators of companies.

Nicolo and Kwast (2002) use the stock prices of banks. According to Gropp et al. (2002), from a supervisory perspective, assets issued by banks are interesting because the market prices of debts and shares can increase the funding cost of banks. Market information is available at a very high frequency and can complement the traditional balance sheet data to check for possible bank weaknesses. These are early signs for the identification of banks to be better scrutinized (GROPP et al., 2002). Of the empirical articles analyzed, the vast majority use market data in their models and analyses, with the advantages and disadvantages discussed already above.

All articles discuss aspects of regulation, either directly or indirectly, given the nature of the subject discussed. Therefore, they are of interest to professionals involved in banking regulation. Research on systemic financial risk is a multifaceted field of study; a proof thereof is the diversity of subjects and objects that are present in the articles: market risk, liquidity risk, credit risk, contagion, leverage, bank consolidation, financial diversification, and bank runs and panics, among others.

2.6 Conclusions

The literature on systemic financial risk is evolving. This finding was expected given the impact of the 2008 financial crisis on financial institutions and the financial system and the repercussions for the global economy. The literature is comprehensive and reflects the very diversity of the subject and the multiple aspects involved in the research. It is also characterized by high quality, which also reveals the growing importance of the subject and the large economic and social costs that are involved in financial crises. The adequate functioning of the financial system fundamentally depends on the confidence of agents to a much greater extent than in other sectors of the economy. Moreover, as argued by (HIPPLER; HASSAN, 2015), the profitability of all firms, financial firms in particular, is negatively affected by increases in macroeconomic and financial stress. The subject involves regulatory aspects as the economy in the broader sense must be protected in addition to investors and depositors. In addition, there are repercussions for the management of portfolios and the monitoring of specific markets.

Section 2.5 presented elements that appeared less frequently in the literature; this was determined based on a considerable sample of 266 articles that were available for download in the *Scopus* and *Web of Science* databases. This work has limitations that result from the method adopted. By changing some criteria, some articles could have been included and others excluded from the sample. The classification categories, relevant at first, could also be modified, depending on the researcher's approach and interests. Nevertheless, findings that can serve as a reference and help compose a research agenda for researchers in the area were presented.

With regard to the most important articles concerning systemic financial risk as viewed by the researchers themselves, a network of 102 articles considered to be important for advancing the subject was built. This article performed an in–depth analysis of the 27 articles that comprise the main path of this research field, in accordance with the previously described method. There is a diversity of objects and approaches, as is characteristic of the literature on the subject. Each article has its merits in standing out as a reference in the literature, be it by performing an analysis that contributes to the field, by proposing innovative paths or useful risk measures for the measurement of systemic financial risk, or by organizing and discussing information on the subject in important reviews. The most recent articles, even without having been citeonlined many times, have affirmed their importance because they are recognized by other recent articles and are linked to an important network of studies.

Once again, the set of articles could have varied, depending on the criteria adopted, with the exclusion of some articles and the inclusion of others; however, what cannot be denied is the relevance of this set of studied articles. In the literature analyzed, many articles focused on analysing the systemic importance of specific institutions. It would be interesting if there were more comprehensive and comparative studies of the measures that propose to measure systemic financial risks, applying them to the same set of banks, discussing the advantages and disadvantages of each approach, and checking where they clash and where they complement each other, which could enhance the monitoring of financial institutions in an interesting manner. This is also a suggestion of this work for future studies.

3 A financial systemic risk indicator using PCA and Markov switching

3.1 Introduction

The financial crisis of 2007 evidenced the need for instruments to detect systemic risk in its early stages, that is, early warning systems. The objective of this study is to establish a systemic risk indicator for the international financial market, using principal components analysis (PCA), the results of which are then submitted to the analysis of regime changes using Markov Switching (MS) models.

In this study, systemic financial risk is identified with the notion of financial stress, in which there may be strong and generalized variation in asset prices. More particularly, the contribution of the paper involves the combination of principal components analysis (PCA) and Markov switching (MS) to establish an indicator of systemic risk.

When using MS on the results of PCA of the correlation matrix of a large and varied number of relevant international market assets, it is assumed that the regime breaks found are more likely to be systemic in nature compared to the application of regime modelling to analyze the behaviour of specific financial variables. In addition, unlike the usual PCA approaches, in which it is not possible to establish a threshold to separate the two regimes, the definition of being in the "mode" of systemic risk in our work is not arbitrary, since the model itself will define the regime.

To establish the model, the study takes into account nearly one hundred assets traded in the international markets, both in developed and emerging countries, belonging to various classes, specifically indexes of stock markets, including volatility indexes; currencies; precious metals; agricultural, metal and energy commodities; sovereign and corporate bonds; and an MBS (*mortgage backed securities*) index. The high number and scope of the assets has the objective of seeking an indicator that signals systemic risk. This work focused on the period 1994–2017, due to the greater number of relevant assets with complete historical series. For robustness checks, additional analysis was conducted for the period 1985–2017, to evaluate the systemic indicator modelled in our study.

In the first stage of the model, an indicator of systemic risk was derived from the Principal Components Analysis, assuming that the assets are coupled, covarying more strongly in scenarios of stress. The covariance ratio explained by the first eigenvalue of the correlation matrix is the initial indicator of systemic risk. Peaks in this indicator show good adherence to periods of stress perceived by market players in the most recent financial crises. The study also analyzes each variable *vis-à-vis* the indicator, allowing us to classify the aggressive assets that benefit from the moments of greater appetite for risk, and safe havens, denominated as defensive, that benefit from periods of flight to quality. This classification will be useful when verifying the risk behaviour of the assets in each of the regimes identified by our study.

In the second stage, the indicator modelled by the PCA was then subjected to regime change analysis using Markov switching techniques. Econometric regime change models address situations where the returns of a variable are drawn from different probability distributions and where the choice of the distribution depends on the likelihood of a given stochastic process (HAMILTON, 2005). The regime change was evaluated with switchings in different moments of the indicator: mean and variance, considered in isolation, and these two moments considered together. The odds that the market will, at any given moment, be in the established regimes (normal or stress) works as a final indicator of systemic financial risk.

The article then discusses and compares the application of the different switchings in the modelling. We also study the model with fewer variables and a longer period (1985–2017) to verify the consistency of the regimes found using a more thorough dataset in a shorter period. This consistency is also tested by breaking the analyzed sample into two distinct periods (1994–2006 and 2007–2017). In addition, alternative indicators were modelled, following the proposed method, using only one asset class, with special attention to stock exchanges indexes, which represent proxies for market portfolios. The stress periods indicated by the models are mapped comparing them with the actual events occurring in the markets, to evaluate the adequacy of the proposed indicators.

The paper is organized as follows. In the next section, we review the literature on principal components analysis techniques and regime change analysis (Markov Switching models) applied to the analysis of systemic financial risk and to the study of regimes in finance and economics. In the following section, we present the method for calculating the indicator and present the methodology and results. Subsequently, we perform an evaluation of the proposed indicator and discuss the results obtained. Finally, we make final considerations, indicate limitations of the study and present opportunities for future research.

3.2 Literature review

3.2.1 Principal Components Analysis and Systemic Risk

A stylized fact in the financial markets is that the correlations of asset returns increase in times of stress. According to Kritzman et al. (2011), not only do correlations increase in stressed markets, but the opposite is also true, i.e., a greater correlation between assets and portfolios makes the market riskier. This fact has been widely used for the proposition of models that assist managers in their search for strategies to increase returns and manage risks. In view of the systemic risk, the increase of correlations in times of stress is also a relevant concern for agents regulating the financial markets.

To illustrate the evidence of the joint behaviour of financial assets, we present in Figure 12 heatmaps that represent the Pearson correlation coefficients calculated in a window of one month (30 running days) among the variables used in this work. Positive high correlations are shown by stronger green tones and high negative correlations are shown by stronger red tones. In the first heatmap, from January 2006, the predominant tones are softer or yellow, which indicates low correlations, both positive and negative, revealing that this period had no great shocks in the markets. In the other two heatmaps, referring to September/October 2008 and November 2011, strong shades of green and red predominate, indicating high correlations, both positive and negative, among asset returns.

Figure 12 – *Heatmaps* of correlations, different periods.

It should be noted that the September/October 2008 period was highly stressed by the collapse of the Lehman Brothers investment bank, which had a major impact on international markets. In November 2011, there was a deepening of the financial crisis due to acute problems involving the solvency of Eurozone countries and the uncertainties regarding the common currency.

The heatmaps suggest that correlations can serve as a raw material for analysing systemic risk. For example, Patro et al. (2013) examine the effectiveness of the correlations of the stock returns of large financial institutions to identify systemic risk. The authors conclude that the correlation of the daily returns of bank stocks is a simple yet useful indicator of systemic risk. Peaks in correlations are compatible with severe market conditions. According to Patro et al. (2013), when interdependencies are low, specific events that affect an individual institution could not spread rapidly through the bank sector and therefore, systemic risk is dependent on scenarios of high correlations among banks.

Billio et al. (2010) use the PCA technique to measure the systemic risk between financial institutions and investment funds in several countries. Their results show that the first major component captures 77% of the variability in the returns of financial institutions in the period 1994–2000, increasing to 83% in the period 2001–2008. Together, the first and second components account for 92% of the return variation, on average, for the whole period (1994–2008). These authors propose several econometric measures based on the analysis of principal components and Granger causality relationships of returns of financial institutions. Their results show that financial industry subsectors presented high interconnections between 2000 and 2008, suggesting the existence of complex and dynamic relationships that eventually increased systemic risk. The authors use PCA to estimate the relevance of common factors that drive returns of financial institutions and to test Granger-causal relationships in the industry. According to the authors, such indirect measures would be able to indicate periods of stress.

Nicolo and Kwast (2002), as measured by asset return correlations of a sample of *large and complex banking organizations* (LCBOs) in the United States, lead to a useful risk indicator, that is increasing over the period analyzed (1988–1999). By their turn, Elsinger et al. (2006), investigating data from Austria, concluded that a similar exposure of bank portfolios accounts for a large portion of systemic risk. According to the authors, the similarity of portfolio exposure could be due to a collective behaviour regarding adjusting the risk level, as suggested by Acharya (2001).

According to Zheng et al. (2012), financial crises are related to growth in correlations between stocks and stock indexes. The authors study US sectoral indexes and suggest that the growth rate of the components can be a metric of systemic risk. Thus, according to Zheng et al. (2012), the greater the variation of the major component, the higher the systemic risk and the more likely a severe scenario will occur.

Using the PCA technique, Kritzman et al. (2011) propose the absorption ratio, which is defined as the variance of returns of assets explained by a fixed number of eigenvalues. According to the authors, a higher absorption ratio implies a vulnerable scenario when assets are strongly coupled and therefore shocks can rapidly disseminate within the markets (KRITZMAN et al., 2011).

Since the crisis of 2007, a stream of literature has appeared that identifies a *risk on-risk off* mode that started to operate in the financial markets. As the name suggests, the agents began to operate jointly as if "switching a key" to higher risk appetite (*risk on*) or to protection (*risk off*), depending on the nature of the affecting events, magnifying the joint behaviour (covariance) of assets. Williams et al. (2012) note that the *RORO* (*risk on-risk off*) factor is one of the most surprising consequences of the financial crisis of 2007. *RORO* is characterized by high correlations, markets moving in unison and binary asset behaviour (safe havens or aggressive assets), with its own fundamentals becoming secondary to risk analysis. In the risk on periods, risk assets tend to rally together and defensive assets tend to fall, and vice versa in the risk off periods. The authors assert that the proportion of variance in returns explained by the first principal component, indicating how far the asset returns are attached, would be an indication of how much the paradigm associated with *RORO* is guiding markets.

3.2.2 Regime Changes and Systemic Risk

In his influential article, Hamilton (1989) proposed an approach to analyze regime changes as a method for modelling non-stationary time series. In Hamilton's approach, the parameters of an autoregression are seen as the result of a Markov process of discrete states. The possibility of regime changes at any given moment, not observed directly, is probabilistically inferred based on the behaviour observed in the time series.

Kim (1994) also became a reference work for regime change researchers, extending Hamilton (1989)'s approach to a general space-state model. This work also brought new contributions by introducing dependency in the regime change process and allowing switching in both the measurement equations and the transition equations.

The Hamilton (1989) and Kim (1994) models became a foundation for widely used approaches by econometrists in the analysis of the evolution of economic variables. For example, Chauvet (1998) proposes a regime switching model based on dynamic factors within business cycles. The model takes into account co-movements of economic variables and asymmetries of the phases of business cycles. According to the author, the results emphasize nonlinearities in business cycles and the usefulness of the procedure to identify a common element within variables that fluctuate in different regimes.

Other researchers also applied regime change models in the analysis of the behaviour of financial variables, especially in the stock markets. Hess (2003) notes that, since they do not rely on linearities, these models can be more effective in capturing typical movements of stock markets, such as jumps and crashes, which have proved long-lasting challenge for researchers. They can also take into account other market characteristics, such as fat tails of return distributions, the clustering of volatility or reversion to the mean. The author also discusses model configuration alternatives and which moment (mean, variance or both) is more suitable to be the switching element that will indicate the regime that the relevant variables are in. Just like Dewachter (2001) showed for the currency market, Hess (2003) states that the switching process is more pronounced for variance.

Researching the stock markets, Schaller and Norden (1997) agrees with Turner et al. (1989) regarding the existence of regime changes in the S&P index since the Second World War. Both used MS models but different tests to reach this result. Within the context of regime changes, Hamilton and Susmel (1994) discuss sudden discrete changes in the volatility behaviour, identifying evidence that an MS model leads to less error than ARCH (*autoregressive conditional heteroskedasticity*) models that do not take into account the likelihood of switching between regimes.

Abdymomunov (2013) explores a regime variation model that extends the SWARCH (*switching autoregressive conditional heteroskedasticity*) model proposed by Hamilton and Susmel (1994) to a multivariate setting, using Markov chains to separate high and low risk conditions and identify shocks to variables that could have systemic implications. The choice of variables is based on liquidity, credit and default risk, which can have impact in the market. According to the author, the results adequately assess a two state Markov chain, depicting high and low volatility of the financial variables. For Abdymomunov (2013), the joint process of changing the volatility regime in the considered variables can be used as an indicator of systemic financial stress in which large and abrupt volatility changes of financial variables and their averages are governed by a two-states Markov chain.

Cambón and Estévez (2016) use the methodology proposed by Holló et al. (2012) to develop an indicator aiming to verify the occurrence of stress in the Spanish financial markets. They utilize 18 variables to construct 6 subindices which are aggregated with the methods of portfolio theory. In the next step, they analyze changes of regime upon this index with the Markov switching and threshold VAR methodologies. According to the authors, the best model setting is achieved by allowing the existence of three regimes and they note that high stress regimes are always preceded by intermediate stress regimes.

Finally, Cevik et al. (2016) use Markov switching methods to identify structural features of Brazil, India, Indonesia, South Africa and Turkey, economies considered as fragile by analysts. Using financial and real economies variables they rely on a dynamic factor model to extract a financial stress index next submitted to Markov switching analysis. This work allowed them to identify a strong relationship between global liquidity and financial stress.

3.3 Methodology and Results

Our study uses the information contained in the values of publicly traded financial assets to construct the systemic risk indicators. The financial data were obtained through the *Bloomberg* platform, the statistical modelling was programmed in *EViews* software, and risk analyses using *value-at-risk* measures were programmed in *Visual Basic for Applications*. A list and description of all the variables used can be found in Appendix A.

To calculate of the profitability of the assets, the log-returns of the prices are used, with the exception of the spreads (US10y30y and US2y10y) and VIX and VDAX volatility indexes, for which the differences are used. For fixed-income assets, whose amounts are provided in the form of rates, we proceeded to the pricing by bringing the maturity value to the present using the reference rates provided. Therefore, we use approximate prices for fixed-income assets. Future research could use complete interest rate term structures to price bonds. However, for the purpose of this work, we are interested in the covariation of these prices, and this approximation is satisfactory. For the purposes of discussion, both returns and differences in spreads and volatilities are generically referred to as assets.

We apply PCA with data starting in 1994, considering the range of important assets with complete series since then. A total of 93 international financial market assets was selected to include the most important asset classes, which have significant volumes of trading and liquidity, issued in the world's major emerging and developed economies.

Financial data are used in the calculation of the indicator with the PCA methodology, with windows of 22, 44 and 65 working days, corresponding to approximately 1, 2 and 3 months in running days. The indicator presented in Figure 2 represents the proportion of the variability of the assets explained by the first eigenvalue of the correlation matrix of these variables. It follows similar behaviour in different windows, but, as expected, smaller windows make the indicator more sensitive to changes in variables, with greater volatility. The lists of the assets used to construct this and the other indicators in this study can be found in Appendix B.

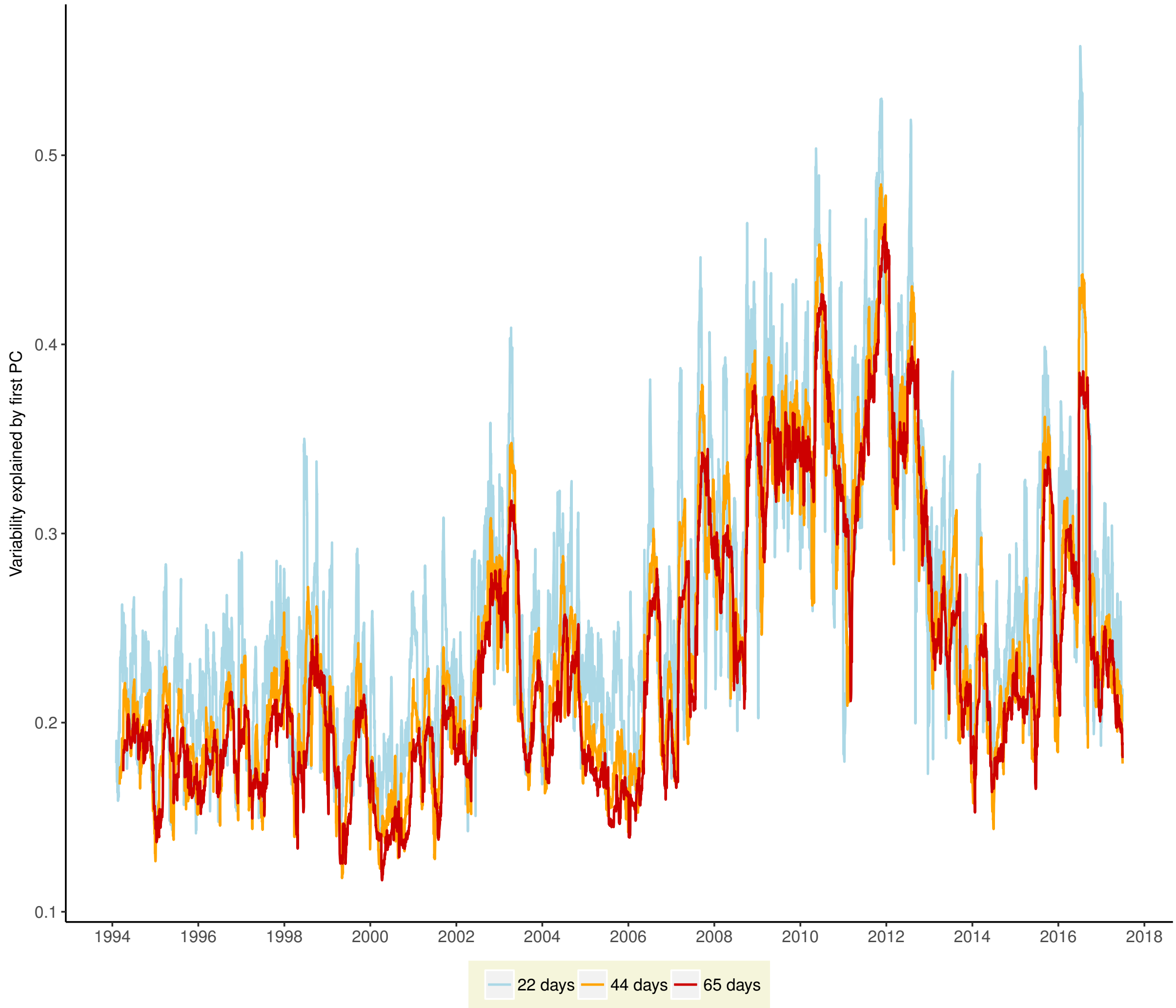

Figure 13 – Indices calculated with 93 assets, windows of 22, 44 and 65 working days.

We can thus analyze the behaviour of the various assets *vis-à-vis* the indicators built with PCA. We identify assets that can be classified as pro-risk assets and others that can be classified as safe havens. The former tends to lose value with the increase of systemic risk and vice versa, that is, it tends to be valued with the decrease of systemic risk. In contrast, safe havens or defensive assets are those that tend to appreciate in times of market stress, due to the search for quality (flight to quality), and vice versa. This classification process is detailed in Appendix C and is used in the following sections.

Usually, when using PCA for the modelling of a systemic risk indicator, there is a need to perform an arbitrary procedure to define the level from which the indicator would be under stress. The methodology proposed in this study, of subjecting the indicator initially calculated by PCA to regime change analysis, avoids this arbitrary procedure, since the Markov switching model itself indicates which regime dominates the market at any given time.

Additionally, applying MS to the indicator extracted in PCA from the correlation matrix of the 93 assets of various classes supports the argument that the indicator is indeed systemic.

As seen in the literature review, most articles that apply MS models to analyze regime changes in financial series use the first component in relation to specific markets, notably stock market indices. However, even though it may also reveal more generalized crisis times, a particular asset or index will have periods of great variation that can be attributed to specific events arising, for example, from geopolitical or climatic problems affecting some commodities or from economic problems restricted to a country that may affect some exchanges or currencies. The use of an eigenvalue indicator of a PCA applied to a representative set of assets allows specific and restricted problems of some markets or countries to have less of an impact on the analysis.

We use switching regression, of the Markovian-type of 2 regimes, which involves switching in the mean of the indicator or in its volatility or even jointly in the mean and volatility. In order to estimate the parameters, the BFGS optimization algorithm (*Broyden-Fletcher-Goldfarb-Shanno* algorithm) is used, which is an iterative method to solve nonlinear optimization problems without restrictions (FLETCHER, 2013). For the purposes of describing the results, we will refer to the normal regime as 1 and to the stress regime as 2. The following results discuss the indicator, which we call the general indicator, built with 93 assets, using a window of data comprising 44 days.

Table 13 shows the results obtained from the estimates of the MS models with different switchings (mean, variance or both) applied to the indicator constructed from the first eigenvalue obtained via PCA. The hypothesis of the existence of regime changes cannot be rejected for any of the switchings analyzed, as can be verified by the p-values. It can be observed that for the switching on the mean in the normal regime, the indicator has an average of approximately 0.20 while in the stress regime, the average of the indicator is approximately 0.34. The p-value analysis shows that the results are quite significant. For the switching in mean and variance, the average of the indicator is 0.325 in the regime of higher systemic risk (regime 2) and the logarithm of the variance is -2.921, which implies a variance of 0.054. For the lower systemic risk regime, the mean of the indicator is 0.196 and the logarithm of the variance is -3.544, which equals a variance of 0.029. With switching in the variance, the logarithm of the variance in the regime of higher systemic risk (regime 2) is -1,124, which is equivalent to 0.325. In the lower systemic risk scenario (regime 1), the variance is 0.200. Analysing these numbers, we see that the mean is smaller and the variance is higher for the switching in the mean and variance relative to switching only in the mean, that is, there is a reallocation between the moments.

	Switchings	Mean	Mean and variance	Variance
Regime 1	C	0.202168	0.19615	
	Std. Error	0.000618	0.000546	
	P-value	0.0000	0.0000	
	log(sigma)	-3.26777	-3.544136	-1.608039
	Std. Error	0.009114	0.01298	0.013075
	P-value	0.0000	0.0000	0.0000
Regime 2	C	0.340759	0.325234	
	Std. Error	0.001062	0.001407	
	P-value	0.0000	0.0000	
	log(sigma)	-3.26777	-2.921316	-1.124256
	Std. Error	0.009114	0.016258	0.0166629
	P-value	0.0000	0.0000	0.0000
	Mean dependent var	0.242071	0.242071	0.24071
	S.E. dependent var	0.073415	0.073415	0.073415
	S.E. of regression	0.037862	0.039091	0.252999
	Sum squared resid	8.720356	9.294168	389.4266
	Durbin-Watson stat	0.065946	0.061937	0.0000982
	Log likelihood	11105.82	11431.4	48.01944
	Akaike info criterion	-3.64799	-3.754649	-0.014466
	Schwarz criterion	-3.64247	-3.74803	-0.010053
	Hannan-Quinn criter.	-3.64607	-3.752352	-0.012935

Table 13 – Estimation results of MS model, different switchings. Independent variable: general index, period: 3/04/1994 to 6/30/2017, 6086 obs.

Table 14 shows the constant transition probabilities between the different regimes and the expected constant durations for the regimes, according to the different switchings. For constant transition probabilities, P(i,k) = P(s_t = k | s_{t-1}=i), rows for i, columns for j. For the mean switching, the constant expected durations suggest that you can expect 107 days of stress regime if you enter one.

Constant transition probabilities	**Switchings**					
	Mean		**Mean and variance**		**Variance**	
Regimes	1	2	1	2	1	2
1	0.996358	0.003642	0.995457	0.004543	0.999013	0.000987
2	0.009324	0.990676	0.008544	0.991456	0.00201	0.99799
Constant expected durations	**Mean**		**Mean and variance**		**Variance**	
Regimes	1	2	1	2	1	2
	274.5827	107.2551	220.1247	117.0469	1013.661	497.5869

Table 14 – Constant transition probabilities and constant expected durations, MS model, different switchings. Independent variable: general index, period: 3/04/1994 to 6/30/2017.

In Figure 14, the general indicator and the probabilities that the indicator is in regime 2 are plotted. In the first graph, the MS modelling is performed with switching in the mean, the second with switching in the mean and variance together and the third with switching in the variance. Shaded areas correspond to periods of systemic financial stress.

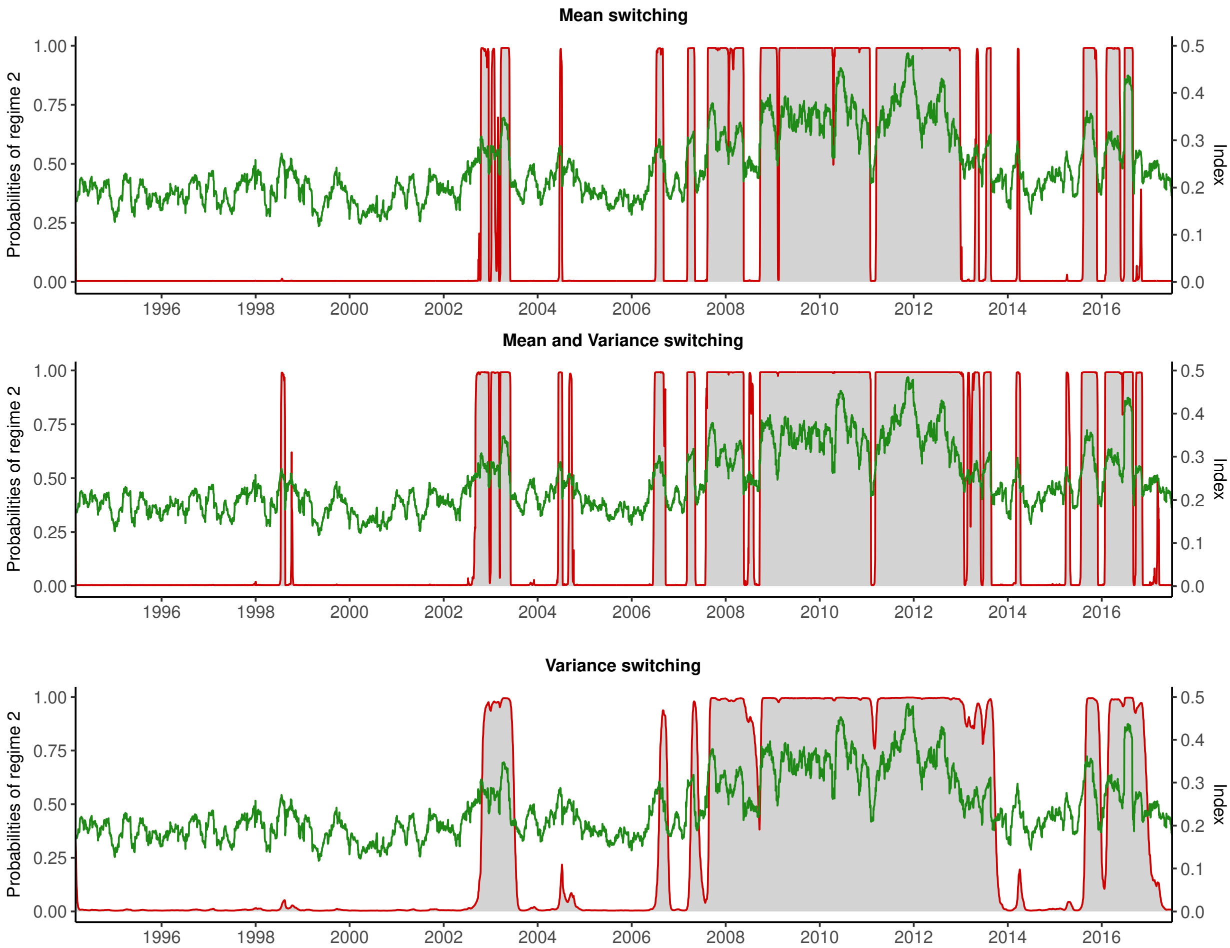

Figure 14 – General indicator plotted with probabilities that series is in regime 2, according to switching in mean, both mean and variance and variance.

In Figure 15, the occurrence of the higher risk regimes can be more easily visualized. Modelling with switching in the mean (dark coloured) shows the highest risk regime in 1709 days for a total of 6086 days of the indicator series (i.e. the indicator was for longer time in the low risk regime, 4418 days). The modelling with switching in mean and variance (intermediate) showed the indicator in the regime of greater risk in 2112 days. The modelling with switching in variance (light coloured shade) shows the indicator at the highest risk regime in 2088 days. It is important to note that the model with switching considering the mean and the variance indicates the risk regime before the other two. In addition, only switching in the mean and variance reveals systemic risk in two moments (in 1998 and 2015), showing the stress regime during more time than the other switchings. It is interesting to further note that the indicator with switching in the variance points to systemic risk for 1294 uninterrupted days between January

2008 and September 2013, depicting the whole period as critical.

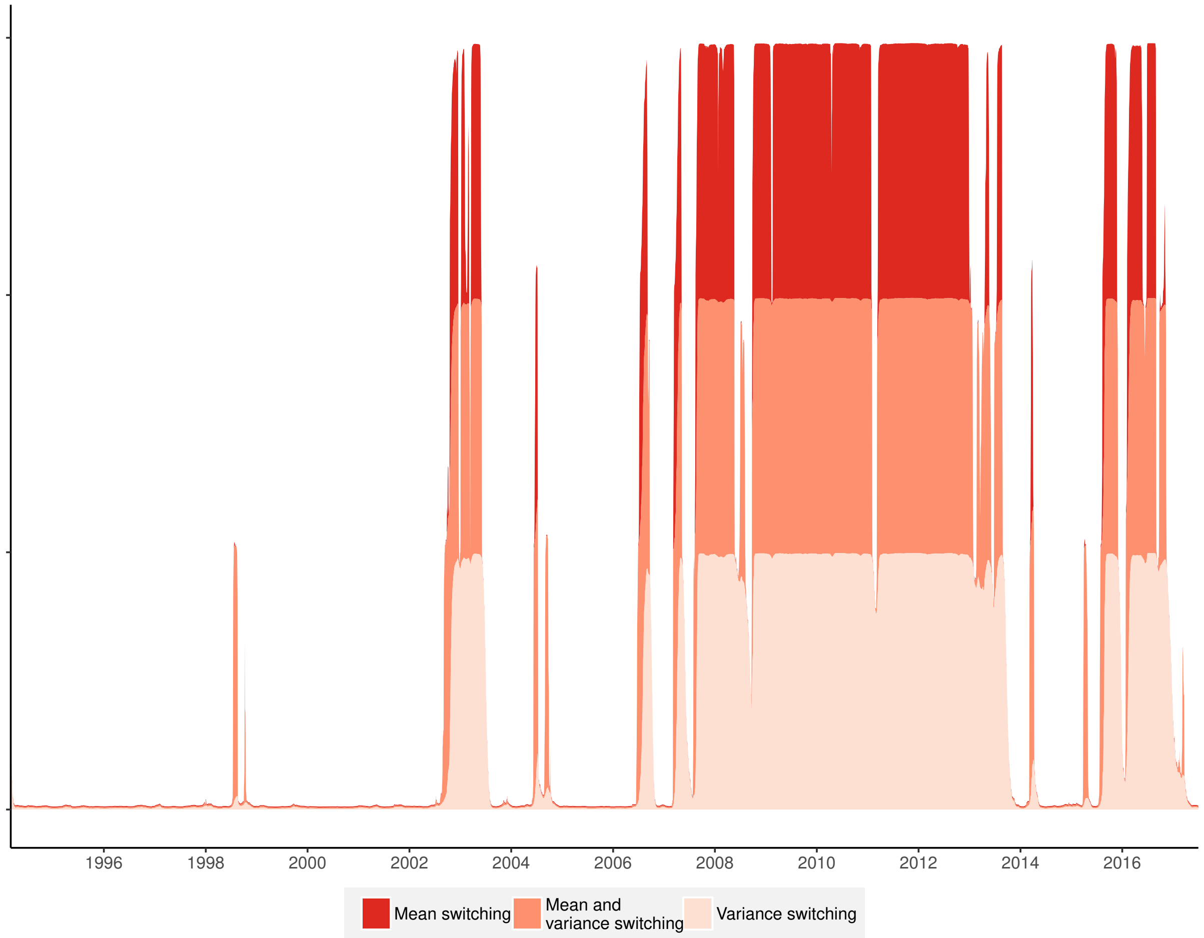

Figure 15 – Ocurrence of stress regime according to general index, MS model, comparative of diffent switchings.

These results refer to Hess (2003) and Dewachter (2001), who analyzed the stock and currency markets and found more pronounced switching in the variance. In our case, where the modelling involves different asset classes, the switching that takes into account both mean and variance is the most pronounced, but in accordance with the above works, the switching using only the mean is less pronounced.

Overall, all models indicate that the market experienced periods of stress in 2003 (Iraq war), 2015 (fears of economic slowdown in China), 2016 (Brexit) and the remarkable cluster of financial stresses between 2007 and 2013, the period of the global financial crisis. However, the MS switching using only the mean is the most parsimonious, indicating the most serious stress scenarios, while the other switchings encompass more days, being more conservative from the viewpoint of risk analysis. The suitability of choosing each of the switchings or their joint use would depend, then, on the objective of being more or less conservative, depending on whether the aim is, for instance, portfolio management or market regulation.

3.4 Discussion of the results

Increasing the degree of asset coupling does not necessarily indicate that assets will depreciate, since agents may be positioning themselves collectively because of a positive market event (e.g. due to relief measures taken by central banks such as quantitative easing), as Williams et al. (2012) emphasize in the discussion of the *RORO* factor. However, according to Kritzman et al. (2011), an indicator pointing to higher systemic risk, even though it does not automatically lead to losses, increases the chances of widespread declines in risk asset prices. In this perspective, a good measure of the effectiveness of the indicator would be to verify whether there is a generalized increase of risk between the assets in moments of stress. Thus, we analyzed the interaction between the indicator and the *value-at-risk* of the assets considered in the study.

Calculations were made as follows: for each day the indicator remained above a 70% probability of being in stress, the historical *VaR* of the period used to calculate the indicator (the previous 44 days) was obtained. The VaR for the normal period was also calculated similarly to the days on which the indicator was less than a 70% probability of the market being in stress. The calculation is made by a historical VaR at the 95% confidence level, which means we extract a value between the third- and fourth-largest losses of each period. At the end, the mean of these values is obtained, reaching the average *VaR* for each regime. To deepen the analysis, we then compared different levels of confidence for the *VaR*.

Analysing the historical VaR of the assets for periods of stress and for the normal periods, we find that the metric is systematically higher for periods of stress, being twice as high for some indexes of banks and small caps , despite the number of days of stress being much smaller than the normal number of days (2112 days of stress by the indicator with switching both in the mean and variance, in a total sample of 6086 days). Table 15 presents the average historical *VaR* of the assets at the 95% confidence level using simple returns and a window of 44 days, corresponding to the variation of the general indicator. Assets are sorted from highest to lowest *VaR* for the stress regime with switching only in the mean.

	Normal			*Stress*			Prop. *Stress*/Normal		
93 assets	**Mean**	**Mean variance**	**Variance**	**Mean**	**Mean variance**	**Variance**	**Mean**	**Mean Variance**	**Variance**
CMT_Natgas	-4.76%	-4.82%	-4.87%	-4.49%	-4.43%	-4.36%	0.9	0.9	0.9
CMT_Oil_WTI	-3.17%	-3.18%	-3.21%	-3.62%	-3.52%	-3.46%	1.1	1.1	1.1
SX_Banks_Euro	-1.80%	-1.70%	-1.71%	-3.61%	-3.44%	-3.38%	2.0	2.0	2.0
SX_Banks_SP500	-1.83%	-1.80%	-1.78%	-3.57%	-3.29%	-3.31%	1.9	1.8	1.9
CMT_Nickel	-2.69%	-2.65%	-2.69%	-3.55%	-3.46%	-3.38%	1.3	1.3	1.3
CMT_Wheat	-2.35%	-2.30%	-2.28%	-3.36%	-3.25%	-3.26%	1.4	1.4	1.4
CMT_Suggar	-2.70%	-2.70%	-2.67%	-3.33%	-3.21%	-3.25%	1.2	1.2	1.2
CMT_Silver	-2.32%	-2.28%	-2.27%	-3.19%	-3.08%	-3.08%	1.4	1.4	1.4
CMT_Palladium	-2.71%	-2.69%	-2.70%	-3.15%	-3.09%	-3.08%	1.2	1.1	1.1
SX_Banks_FTSE	-1.89%	-1.84%	-1.84%	-3.12%	-2.96%	-2.93%	1.7	1.6	1.6
CMT_Cotton	-2.31%	-2.30%	-2.32%	-2.95%	-2.84%	-2.80%	1.3	1.2	1.2
CMT_Coffee	-3.60%	-3.67%	-3.70%	-2.91%	-2.91%	-2.88%	0.8	0.8	0.8
CMT_Corn	-2.09%	-2.05%	-2.04%	-2.90%	-2.81%	-2.82%	1.4	1.4	1.4
SX_IBOV	-2.89%	-2.92%	-2.97%	-2.72%	-2.69%	-2.62%	0.9	0.9	0.9
SX_Banks_Nikkei	-2.11%	-2.07%	-2.10%	-2.65%	-2.61%	-2.56%	1.3	1.3	1.2
VOL_VIX	-1.58%	-1.55%	-1.58%	-2.61%	-2.46%	-2.38%	1.7	1.6	1.5
SX_Russell2000	-1.56%	-1.53%	-1.55%	-2.61%	-2.46%	-2.40%	1.7	1.6	1.5
SX_CAC	-1.71%	-1.67%	-1.71%	-2.60%	-2.48%	-2.40%	1.5	1.5	1.4
SX_IBEX	-1.72%	-1.69%	-1.71%	-2.58%	-2.47%	-2.42%	1.5	1.5	1.4
SX_Nikkei	-1.92%	-1.90%	-1.92%	-2.58%	-2.49%	-2.45%	1.3	1.3	1.3
SX_DAX	-1.80%	-1.76%	-1.81%	-2.53%	-2.45%	-2.36%	1.4	1.4	1.3
CMT_Soybean	-2.09%	-2.06%	-2.08%	-2.52%	-2.49%	-2.44%	1.2	1.2	1.2

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	Normal			*Stress*			Prop. *Stress*/Normal		
93 assets	**Mean**	**Mean variance**	**Variance**	**Mean**	**Mean variance**	**Variance**	**Mean**	**Mean Variance**	**Variance**
CMT_Oil_Stoxx	-1.79%	-1.75%	-1.79%	-2.51%	-2.43%	-2.35%	1.4	1.4	1.3
SX_HSI	-1.96%	-1.96%	-2.01%	-2.50%	-2.39%	-2.30%	1.3	1.2	1.1
SX_OMX	-1.78%	-1.75%	-1.80%	-2.46%	-2.37%	-2.27%	1.4	1.3	1.3
VOL_VDAX	-1.56%	-1.52%	-1.57%	-2.35%	-2.26%	-2.16%	1.5	1.5	1.4
SX_Kospi	-2.26%	-2.30%	-2.37%	-2.28%	-2.20%	-2.08%	1.0	1.0	0.9
SX_Nasdaq	-2.33%	-2.37%	-2.42%	-2.26%	-2.19%	-2.11%	1.0	0.9	0.9
SX_Stoxx_Small	-1.14%	-1.10%	-1.13%	-2.20%	-2.07%	-2.00%	1.9	1.9	1.8
CMT_Platinum	-1.79%	-1.77%	-1.74%	-2.16%	-2.12%	-2.17%	1.2	1.2	1.2
SX_MSCI_EM	-1.42%	-1.38%	-1.44%	-2.14%	-2.06%	-1.95%	1.5	1.5	1.4
SX_FTSE	-1.37%	-1.34%	-1.37%	-2.10%	-2.03%	-1.96%	1.5	1.5	1.4
SX_SP500	-1.32%	-1.29%	-1.32%	-2.10%	-1.99%	-1.92%	1.6	1.5	1.5
FX_CHF	-1.49%	-1.46%	-1.47%	-2.04%	-1.98%	-1.96%	1.4	1.4	1.3
CMT_Agric	-1.43%	-1.42%	-1.41%	-2.02%	-1.93%	-1.93%	1.4	1.4	1.4
SX_Retail_Stoxx	-1.37%	-1.33%	-1.33%	-2.00%	-1.95%	-1.94%	1.5	1.5	1.5
SX_Swiss	-1.44%	-1.41%	-1.44%	-1.93%	-1.89%	-1.82%	1.3	1.3	1.3
SX_DJones	-1.27%	-1.25%	-1.29%	-1.92%	-1.83%	-1.76%	1.5	1.5	1.4
SX_Mexbol	-1.90%	-1.93%	-1.98%	-1.89%	-1.84%	-1.75%	1.0	1.0	0.9
SX_Sidney	-1.11%	-1.09%	-1.10%	-1.88%	-1.77%	-1.74%	1.7	1.6	1.6
SX_Toronto	-1.22%	-1.21%	-1.22%	-1.86%	-1.76%	-1.72%	1.5	1.5	1.4
CMT_CRB	-1.31%	-1.30%	-1.30%	-1.85%	-1.76%	-1.75%	1.4	1.4	1.4
CMT_Gold	-1.31%	-1.27%	-1.25%	-1.78%	-1.75%	-1.77%	1.4	1.4	1.4

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	Normal			***Stress***			**Prop. *Stress*/Normal**		
93 assets	**Mean**	**Mean variance**	**Variance**	**Mean**	**Mean variance**	**Variance**	**Mean**	**Mean Variance**	**Variance**
FI_Libor_USA6m	-1.28%	-1.23%	-1.24%	-1.77%	-1.78%	-1.75%	1.4	1.4	1.4
FX_CNY	-1.14%	-1.10%	-1.12%	-1.66%	-1.63%	-1.57%	1.5	1.5	1.4
CMT_Roll_BBG	-1.06%	-1.04%	-1.04%	-1.63%	-1.55%	-1.54%	1.5	1.5	1.5
FI_Libor_UK6m	-1.38%	-1.41%	-1.44%	-1.49%	-1.43%	-1.37%	1.1	1.0	1.0
FX_SEK	-0.98%	-0.97%	-0.98%	-1.47%	-1.41%	-1.38%	1.5	1.5	1.4
FX_CLP	-0.95%	-0.95%	-0.95%	-1.44%	-1.36%	-1.34%	1.5	1.4	1.4
FX_TWD	-0.99%	-0.99%	-0.99%	-1.33%	-1.27%	-1.25%	1.3	1.3	1.3
FX_RUB	-0.98%	-0.97%	-0.97%	-1.33%	-1.28%	-1.26%	1.4	1.3	1.3
FX_PHP	-0.99%	-0.99%	-0.99%	-1.26%	-1.21%	-1.21%	1.3	1.2	1.2
FX_HKD	-0.79%	-0.76%	-0.75%	-1.11%	-1.12%	-1.12%	1.4	1.5	1.5
FX_PEN	-0.85%	-0.85%	-0.86%	-1.11%	-1.06%	-1.05%	1.3	1.2	1.2
FX_TRY	-1.11%	-1.11%	-1.14%	-1.05%	-1.06%	-1.00%	0.9	1.0	0.9
FX_COP	-0.60%	-0.59%	-0.59%	-1.04%	-0.99%	-0.97%	1.7	1.7	1.6
FX_EUR	-0.71%	-0.70%	-0.70%	-1.02%	-0.99%	-0.98%	1.4	1.4	1.4
FX_DXY	-0.97%	-0.97%	-0.97%	-1.00%	-0.98%	-0.99%	1.0	1.0	1.0
FX_INR	-0.85%	-0.85%	-0.85%	-1.00%	-0.97%	-0.96%	1.2	1.1	1.1
FI_Esp10y	-0.74%	-0.74%	-0.73%	-0.99%	-0.95%	-0.96%	1.3	1.3	1.3
FX_JPY	-0.75%	-0.74%	-0.73%	-0.99%	-0.96%	-0.96%	1.3	1.3	1.3
FX_NZD	-0.95%	-0.94%	-0.93%	-0.95%	-0.96%	-0.97%	1.0	1.0	1.0
FX_IDR	-0.71%	-0.71%	-0.72%	-0.84%	-0.81%	-0.80%	1.2	1.2	1.1
FX_MXN	-1.44%	-1.48%	-1.54%	-0.82%	-0.86%	-0.77%	0.6	0.6	0.5

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	Normal			***Stress***			**Prop. *Stress*/Normal**		
93 assets	**Mean**	**Mean variance**	**Variance**	**Mean**	**Mean variance**	**Variance**	**Mean**	**Mean Variance**	**Variance**
SX_Food_DJ	-0.75%	-0.76%	-0.75%	-0.81%	-0.78%	-0.80%	1.1	1.0	1.1
FX_NOK	-0.43%	-0.41%	-0.40%	-0.73%	-0.70%	-0.73%	1.7	1.7	1.8
FI_Can10y	-0.72%	-0.72%	-0.73%	-0.71%	-0.70%	-0.70%	1.0	1.0	1.0
FI_Germ10y	-0.59%	-0.60%	-0.59%	-0.71%	-0.68%	-0.69%	1.2	1.1	1.2
FI_Fran10y	-0.62%	-0.63%	-0.62%	-0.67%	-0.65%	-0.66%	1.1	1.0	1.1
FX_THB	-0.65%	-0.65%	-0.67%	-0.65%	-0.65%	-0.63%	1.0	1.0	0.9
FX_BRL	-0.54%	-0.55%	-0.54%	-0.62%	-0.60%	-0.61%	1.1	1.1	1.1
FX_ZAR	-0.45%	-0.44%	-0.45%	-0.55%	-0.55%	-0.54%	1.2	1.2	1.2
FI_Libor_UK3m	-0.62%	-0.62%	-0.64%	-0.54%	-0.55%	-0.52%	0.9	0.9	0.8
CORP_IG_Barc	-0.44%	-0.44%	-0.44%	-0.52%	-0.51%	-0.51%	1.2	1.1	1.2
FI_USA6m	-0.48%	-0.47%	-0.47%	-0.51%	-0.50%	-0.51%	1.1	1.1	1.1
SX_JPM_Global	-0.85%	-0.88%	-0.90%	-0.46%	-0.48%	-0.45%	0.5	0.6	0.5
FX_AUD	-0.38%	-0.38%	-0.38%	-0.43%	-0.42%	-0.43%	1.1	1.1	1.1
FI_Libor_USA1m	-0.38%	-0.37%	-0.37%	-0.41%	-0.43%	-0.42%	1.1	1.1	1.1
CORP_AAA	-0.27%	-0.27%	-0.26%	-0.37%	-0.35%	-0.35%	1.4	1.3	1.3
FX_SGD	-0.38%	-0.37%	-0.36%	-0.36%	-0.39%	-0.40%	0.9	1.0	1.1
CORP_BAA	-0.26%	-0.26%	-0.26%	-0.35%	-0.33%	-0.34%	1.4	1.3	1.3
FI_USA10y	-0.45%	-0.45%	-0.45%	-0.31%	-0.32%	-0.32%	0.7	0.7	0.7
MBS_US_Barc	-0.26%	-0.26%	-0.26%	-0.24%	-0.23%	-0.24%	0.9	0.9	0.9
FX_GBP	-0.07%	-0.06%	-0.05%	-0.14%	-0.14%	-0.15%	2.2	2.5	2.9
SPR_US2y10y	-0.08%	-0.09%	-0.09%	-0.06%	-0.06%	-0.06%	0.8	0.7	0.7

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	Normal			*Stress*			Prop. *Stress*/Normal		
93 assets	**Mean**	**Mean variance**	**Variance**	**Mean**	**Mean variance**	**Variance**	**Mean**	**Mean Variance**	**Variance**
FX_KRW	-0.04%	-0.04%	-0.04%	-0.04%	-0.04%	-0.04%	1.2	1.1	1.0
SPR_US10y30y	-0.07%	-0.08%	-0.08%	-0.03%	-0.03%	-0.03%	0.4	0.4	0.4
FX_CAD	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%	0.8	0.8	0.8
FI_USA_CredGov	-0.02%	-0.02%	-0.02%	-0.01%	-0.01%	-0.01%	0.7	0.7	0.7
FI_Swiss10y	-0.01%	-0.01%	-0.02%	-0.01%	-0.01%	-0.01%	0.4	0.4	0.4
FI_Japan10y	-0.01%	-0.01%	-0.01%	0.00%	0.00%	0.00%	0.5	0.4	0.4
FI_UK10Y	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.9	0.8	0.7
FI_Australia	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%	0.7	0.7	0.7

Table 15 – Average historical *VaR* (95% confidence level) and proportion between regimes.

From the results obtained, it can be observed that in the systemic risk regime, the average *VaR* of the analyzed assets is generally higher, reaching double the risk in some cases. In the mean of all 93 assets analyzed, the average *VaR* in the normal regime (using switching just on the mean) is -1.23%, while in the stress regime it is -1.58%, an increase of 29%. This analysis also confirms that there are assets that can be considered pro-risk while others are defensive (see Table 29, in Appendix C).

When analysing only the assets according to Table 29, the pro-risk assets have an average *VaR* of -2.05% for the stress periods and of -1.50% for the normal periods (mean switching). On average, comparing each asset in different regimes, the risk increase is approximately 37% for stress periods, and 25 of 28 assets had higher *VaR* in this regime. This result is even more interesting if we consider that the number of days in the normal regime is approximately double the periods of stress, since a much larger sample for the *VaR* calculation could allow larger losses to arise if the segregation of risk regimes was not really effective. In contrast, the defensive assets have a *VaR* of -0.55% and -0.45% in the stress and normal regimes, respectively. And by computing the comparative of each asset in different regimes, the average increase is only 3% higher in the periods of stress, confirming that they are a flight for quality asset. It is observed that 7 of the 19 conservative assets present even lower *VaR* during stress periods. Other assets, which were not classified in Table 29, have idiosyncratic risk prevailing over the systemic risk. These assets often went through declines when the market was in more favorable times. For example, the Ibovespa (SX_Ibov) has a *VaR* of -2.72% for the stress regime and of -2.89% for normal periods, a ratio of 0.9, which is well below those calculated, in general, for the other risky assets.

To get a sense of the adequacy of the general indicator built via PCA and MS to depict systemic risk, Table 16 shows the periods of stress indicated by our model. By verifying the shown dates, one can affirm that in the stress periods suggested by the indicator, there were quite shocking events for the dynamics of the international financial markets, as listed in Table 17.

Mean			Mean and variance			Variance		
Start	End	Days	Start	End	Days	Start	End	Days
			7/17/98	8/17/98	22			
10/17/02	11/29/02	32	9/5/02	12/18/02	75	10/30/02	6/25/03	171
12/2/02	12/16/02	11						
1/8/03	1/31/03	18	1/3/03	3/7/03	46			
3/20/03	5/27/03	49	3/17/03	6/3/03	57			
6/22/04	7/8/04	13	6/10/04	7/9/04	22			
			9/1/04	9/22/04	16			
7/10/06	9/1/06	40	6/26/06	9/8/06	55	8/9/06	9/29/06	38
			9/12/06	9/19/06	6			
3/13/07	5/4/07	39	3/7/07	5/8/07	45	4/11/07	5/28/07	34
8/15/07	1/23/08	116	8/1/07	5/20/08	210	8/27/07	8/27/08	263
1/25/08	5/19/08	82						
			7/1/08	8/1/08	24			
9/26/08	2/5/09	95	9/23/08	2/1/11	616	10/1/08	9/16/13	1294
2/20/09	4/14/10	299						
4/19/10	1/26/11	203						
3/16/11	12/26/12	466	3/9/11	1/23/13	491			
			2/22/13	3/13/13	14			
4/30/13	5/17/13	14	3/27/13	5/30/13	47			
7/18/13	8/21/13	25	6/27/13	8/23/13	42			
3/18/14	3/28/14	9	3/7/14	4/8/14	23			
			3/31/15	4/24/15	19			
8/11/15	11/23/15	75	7/27/15	11/30/15	91	8/28/15	12/17/15	80
2/5/16	5/23/16	77	1/27/16	8/31/16	156	2/19/16	12/6/16	208
6/27/16	8/29/16	46						
			9/23/16	11/10/16	35			
Totals of days		1709			2112			2088

Table 16 – Dates of periods of stress according general index, MS model, different switchings.

Period	Event
1998	Russia financial crisis.
July 1998	Asia financial crisis.
2002	Burst of internet bubble.
April 2003	Beginning of Iraq War, tensions already felt in markets since the beginning of year.
2007–2013	Global financial crisis and Great Recession, with many problems worsening each other: mortgage markets crisis, bank failures, European debt crisis and risk for the European project, Euro currency under risk, big interventions managed by central banks, generalized downgrades of financial institutions and countries.
2015–2016	Speculations on China economic slowdown and Brexit.
2016–2017	Uncertanties caused by Donald Trump election.

Table 17 – Events of stress in international financial markets.

We will now check the behaviour of the stress indicator if only one asset class is used in its construction, in this case stock indexes, as was done in Hess (2003), who studied the stock market using Markov switching techniques. In the literature, these assets are considered proxies for the market portfolios. Thus, one could ask whether they can replace our more general index without loss of quality in the measurement of stress in the markets. Table 18 summarizes the MS estimation data for different switchings and Table 19 presents the results of the constant transition probabilities between the regimes and the expected long durations.

	Switchings	**Mean**	**Mean and variance**	**Variance**
Regime 1	C	0.409235	0.412341	
	Std. Error	0.001422	0.001628	
	P-value	0.0000	0.0000	
	log(sigma)	-2.84864	-2.795922	-0.966146
	Std. Error	0.009176	0.013561	0.032118
	P-value	0.0000	0.0000	0.0000
Regime 2	C	0.558401	0.561526	
	Std. Error	0.001414	0.00158	
	P-value	0.0000	0.0000	
	log(sigma)	-2.84864	-2.910576	-0.640354
	Std. Error	0.009176	0.014911	0.012716
	P-value	0.0000	0.0000	0.0000
	Mean dependent var	0.484948	0.484948	0.484948
	S.E. dependent var	0.094435	0.094435	0.094435
	S.E. of regression	0.056725	0.056654	0.494137
	Sum squared resid	19.5733	19.52106	1485.54
	Durbin-Watson stat	0.065545	0.065843	0.000643
	Log likelihood	8518.243	8532.799	-4253.722
	Akaike info criterion	-2.79765	-2.802103	1.399186
	Schwarz criterion	-2.79213	-2.795484	1.403598
	Hannan-Quinn criter.	-2.79573	-2.799806	1.400717

Table 18 – Estimation results of MS model, different switchings. Inpendent variable: stocks index, period: 3/04/1994 to 6/30/2017, 6086 obs.

Constant transition probabilities	**Switchings**					
	Mean		**Mean and variance**		**Variance**	
Regimes	1	2	1	2	1	2
1	0.991613	0.008387	0.991821	0.008179	0.99804	0.00196
2	0.00845	0.99155	0.008942	0.991058	0.000761	0.999239
Constant expected durations	**Mean**		**Mean and variance**		**Variance**	
	1	2	1	2	1	2
	119.2376	118.3375	122.2636	111.8302	510.1304	1313.685

Table 19 – Constant transition probabilities and expected durations according to different switchings. Independent variable: stocks index, window of 44 working days, period: 3/04/1994 to 6/30/2017.

Figure 16 illustrates the indicator using PCA and MS techniques applied only to stock indexes, plotted together with the probabilities that the series is in regime 2 (stress) for the different switchings.

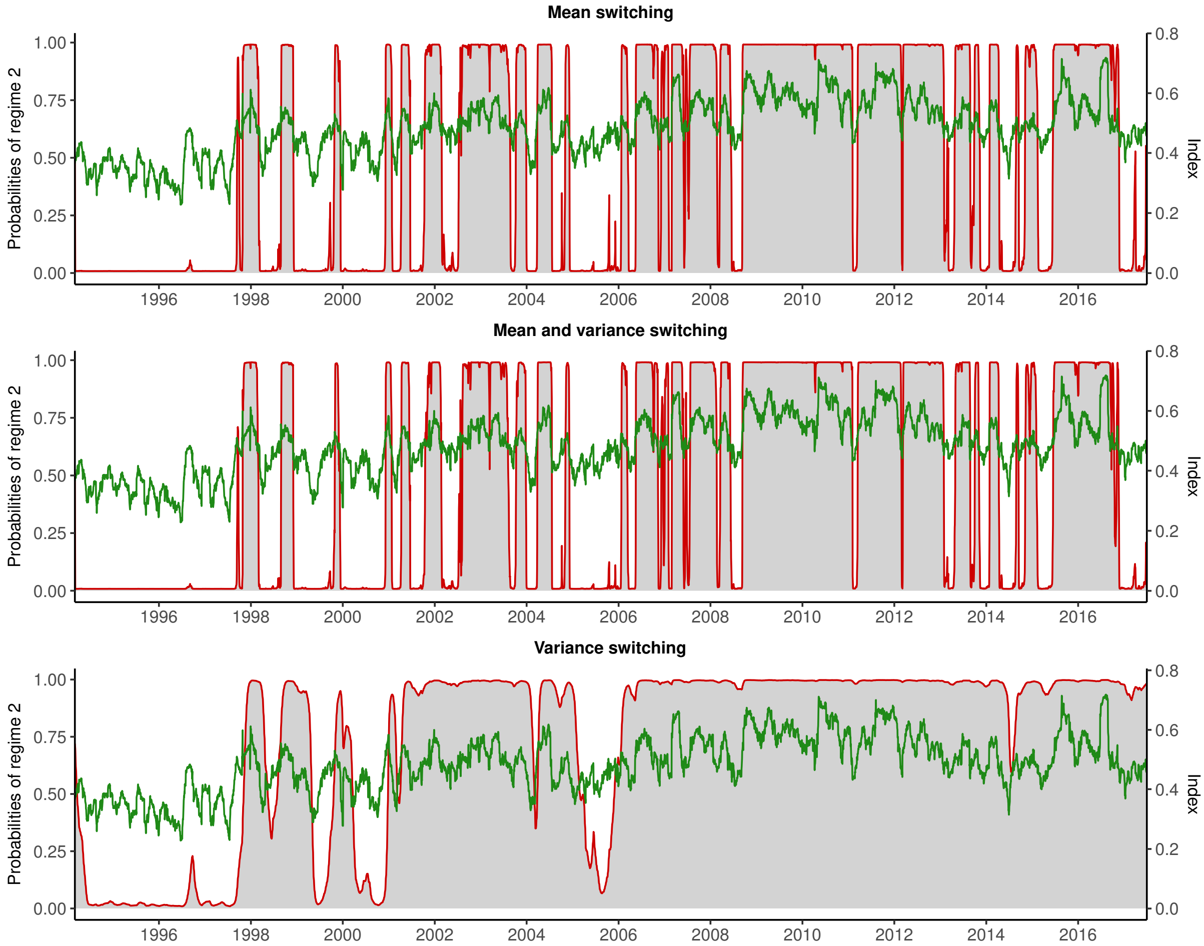

Figure 16 – Stocks index plotted with probabilities that series is in regime 2, according to switching in mean, both mean and variance and variance.

Table 18 confirms that the existence of regime breaks cannot be rejected, which is consistent with the work of Turner et al. (1989) for this asset class. Similarly to Hess (2003), our analysis confirms the sharpest switching in the variance, as can be seen in Figure 16.

The index calculated only with indexes of actions points to stress regimes in many other moments compared to the general index, as is verified by Table 20 and Figure 17. The switching in mean, for example, suggests 3050 days under stress against 1709 days for the general indicator. The hypothesis is that this indicator constructed only with stock indexes would identify, in addition to more generalized risk events, scenarios of stress more related to the stock markets that did not necessarily spread to other asset markets. In this sense, the original indicator involving several classes of assets would be more appropriate for the objective of discriminating periods of risk that are more markedly systemic.

	Mean	Mean and variance	Variance
General	1709	2112	2088
Stocks	3050	2889	4346

Table 20 – Number of days of stress regime according to the indicators.

Figure 17 – Comparative of occurrence of regime 2 according to general indicator and stocks indicator, MS model, mean switching.

Table 21 shows, for comparison purposes, the average *VaR* (95% confidence level) in the different regimes and switchings for the general and stock indicators, built via PCA and MS. It can be noticed that the indicator constructed with stock indexes reveals smaller risks for both normal periods and periods of stress. Thus, this indicator would point to stress regimes starting in lower generalized risk levels. This may be desirable if the purpose of the indicator is conservative portfolio management. In contrast, it can be said that it would not be so effective to point out the moments of stress that are effectively generalized, which would be expected of a reliable indicator of systemic risk.

	Normal Regime		Stress Regime	
	Stocks index	**Gen. index**	**Stocks index**	**Gen. index**
All assets	-1.16%	-1.23%	-1.48%	-1.58%
Pro-Risk	-1.42%	-1.50%	-1.88%	-2.05%
Safe Havens	-0.44%	-0.45%	-0.52%	-0.55%

Table 21 – Comparative of performance between general index and stocks index, according to average *VaR* (95%) in each regime.

In Figure 18, we can see the average *VaR* plots for all assets and only for pro-risk assets and safe havens assets separately (a classification of pro-risk assets and safe havens can be found in Table 29 of Appendix C). The *VaR* is calculated for each regime indicated by the general and stock indicators in different switchings and for different levels of confidence. The results again show that the overall general indicator always points to larger risks in both regimes, regardless of the type of asset and the level of confidence established.

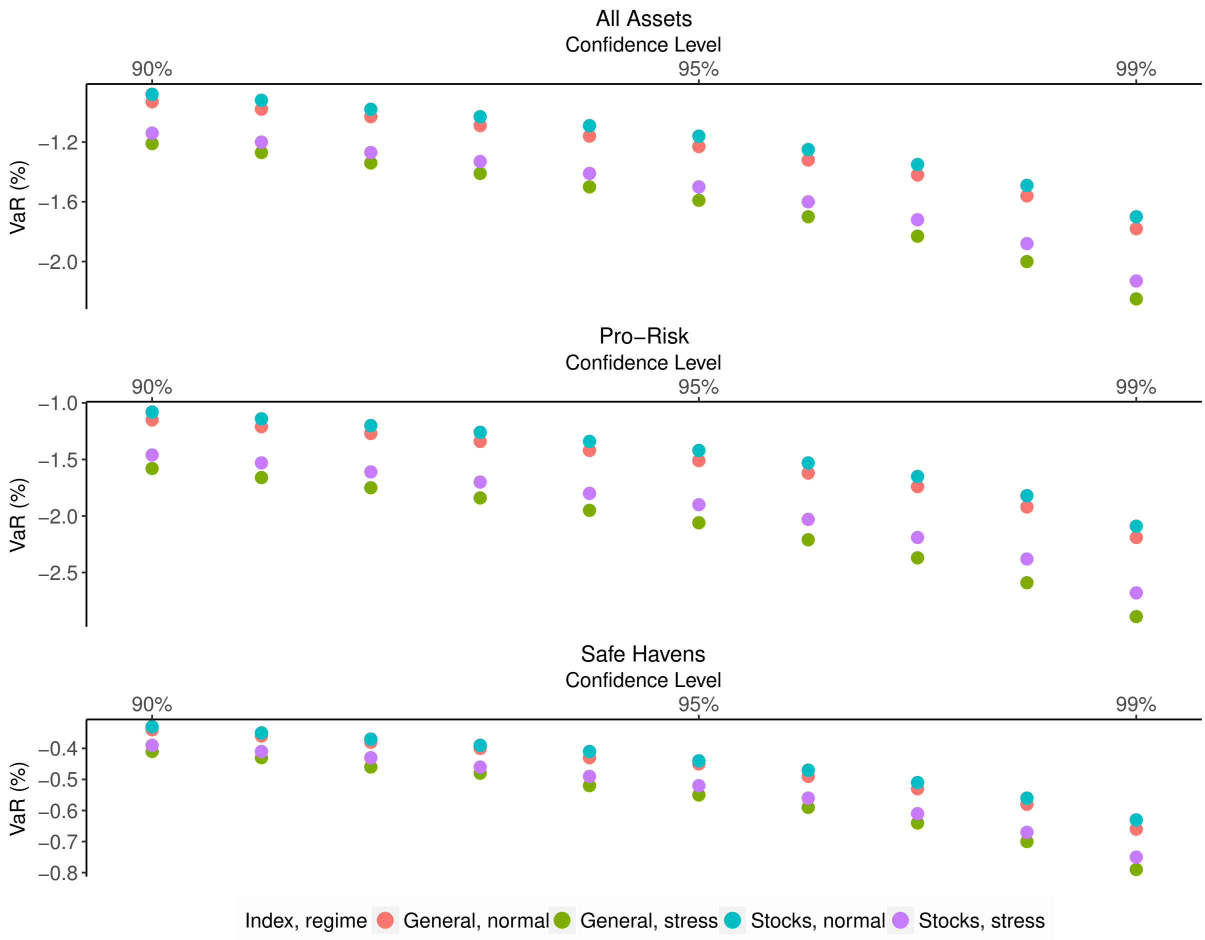

Figure 18 – Average *VaR* for different assets groups and different confidence levels.

Finally, we compared indicators constructed with other asset classes beyond stock indexes: commodities, FX (foreign exchanges) and bonds. Looking at Figure 19, it is interesting that the bonds indicator suggests regime 2 for a much longer period than the other indicators.

This result can be explained by the fact that fixed income securities tend to vary much more in unison than the assets of other classes, since some countries such the United States have a great influence on interest rates in other countries. Thus, the indicator using bonds would not point out to risk of stress. Quite the opposite, we see that in the period of the financial crisis, while the other indicators point to the stress regime, the bond indicator often does not, suggesting that the fundamentals and risks of each country came to prevail in relation to the normal dynamics of greater interconnection among interest rates.

The commodities and FX (currencies) indicators suggest fewer stress days than the stock market indicator. However, again, it is the general indicator that shows a more selective occurrence of regime 2. Comparing the VaR calculated for the stress regimes indicated by the different indicators (Table 22), we find that when the general indicator points to a stress regime, the average loss expected for the assets is generally higher.

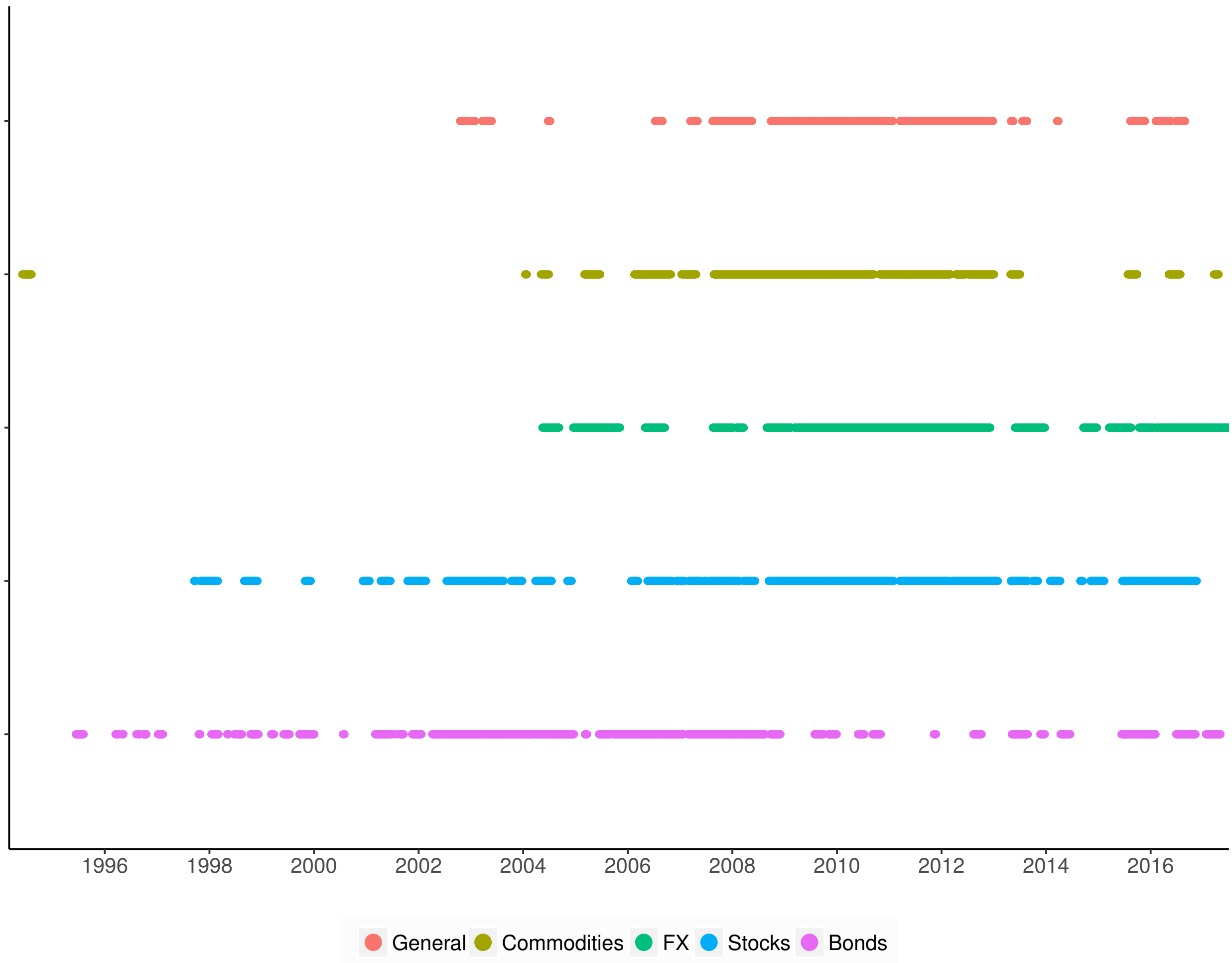

Figure 19 – Occurrence of regime 2 according to indicators constructed with especific classes of assets, window of 44 working days, mean switching.

Normal regime					
	Indicator constructed using				
Asset classes	Bonds	Commod.	FX	Stocks	General
Bonds	-0.46%	-0.45%	-0.46%	-0.45%	-0.46%
Commod.	-2.45%	-2.32%	-2.38%	-2.28%	-2.35%
FX	0.80%	-0.76%	-0.74%	-0.70%	-0.75%
Stocks	-1.87%	-1.75%	-1.85%	-1.59%	-1.71%
General	-1.32%	-1.24%	-1.27%	-1.16%	-1.23%
Stress regime					
	Indicator constructed using				
Asset classes	Bonds	Commod.	FX	Stocks	General
Bonds	-0.49%	-0.52%	-0.50%	-0.50%	-0.52%
Commod.	-2.55%	-2.86%	-2.66%	-2.69%	-2.84%
FX	-0.80%	-0.88%	-0.88%	-0.89%	-0.93%
Stocks	-1.87%	-2.11%	-1.91%	-2.13%	-2.28%
General	-1.34%	-1.52%	-1.42%	-1.48%	-1.58%

Table 22 – Comparative of average VaR for each assets class in different regimes according to different indicators, mean switching, windows of 44 working days.

3.5 Conclusions

In this study, we sought to model a systemic risk indicator for the international financial market. Using a large number of assets with complete series from 1994 to 2017 that belong to several asset classes from the most important developed and emerging countries, we proposed a systemic financial risk indicator.

The study of these variables *vis-à-vis* the indicator using PCA allowed us to map which assets work as safe havens and which ones are riskier. This indicator can be very useful in helping portfolio managers pick assets and define allocation strategies. Thus, the systemic risk indicator not only helps regulators establish mechanisms to prevent markets from severe crises, but also allows managers of financial institutions and fund managers to choose assets when facing different market regimes.

By combining principal components analysis and Markov switching modelling across a broad base of financial variables, the study contributes to research on financial systemic risk. By applying MS to the indicator generated by the PCA, it can be argued that regime breaks are more likely to be systemic in nature compared to the application of regime change modelling to analyze the behaviour of specific variables such as indexes of stocks, bonds or currencies separately.

Moreover, the threshold for separating the two regimes is our study is not arbitrary since the definition of being in the "mode" of systemic risk is automatically generated by the MS mechanism.

The final indicator generated by PCA and MS was evaluated for the ability to reveal a generalized risk increase among assets, asserting the usefulness of the indicator, since the average historical VaR (95% confidence level) was systematically and considerably higher. Moreover, for the pro-risk assets, the increase in average VaR during stress times compared to normal times was even higher. On the other hand, by computing the comparative of each defensive asset in different regimes, the average increase was only 3% in the periods of stress, confirming their status as flight to quality assets.

In this study, we also investigated whether this general indicator of systemic risk could be replaced by an indicator built only with stock indexes, that is, the so-called market portfolios. The indicator constructed with stock indexes points to stress regimes on many more days than the general indicator (3050 versus 1079 when allowing switching in the mean). By analysing the *VaR* of the assets for the different regimes, it is verified that the indicator constructed only with indexes of stocks is more conservative, since it points to the stress regime in less-risky scenarios, on average. This may be desirable if the purpose of the indicator is to conservatively manage assets portfolios, but it is less effective as a systemic risk indicator. This comparison could be extended to other asset classes.

In addition, one may ask whether the general indicator, even using several asset classes, could not be built from a smaller number of variables. The PCA and MS procedures could be performed through an appropriate process of selecting the best and most synthetic variables. However, a wider number of variables can generally be convenient in the sense of diluting any possible correlation breaks of specific variables, as was observed in our study. A parsimonious selection of assets, not having been addressed, is a limitation of this work and suggests a direction for future studies.

Considering the results obtained, it is emphasized that the developed indicators were able to reveal moments of stress in the international financial markets. Thus, modelling based on PCA and MS is promising for evaluating the aggregate behaviour of financial variables in order to analyze systemic risk. Notably, 2007–2013 appears as a large cluster of systemic risk, confirming the seriousness of the period in international financial markets.

One question that arises is whether, since this crisis, markets are still operating in a new "mode", since the indicator has revealed very few moments of pre-crisis stress but has already signalled another three periods of crisis after 2013. Are the agents more prone to herd behaviour as a memory of that period? Could this result reflect technological advances and market interconnections that are changing the financial markets and imposing new systemic risk factors? It may still be too early to answer this issue, but it is a question that merits to be addressed in future work.

Another point to note is that the effectiveness of the indicator can be gauged, but these methodologies are limited. There is always the possibility of comparing the indicator with other existing metrics, checking adherence to known periods of stress or even measuring the indicator against the average risk level of the traded assets, as we conducted in the last two procedures of this work. Another form of benchmarking, which would also be of practical use, would be to verify the effectiveness of the indicator for forecasting systemic crises and for making allocation decisions in portfolio management, which are also opportunities for further researches.

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Appendices

Appendix A – Description of variables and composition of indicators

Each asset class has a code to facilitate identification:

- CMT - Commodities;
- CORP - Corporates;
- FI - Fixed Income;
- FX - Foreign Exchanges (currencies);
- MBS - Mortgage backed securities index;
- SPR - Spreads;
- SX - Stock Exchanges indices;
- VOL - Volatillity.

Abbreviations used in this work, tickers used by the Bloomberg information provider and descriptions of the variables given by the provider.

- CMT_Agric - BCOMAG Index - Bloomberg Agriculture Subindex - Composed of futures contracts on coffee, corn, cotton, soybeans, soybean oil, soybean meal, sugar and wheat. Quoted in USD.
- CMT_Coffee - KC1 Comdty - Generic 1st 'KC' Future. NYB-ICE Futures US Softs. Prices physical delivery of Arabica coffee, from 19 countries of origin in ports in U.S. and Europe.
- CMT_Corn - C1 Comdty - Generic 1st 'C ' Future CBT - Chicago Board of Trade. Corn Nr. 2 Yellow at par and substitutions.
- CMT_Cotton - CT1 Comdty - Generic 1st 'CT' Future NYB-ICE Futures US Softs. The cotton No.2 contract is the benchmark for the global cotton trading community. Prices physical delivery of US-grown, exchange-grade product.
- CMT_CRB - CRY Index - Thomson Reuters/Core Commodity CRB Commodity Index Excess Return, arithmetic average of commodity futures prices with monthly rebalancing. Currency: USD.

- CMT_Gold - XAU Curncy - Philadelphia Stock Exchange Gold and Silver Index, cap-weighted, includes leading companies in gold and silver mining. Curncy: USD.
- CMT_Natgas - NG1 Comdty - Natural Gas Futures (HH). Generic 1st 'NG' Future NYM-New York Mercantile Exchange.
- CMT_Nickel -LMNIDS03 LME Comdty - LME NICKEL3MO ($). London Metal Exchange. Unit USD/MT.
- CMT_Oil_WTI - USCRWTIC Index - Bloomberg West Texas Intermediate (WTI) Cushing Crude Oil Spot Price. Prices are on a free-on-board basis. Currency: USD.
- CMT_Palladium - XPD BGN Curncy - XPDUSD Spot Exchange Rate - Price of 1 XPD in USD. The per Troy ounce spot price for Palladium, 99.95% purity. Country: USA.
- CMT_Platinum - XPT BGN Curncy - XPTUSD Spot Exchange Rate, price of 1 XPT in USD. Per Troy ounce spot price for Platinum, 99.95% purity. Country: USA.
- CMT_Roll_BBG - BCOMRS Index - Bloomberg Roll Select Commodity Index, version of Bloomberg Commodity Index (BCOM), aims to mitigate effects of contango on index performance. Currency: USD.
- CMT_Silver - XAG BGN Curncy - XAGUSD Spot Exchange Rate - Price of 1 XAG in USD. The Silver Spot price is quoted as US Dollars per Troy Ounce.
- CMT_Soybean - S 1 Comdty - Soybean Futures. Generic 1st 'S ' Future CBT-Chicago Board of Trade.
- CMT_Sugar - SB1 Comdty Generic 1st 'SB' Future NYB-ICE Futures US Softs. No. 11 contract is world benchmark for raw sugar trading. Prices physical delivery of raw cane sugar, free-on-board in country of origin.
- CMT_Wheat - W 1 Comdty - Chicago SRW Wheat Futures. Generic 1st 'W ' Future CBT-Chicago Board of Trade.
- CORP_AAA - MOODCAAA Index - Moody's Bond Indices Corporate AAA. Country: United States.
- CORP_BAAA - MOODCBAA Index - Moody's Bond Indices Corporate BAA.
- CORP_IG_Barc - LUACTRUU Index - Bloomberg Barclays US Corporate Total Return Value Unhedged USD, measures the investment grade, fixed-rate, taxable corporate bond market. Includes USD denominated securities publicly issued by US and non-US industrial, utility and financial issuers. Members: 5901.

- FI_Australia - BAUBIL Index - Bloomberg AusBond Bank Bill Index, engineered to measure the Australian money market by representing a passively managed short term money market portfolio. Comprised of 13 synthetic instruments defined by rates interpolated from the RBA 24-hour cash rate, 1M BBSW, and 3M BBSW.
- FI_Can10y - GCAN10YR Index - Canadian Govt Bonds 10 Year Note. Currency: CAD. The rates are comprised of Generic Canadian government bills/notes/bonds.
- FI_Esp10y - GTESP10Y Govt - SPGB 1.3 10/31/26 Corp. Spain Government bond 10 years. Currency: EUR.
- FI_Fran10y - GTFRF10Y Govt – Bond genérico de 10 anos. Government of France bond. Currency: EUR. Bond Ratings: Moody's: Aa2u, Fitch: AA.
- FI_Germ10y - GTDEM10Y Govt - Bond genérico de 10 anos. Government of Germany bond. Currency: EUR. Bond Ratings: Moody's: Aaau, Fitch: AAA.
- FI_Japan10y - JGBS10 Index - Japan Govt Bonds 10 Year Note Generic Bid Yield. Comprised of Generic government bills and bonds. Currency: Yen.
- FI_Libor_UK3m - BP0003M Index - ICE LIBOR GBP 3 Month. ICE Benchmark Administration Fixing for British Pound. Average of quotations provided by banks. Currency: British Pound. Country: Britain.
- FI_Libor_UK6m - BP0006M Index - ICE LIBOR GBP 6 Month. ICE Benchmark Administration Fixing for British Pound. Average of quotations provided by banks. Currency: British Pound. Country: Britain.
- FI_Libor_USA1m - US0001M Index -ICE LIBOR USD 1 Month. London Interbank Offered Rate - ICE Benchmark Administration Fixing for US Dollar. Average of quotations provided by banks. Curncy.: USD. Country: USA.
- FI_Libor_USA6m - US0006M Index - ICE LIBOR USD 6 Month. London Interbank Offered Rate - ICE Benchmark Administration Fixing for US Dollar. Average of quotations provided by banks. Curncy.: USD. Country: USA.
- FI_Swiss10Y - GSWISS10 Index - Switzerland Govt Bonds 10 Year Note Generic Bid Yield. Currency: swiss franc.
- FI_UK10y - GUKG10 Index - UK Govt Bonds 10 Year Note Generic Bid Yield. The rates are comprised of Generic United Kingdom government bills and bonds.Currency: British Pound. Country: Britain.
- FI_USA6m - USGG6M Index - US Generic Govt 6 Month Yield. Yields are yield to maturity and pre-tax. The rates are comprised of Generic United States on-the-run government bill/note/bond indices. Currency: US dollar. Country: USA.

- FI_USA10y - Generic 1st 'TY' Future CBT - Chicago Board of Trade 10-Year US Treasury Note Futures. Settlement Methodology: Federal Reserve book-entry wire-transfer system. Source of info: cmegroup.com.

- FI_USA_CredGov - LUGCTRUU Index - Bloomberg Barclays US Aggregate Government/Credit Total Return Value Unhedged USD is a broad-based benchmark, measures non-securitized component US Aggregate Index. Includes investment grade, US dollar-denominated, fixed-rate Treasuries, government-related and corporate securities. Members: 7438.

- FX_AUD - AUD Curncy - AUDUSD Spot Exchange Rate - Price of 1 AUD in USD. The Australian dollar is the official currency of the Commonwealth of Australia. Floating and convertible currency.

- FX_BRL - BRLUSD Curncy - BRLUSD Spot Exchange Rate - Price of 1 BRL in USD. Brazilian real, official currency of Federative Republic of Brazil. Free floating.

- FX_CAD - CADUSD curncy - CADUSD Spot Exchange Rate - Price of 1 CAD in USD. The Canadian dollar is the official currency of Canada.

- FX_CHF - CHFUSD Spot Exchange Rate - Price of 1 CHF in USD. The Swiss franc is the official currency of Switzerland.

- FX_CLP - CLPUSD Curncy - CLPUSD Spot Exchange Rate - Price of 1 CLP in USD. The Chilean peso is the official currency of the Republic of Chile.

- FX_CNY - CNYUSD Spot Exchange Rate - Price of 1 CNY in USD. The Chinese renminbi (yuan) is the official currency of The People's Republic of China.

- FX_COP - COPUSD Curncy - COPUSD Spot Exchange Rate - Price of 100 COP in USD. The Colombian peso is the official currency of the Republic of Colombia.

- FX_DXY - DXY Index - The U.S. Dollar Index (USDX) indicates the general int'l value of the USD. The USDX does this by averaging the exchange rates between the USD and major world currencies.The ICE US computes this by using the rates supplied by some 500 banks.

- FX_EUR - EUR Curncy - EURUSD Spot Exchange Rate - Price of 1 EUR in USD. The euro is the official currency of the European Economic & Monetary Union.

- FX_GBP - GBP Curncy - GBPUSD Spot Exchange Rate - Price of 1 GBP in USD. The British Pound Sterling is the official currency of The United Kingdom.

- FX_HKD - HKDUSD Spot Exchange Rate - Price of 1 HKD in USD. The Hong Kong dollar is the official currency of Hong Kong. Free floating. Convertible.

- FX_IDR - IDRUSD Spot Exchange Rate - Price of 1,000 IDR in USD. The Indonesian rupiah is the official currency of the Republic of Indonesia. Free floating. Convertible.
- FX_INR - INRUSD Spot Exchange Rate - Price of 1 INR in USD. The Indian rupee is the official currency of India. Free floating. Convertible.
- FX_JPY - JPYUSD Curncy - USDJPY Spot Exchange Rate - Price of 1 USD in JPY - The Japanese yen is the official currency of Japan.
- FX_KRW - KRWUSD Spot Exchange Rate - Price of 100 KRW in USD. South Korean won, official currency of Republic of Korea. Free floating. Convertible.
- FX_MXN - MXNUSD Spot Exchange Rate - Price of 1 MXN in USD. The Mexican peso is the official currency of Mexico.
- FX_NOK - NOKUSD Spot Exchange Rate - Price of 1 NOK in USD. The Norwegian krone is the official currency of the Kingdom of Norway.
- FX_NZD - NZD Curncy - NZDUSD Spot Exchange Rate - Price of 1 NZD in USD. The New Zealand dollar is the official currency of New Zealand.
- FX_PEN - PENUSD Spot Exchange Rate - Price of 1 PEN in USD. The Peruvian Sol Spot is the official currency of The Republic of Peru.
- FX_PHP - PHPUSD Spot Exchange Rate - Price of 1 PHP in USD. The Philippine peso is the official currency of The Republic of the Philippines.
- FX_RUB - RUBUSD Spot Exchange Rate - Price of 1 RUB in USD. The Russian ruble is the official currency of The Russian Federation. Free floating. Convertible.
- FX_SEK - SEKUSD Spot Exchange Rate - Price of 1 SEK in USD. The Swedish krona is the official currency of Sweden.
- FX_SGD - SGDUSD Spot Exchange Rate - Price of 1 SGD in USD. The Singapore dollar is the official currency of the Republic of Singapore. Convertible.
- FX_THB - THBUSD Spot Exchange Rate - Price of 1 THB in USD. The Thai baht is the official currency of Thailand. Free floating. Convertible.
- FX_TRY - TRYUSD Spot Exchange Rate - Price of 1 TRY in USD. The Turkish lira is the official currency of the Republic of Turkey. Free floating. Convertible.
- FX_TWD - TWDUSD Spot Exchange Rate - Price of 1 TWD in USD. The New Taiwan dollar is the official currency of Taiwan. Free floating. Convertible offshore.
- FX_ZAR - ZARUSD Spot Exchange Rate - Price of 1 ZAR in USD. The South African rand is the official currency of The Republic of South Africa. Free floating.

- MBS_US_Barc - LUMSTRUU Index - Bloomberg Barclays US Mortgage Backed Securities (MBS) Index Total Return Value Unhedged USD, tracks agency mortgage backed pass-through securities guaranteed by Ginnie Mae (GNMA), Fannie Mae (FNMA), and Freddie Mac (FHLMC). Members: 346.

- SPR_US10y30y - USYC1030 Index - Market Matrix US Sell 10 Year & Buy 30 Year Bond Yield Spread, replicates selling the current 10 year US Treasury Note and buying the current 30 year US Treasury Bond factoring by 100. Currency: USD.

- SPR_US2y10y - USYC2Y10 Index - Market Matrix US Sell 2 Year & Buy 10 Year Bond Yield Spread. This spread is a calculated Bloomberg yield spread that replicates selling the current 2 year US Treasury Note and buying the current 10 year US Treasury Note factoring by 100. Currency: USD.

- SX_SX_Banks_Euro - SX7E Index - EURO STOXX Banks (Price) Index, cap-weighted, includes countries in EMU involved in banking sector. Curncy: EUR.

- SX_Banks_FTSE - F3BANK Index - FTSE 350 Banks Index, cap-weighted, designed to measure performance of banking sector of FTSE 350 Index. Currency: GBP.

- SX_Banks_Nikkei - N5BANK Index - Nikkei 500 Banks Index, subgroup index of the Nikkei 500 Index, consists of all the bank related equities listed. Currency: JPY.

- SX_Banks_SP500 - S5BANKX Index - Standard and Poor's 500 Banks Industry Group Index GICS Level 2, capitalization-weighted. Members: 17. Currency: USD.

- SX_CAC – CAC 40 Index, most widely-used indicator of Paris market, reflects performance of 40 largest equities listed in France, measured by free-float market-cap and liquidity.

- SX_DAX - DAX Index - Deutsche Boerse AG German Stock Index DAX, total return index of 30 selected German blue chips traded on Frankfurt Stock Exchange, equities use free float shares in index calculation. Members: 30. Currency: EUR.

- SX_DJones - INDU Index - Dow Jones Industrial Average, price-weighted average of 30 blue-chip stocks that are generally the leaders in their industry.

- SX_Food_DJ - DJUSFD Index - Dow Jones US Total Market Food Retailers & Wholesalers Index, weighted using free-float market capitalization, quoted in USD.

- SX_FTSE - UKX Index - FTSE 100 Index, capitalization-weighted of 100 most highly capitalized companies traded on the London Stock Exchange. Currency: GBP.

- SX_HSI - HSI index - Hong Kong Hang Seng Index, free-float cap-weighted index of selection of companies in Hong Kong Stock Exchange. Members: 50. Curncy.: HKD.

- SX_IBEX - IBEX 35 Index, official index of the Spanish Continuous Market, comprises the 35 most liquid stocks traded on the Continuous market. Currency: EUR.
- SX_IBOV - IBOV Index - Ibovespa Brasil Sao Paulo Stock Exchange Index, gross total return index weighted by market value to free float. Members: 58. Curncy: BRL.
- SX_JPM_Global - JPEIGLBL Index - J.P. Morgan EMBI Global Total Return Index. Currency: US Dollar.
- SX_Kospi - KOSPI index - Korea Stock Exchange KOSPI Index, cap-weighted of all common shares on Korean Stock Exchanges. Members:769. Curncy: KRW.
- SX_Mexbol - MEXBOL Index - Mexican Stock Exchange Mexican Bolsa IPC (Indice de Precios y Cotizaciones) Index, capitalization-weighted.
- SX_MSCI_EM - MXEF Index - MSCI Emerging Markets Index, free-float weighted equity index, captures large and mid cap representation across 24 EM countries, covers approximately 85% of free float-adjusted market capitalization in each country.
- SX_Nasdaq - NDX index - NASDAQ 100 Stock Index, modified cap-weighted index of 100 largest and most active non-financial domestic and int'l issues listed on NASDAQ (exchange hub for technology companies). Curncy: USD. Country: USA.
- SX_Nasdaq_Comp[1] - CCMP Index - NASDAQ Composite Index, a broad-based cap-weighted index of stocks in all three NASDAQ tiers: Global Select, Global Market and Capital Market.
- SX_Nikkei - NKY index - Nikkei-225 Stock Average, price-weighted average of 225 top-rated companies listed in Tokyo Stock Exchange. Curncy: JPY. Country: Japan.
- SX_Oil_Stoxx - SXEP Index - STOXX Europe 600 Oil & Gas Price EUR, capitalization-weighted, includes European companies involved in energy sector. Members: 20.
- SX_OMX - OMX Index. OMX Stockholm 30 Index, market-weighted, consists of the 30 most actively traded stocks on the Stockholm Exchange.
- SX_Retail_Stoxx - SXRP Index. The STOXX 600 Retail (Price) Index, cap-weighted, includes European companies involved in retail sector. The parent index is SXXP.
- SX_Russell2000 - RTY Index - The Russell 2000 Index comprises smallest 2000 companies in the Russell 3000 Index (8% of its market capitalization).
- SX_Sidney - AS51 Index - The S&P/ASX 200 measures performance of 200 largest index-eligible stocks listed on ASX by float-adjusted market capitalization.

[1] Used only in indicator started in 1985.

- SX_SP500 - SPX Index - Standard and Poor's 500 Index is a cap-weighted index of 500 stocks negotiated in NYSE - New York Stock Exchange, designed to measure performance of the broad domestic economy through all major industries.
- SX_Stoxx_Small - SCXP Index - STOXX Europe Small 200 Price EUR, designed to provide representation of small capitalization companies in Europe.
- SX_Swiss - SMI Index - Swiss Market Index, index of the largest and most liquid stocks traded on the Geneva, Zurich, and Basel Stock Exchanges. Currency: CHF.
- SX_Toronto - SPTSX Index - The S&P/Toronto Stock Exchange Composite Index, cap-weighted index designed to measure market activity of stocks listed on TSX.
- VOL_VDAX - V1X Index - Deutsche Borse VDAX-NEW Volatility Index, measures volatility of German equity markets. Based on the underlying DAX Index options traded on Eurex.
- VOL_VIX - VIX Index – Chicago Board Options Exchange SPX Volatility Index, reflects a market estimate of future volatility, based on the weighted average of the implied volatilities for a wide range of strikes.

Appendix B – Composition of indicators

General index is composed by 93 variables already described. The composition of other indices are listed in the following tables:

SX_CAC	SX_IBEX	SX_Nasdaq	SX_Stoxx_Small
SX_DAX	SX_IBOV	SX_OMX	SX_Swiss
SX_DJones	SX_Kospi	SX_Russell2000	SX_Toronto
SX_FTSE	SX_Mexbol	SX_Sidney	
SX_HSI	SX_MSCI_EM	SX_SP500	

Table 23 – Variables used in calculation of stocks index (18 variables).

CMT_Agric	CMT_CRB	CMT_Oil_WTI	CMT_Silver
CMT_Coffee	CMT_Gold	CMT_Palladium	CMT_Soybean
CMT_Corn	CMT_Natgas	CMT_Platinum	CMT_Sugar
CMT_Cotton	CMT_Nickel	CMT_Roll_BBG	CMT_Wheat

Table 24 – Variables used in calculation of commodities index (16 variables).

CORP_AAA	FI_Esp10y	FI_Libor_UK6m	FI_USA6m
CORP_BAAA	FI_Fran10y	FI_Libor_USA1m	FI_USA10y
CORP_IG_Barc	FI_Germ10y	FI_Libor_USA6m	FI_USA_CredGov
FI_Australia	FI_Japan10y	FI_Swiss10Y	
FI_Can10y	FI_Libor_UK3m	FI_UK10y	

Table 25 – Variables used in calculation of bonds index (18 variables).

FX_AUD	FX_DXY	FX_KRW	FX_SEK
FX_BRL	FX_EUR	FX_MXN	FX_SGD
FX_CAD	FX_GBP	FX_NOK	FX_THB
FX_CHF	FX_HKD	FX_NZD	FX_TRY
FX_CLP	FX_IDR	FX_PEN	FX_TWD
FX_CNY	FX_INR	FX_PHP	FX_ZAR
FX_COP	FX_JPY	FX_RUB	

Table 26 – Variables used in calculation of FX (foreign exchange) index (27 variables).

CMT_Coffee	FI_USA10y	FX_JPY	SX_DJones
CMT_Cotton	FI_USA6m	FX_KRW	SX_FTSE
CMT_Gold	FX_AUD	FX_NOK	SX_HSI
CMT_Oil_WTI	FX_CAD	FX_NZD	SX_Kospi
CMT_Silver	FX_CHF	FX_SEK	SX_Nasdaq
CMT_Soybean	FX_DXY	FX_THB	SX_Nasdaq_Comp
CMT_Suggar	FX_EUR	FX_ZAR,	SX_Nikkei
CMT_Wheat	FX_GBP	SPR_US2y10y	SX_SP500
Corp_AAA	FX_HKD	SX_Banks_Nikkei	SX_Toronto
FI_Libor_USA1m	FX_INR	SX_DAX	

Table 27 – Variables used in calculation of index_1985 (39 variables).

Appendix C – Analysis of the behaviour of the assets against the indicator

We will verify the behaviour of the variables *vis-à-vis* the risk indicator obtained through the PCA. This study allows the classification in pro-risk assets that benefit from scenarios of greater risk appetite, or safe havens (defensive) that benefit from periods of flight to quality, a classification that will be useful when assessing the risk of the assets (evaluated by the historical *value-at-risk* at the 95% confidence level) in the different systemic risk regimes.

Various univariate simple regressions are performed in which the dependent variable was the mean of the indicator in the last 44 days minus the mean of the indicator in the previous 44 days and the independent variable was the cumulative return of the asset in the last 44 days. The purpose of this procedure is to identify the type of asset (pro-risk or defensive) from the investigation of the association between the variation of the indicator mean and profitability of asset return. Due to the aim of just classifying assets, we do not focus on causality or endogeneity in the regression model.

The results are shown in Table 28. Positive slopes are marked in green and negative in red. The t coefficient of the coefficient is marked in yellow if the result is not significant at 95%.

93 assets	All sample					1994–2006					2007–2017				
	r^2	slope	t-stat	c	c t-st	r^2	slope	t-stat	c	c t-st	r^2	slope	t-stat	c	c t-st
CMT_Agric	0.015	-0.063	-9.44	0.00	-0.40	0.018	-0.066	-7.7	0.00	-0.96	0.013	-0.062	-6.07	0.00	0.14
CMT_Coffee	0.000	0.006	1.53	0.00	0.21	0.002	-0.009	-2.5	0.00	-0.21	0.007	0.036	4.37	0.00	0.33
CMT_Corn	0.020	-0.047	-10.99	0.00	0.43	0.029	-0.047	-9.9	0.00	0.18	0.015	-0.047	-6.56	0.00	0.39
CMT_Cotton	0.025	-0.052	-12.36	0.00	0.18	0.003	-0.015	-3.2	0.00	-0.36	0.051	-0.084	-12.08	0.00	0.97
CMT_CRB	0.012	-0.061	-8.37	0.00	0.47	0.001	-0.015	-1.6	0.00	0.13	0.022	-0.088	-7.86	0.00	-0.46
CMT_Gold	0.006	0.052	6.16	0.00	-0.65	0.001	0.017	1.7	0.00	-0.39	0.012	0.078	5.72	0.00	-0.53
CMT_Natgas	0.000	0.004	1.49	0.00	0.18	0.001	0.004	1.5	0.00	-0.30	0.000	0.004	0.81	0.00	0.44
CMT_Nickel	0.000	-0.003	-0.93	0.00	0.22	0.001	-0.006	-1.4	0.00	0.05	0.000	-0.001	-0.19	0.00	0.35
CMT_Oil_WTI	0.007	-0.023	-6.54	0.00	0.51	0.001	-0.007	-1.7	0.00	0.03	0.013	-0.034	-6.02	0.00	0.23
CMT_Palladium	0.006	-0.022	-6.02	0.00	0.75	0.027	-0.033	-9.6	0.00	0.54	0.000	-0.004	-0.60	0.00	0.44
CMT_Platinum	0.000	-0.009	-1.65	0.00	0.31	0.001	0.010	1.3	0.00	-0.45	0.002	-0.018	-2.13	0.00	0.31
CMT_Roll_BBG	0.010	-0.065	-7.95	0.00	0.91	0.003	-0.034	-3.0	0.00	0.73	0.016	-0.081	-6.61	0.00	-0.11
CMT_Silver	0.001	-0.014	-2.97	0.00	0.42	0.000	0.007	1.2	0.00	-0.34	0.005	-0.026	-3.62	0.00	0.49
CMT_Soybean	0.012	-0.042	-8.57	0.00	0.40	0.012	-0.033	-6.3	0.00	-0.21	0.013	-0.050	-5.97	0.00	0.67
CMT_Suggar	0.000	-0.006	-1.72	0.00	0.22	0.003	0.013	3.3	0.00	-0.18	0.005	-0.023	-3.78	0.00	0.46
CMT_Wheat	0.000	-0.006	-1.45	0.00	0.23	0.005	-0.021	-3.9	0.00	0.03	0.000	0.003	0.41	0.00	0.38
CORP_AAA	0.050	0.780	17.71	0.00	-1.70	0.011	0.288	6.1	0.00	-0.94	0.098	1.300	17.22	0.00	-1.14
CORP_BAA	0.004	0.185	4.61	0.00	-0.23	0.007	0.237	4.9	0.00	-0.75	0.002	0.152	2.41	0.00	0.19
CORP_IG_Barc	0.011	0.187	8.32	0.00	-3.25	0.011	0.159	5.9	0.00	-3.17	0.012	0.207	5.83	0.00	-1.51
FI_Australia	0.005	1.101	5.76	-0.01	-5.40	0.000	0.362	1.1	0.00	-1.11	0.014	1.990	6.26	-0.01	-5.57
FI_Can10y	0.015	0.170	9.58	0.00	-1.43	0.005	0.071	4.1	0.00	-0.97	0.032	0.336	9.54	0.00	-1.00
FI_Esp10y	0.011	0.110	8.12	0.00	-1.01	0.008	0.077	5.0	0.00	-1.27	0.014	0.138	6.17	0.00	-0.13

Continue on next page

Continued from previous page

	All sample					1994–2006					2007–2017				
93 assets	**r^2**	**slope**	**t-stat**	**c**	**c t-st**	**r^2**	**slope**	**t-stat**	**c**	**c t-st**	**r^2**	**slope**	**t-stat**	**c**	**c t-st**
FI_Fran10y	0.029	0.242	13.41	0.00	-1.92	0.011	0.114	5.9	0.00	-1.12	0.050	0.376	12.01	0.00	-1.54
FI_Germ10y	0.034	0.269	14.46	0.00	-2.18	0.011	0.122	6.1	0.00	-1.08	0.060	0.430	13.20	0.00	-2.09
FI_Japan10y	0.020	0.273	11.13	0.00	-1.33	0.034	0.216	10.7	0.00	-1.51	0.021	0.566	7.58	0.00	-1.16
FI_Libor_UK3m	0.010	4.739	7.72	0.00	-0.58	0.000	-0.543	-0.7	0.00	-0.19	0.024	7.658	8.19	0.00	-1.18
FI_Libor_UK6m	0.013	2.671	8.81	0.00	-0.70	0.000	0.252	0.7	0.00	-0.19	0.029	4.334	9.02	0.00	-1.36
FI_Libor_USA1m	0.023	19.280	11.76	0.00	-0.53	0.016	13.554	7.2	0.00	0.06	0.028	24.018	8.91	0.00	-1.02
FI_Libor_USA6m	0.011	2.454	8.01	0.00	-0.39	0.021	2.597	8.4	0.00	-0.08	0.006	2.289	3.98	0.00	-0.35
FI_Swiss10Y	0.049	0.390	17.64	0.00	-2.61	0.021	0.188	8.4	0.00	-1.43	0.089	0.676	16.39	0.00	-2.51
FI_UK10Y	0.068	0.344	20.93	0.00	-3.21	0.012	0.120	6.4	0.00	-1.24	0.130	0.540	20.24	0.00	-2.91
FI_USA_CredGov	0.045	0.493	16.76	0.00	-7.72	0.024	0.265	8.9	0.00	-4.83	0.076	0.827	14.99	-0.01	-5.66
FI_USA10Y	0.051	0.340	18.04	0.00	-0.69	0.038	0.207	11.4	0.00	-0.36	0.077	0.563	15.06	0.00	-1.11
FI_USA6M	0.039	4.980	15.55	0.00	-1.06	0.041	3.631	11.8	0.00	-0.04	0.045	7.374	11.41	0.00	-2.06
FX_AUD	0.000	-0.003	-0.29	0.00	0.21	0.000	-0.001	0.0	0.00	-0.19	0.000	-0.004	-0.27	0.00	0.37
FX_BRL	0.009	-0.048	-7.22	0.00	-0.80	0.010	-0.036	-5.7	0.00	-1.17	0.009	-0.069	-5.12	0.00	-0.11
FX_CAD	0.005	0.088	5.42	0.00	0.17	0.005	0.092	4.2	0.00	-0.62	0.005	0.088	3.64	0.00	0.61
FX_CHF	0.005	0.067	5.51	0.00	-0.13	0.029	0.121	9.9	0.00	-0.58	0.000	-0.002	-0.09	0.00	0.38
FX_CLP	0.012	-0.100	-8.36	0.00	-0.44	0.011	-0.087	-6.1	0.00	-0.68	0.012	-0.109	-5.71	0.00	-0.06
FX_CNY	0.001	-0.133	-2.06	0.00	0.63	0.021	-1.219	-8.4	0.00	2.68	0.000	0.002	0.02	0.00	0.36
FX_COP	0.001	-0.023	-2.29	0.00	-0.19	0.059	-0.181	-14.2	0.00	-4.62	0.005	0.057	3.77	0.00	0.62
FX_DXY	0.006	-0.094	-6.09	0.00	0.28	0.020	-0.131	-8.2	0.00	-0.48	0.001	-0.054	-1.93	0.00	0.51
FX_EUR	0.003	0.050	3.93	0.00	0.25	0.024	0.119	9.0	0.00	-0.46	0.000	-0.024	-1.05	0.00	0.31

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93 assets	All sample					1994–2006					2007–2017				
	r^2	slope	t-stat	c	c t-st	r^2	slope	t-stat	c	c t-st	r^2	slope	t-stat	c	c t-st
FX_GBP	0.002	-0.055	-3.74	0.00	0.08	0.004	0.065	3.6	0.00	-0.58	0.012	-0.132	-5.69	0.00	-0.53
FX_HKD	0.033	4.286	14.31	0.00	0.70	0.007	-1.963	-4.9	0.00	-0.49	0.094	7.318	16.89	0.00	0.64
FX_IDR	0.006	-0.028	-5.96	0.00	-0.50	0.016	-0.027	-7.3	0.00	-1.15	0.002	-0.045	-2.03	0.00	0.09
FX_INR	0.009	-0.129	-7.21	0.00	-1.08	0.027	-0.238	-9.6	0.00	-2.27	0.004	-0.084	-3.20	0.00	-0.14
FX_JPY	0.044	0.183	16.55	0.00	0.42	0.003	0.034	3.0	0.00	-0.08	0.123	0.399	19.62	0.00	0.04
FX_KRW	0.005	-0.047	-5.66	0.00	-0.02	0.026	-0.069	-9.3	0.00	-0.45	0.000	0.007	0.35	0.00	0.40
FX_MXN	0.000	0.014	1.59	0.00	0.52	0.010	0.046	5.7	0.00	1.13	0.003	-0.052	-2.83	0.00	-0.09
FX_NOK	0.000	0.013	1.09	0.00	0.24	0.036	0.147	11.0	0.00	-0.65	0.008	-0.086	-4.55	0.00	-0.06
FX_NZD	0.000	-0.008	-0.80	0.00	0.23	0.000	-0.005	-0.4	0.00	-0.17	0.000	-0.011	-0.65	0.00	0.38
FX_PEN	0.002	0.080	3.28	0.00	0.65	0.009	-0.156	-5.5	0.00	-1.63	0.015	0.253	6.43	0.00	0.45
FX_PHP	0.009	-0.106	-7.35	0.00	-0.71	0.030	-0.125	-10.1	0.00	-2.10	0.001	-0.051	-1.37	0.00	0.37
FX_RUB	0.000	-0.008	-1.57	0.00	-0.16	0.001	-0.006	-1.4	0.00	-0.57	0.000	-0.014	-1.15	0.00	0.19
FX_SEK	0.001	0.020	1.77	0.00	0.24	0.009	0.071	5.5	0.00	-0.38	0.000	-0.020	-1.06	0.00	0.30
FX_SGD	0.000	-0.025	-1.17	0.00	0.24	0.012	-0.139	-6.2	0.00	-0.22	0.003	0.107	2.73	0.00	0.18
FX_THB	0.017	-0.113	-10.13	0.00	-0.28	0.036	-0.100	-11.0	0.00	-1.11	0.010	-0.181	-5.30	0.00	0.55
FX_TRY	0.003	-0.027	-3.88	0.00	-1.41	0.006	-0.028	-4.5	0.00	-2.49	0.001	-0.031	-1.86	0.00	-0.09
FX_TWD	0.008	-0.154	-6.87	0.00	-0.04	0.020	-0.180	-8.3	0.00	-1.07	0.003	-0.118	-2.70	0.00	0.53
FX_ZAR	0.000	-0.007	-0.89	0.00	0.07	0.013	-0.055	-6.5	0.00	-1.12	0.004	0.048	3.25	0.00	0.86
MBS_US_Barc	0.043	0.701	16.39	-0.01	-9.77	0.014	0.293	6.8	0.00	-4.64	0.093	1.380	16.79	-0.01	-8.65
SPR_US10y30y	0.004	1.779	4.64	0.00	0.11	0.038	4.228	11.3	0.00	-0.02	0.002	-1.677	-2.29	0.00	0.52
SPR_US2y10y	0.003	-0.871	-4.40	0.00	0.17	0.009	1.240	5.4	0.00	0.22	0.021	-2.475	-7.75	0.00	0.82

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	All sample					1994–2006					2007–2017				
93 assets	**r^2**	**slope**	**t-stat**	**c**	**c t-st**	**r^2**	**slope**	**t-stat**	**c**	**c t-st**	**r^2**	**slope**	**t-stat**	**c**	**c t-st**
SX_Banks_Euro	0.012	-0.037	-8.62	0.00	0.28	0.033	-0.062	-10.6	0.00	1.89	0.006	-0.026	-4.19	0.00	-0.16
SX_Banks_FTSE	0.011	-0.040	-8.16	0.00	0.46	0.008	-0.032	-5.1	0.00	0.92	0.013	-0.045	-5.98	0.00	-0.35
SX_Banks_Nikkei	0.018	-0.055	-10.61	0.00	-0.59	0.003	-0.017	-3.1	0.00	-0.46	0.040	-0.099	-10.71	0.00	-0.29
SX_Banks_SP500	0.000	-0.007	-1.52	0.00	0.30	0.007	-0.034	-4.8	0.00	0.85	0.000	0.002	0.36	0.00	0.39
SX_CAC	0.006	-0.039	-6.07	0.00	0.73	0.032	-0.069	-10.4	0.00	1.50	0.000	-0.005	-0.44	0.00	0.37
SX_DAX	0.017	-0.058	-10.14	0.00	1.64	0.064	-0.082	-14.9	0.00	2.12	0.002	-0.023	-2.16	0.00	0.64
SX_DJones	0.007	-0.057	-6.69	0.00	1.56	0.049	-0.116	-12.9	0.00	3.23	0.000	0.001	0.08	0.00	0.36
SX_Food_DJ	0.003	-0.031	-4.05	0.00	0.73	0.018	-0.059	-7.8	0.00	0.99	0.000	0.009	0.58	0.00	0.31
SX_FTSE	0.001	-0.025	-2.91	0.00	0.52	0.017	-0.072	-7.6	0.00	1.09	0.001	0.017	1.18	0.00	0.32
SX_HSI	0.004	-0.023	-4.72	0.00	0.54	0.036	-0.054	-11.1	0.00	0.82	0.001	0.019	1.97	0.00	0.28
SX_IBEX	0.004	-0.026	-4.60	0.00	0.63	0.033	-0.063	-10.6	0.00	2.04	0.001	0.013	1.30	0.00	0.43
SX_IBOV	0.000	0.001	0.26	0.00	0.16	0.005	-0.013	-3.9	0.00	0.70	0.008	0.041	4.63	0.00	0.09
SX_JPM_Global	0.001	0.020	2.02	0.00	-0.41	0.000	-0.004	-0.5	0.00	-0.02	0.005	0.082	3.61	0.00	-0.60
SX_Kospi	0.003	-0.018	-4.08	0.00	0.44	0.013	-0.024	-6.5	0.00	0.06	0.000	0.006	0.48	0.00	0.32
SX_MEXBOL	0.003	-0.021	-3.99	0.00	1.07	0.029	-0.045	-9.9	0.00	2.44	0.006	0.050	3.96	0.00	-0.20
SX_MSCI_EM	0.011	-0.040	-8.16	0.00	0.62	0.073	-0.081	-16.1	0.00	1.03	0.000	0.003	0.32	0.00	0.37
SX_Nasdaq	0.009	-0.037	-7.58	0.00	1.61	0.016	-0.031	-7.2	0.00	1.03	0.008	-0.053	-4.55	0.00	1.40
SX_Nikkei	0.044	-0.096	-16.58	0.00	0.16	0.050	-0.083	-13.1	0.00	-0.68	0.042	-0.107	-10.97	0.00	0.73
SX_Oil_Stoxx	0.008	-0.047	-7.13	0.00	0.77	0.044	-0.088	-12.2	0.00	2.36	0.000	-0.011	-0.96	0.00	0.32
SX_OMX	0.011	-0.049	-8.31	0.00	1.41	0.051	-0.072	-13.3	0.00	2.32	0.000	-0.006	-0.47	0.00	0.41
SX_Retail_Stoxx	0.001	-0.020	-2.52	0.00	0.41	0.033	-0.089	-10.6	0.00	1.52	0.004	0.045	3.40	0.00	0.39

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	All sample					1994–2006					2007–2017				
93 assets	**r^2**	**slope**	**t-stat**	**c**	**c t-st**	**r^2**	**slope**	**t-stat**	**c**	**c t-st**	**r^2**	**slope**	**t-stat**	**c**	**c t-st**
SX_Russel2000	0.025	-0.076	-12.40	0.00	2.04	0.059	-0.093	-14.3	0.00	2.52	0.011	-0.059	-5.63	0.00	0.95
SX_Sidney	0.009	-0.070	-7.54	0.00	1.24	0.037	-0.134	-11.2	0.00	3.11	0.003	-0.038	-2.65	0.00	0.41
SX_SP500	0.010	-0.064	-7.92	0.00	1.68	0.031	-0.092	-10.2	0.00	2.36	0.003	-0.041	-3.01	0.00	0.74
SX_Stoxx_Small	0.028	-0.083	-13.25	0.00	1.25	0.098	-0.125	-18.8	0.00	1.63	0.006	-0.045	-4.23	0.00	0.63
SX_Swiss	0.007	-0.046	-6.29	0.00	0.98	0.027	-0.066	-9.4	0.00	1.73	0.000	-0.013	-0.87	0.00	0.38
SX_Toronto	0.027	-0.098	-12.92	0.00	1.99	0.071	-0.120	-15.8	0.00	3.17	0.009	-0.071	-5.10	0.00	0.62
VOL_VDAX	0.001	0.018	2.50	0.00	0.22	0.013	0.051	6.4	0.00	-0.14	0.000	-0.010	-0.84	0.00	0.37
VOL_VIX	0.000	0.012	1.46	0.00	0.21	0.005	0.041	3.9	0.00	-0.16	0.000	-0.002	-0.21	0.00	0.37

Table 28 – Regression of cumulative return of each asset in 44 days against variation of average general index.

It should be noted that, despite the low coefficients of determination, according to Gujarati (2006), the researcher should be more concerned with the logical or theoretical relevance of the relationship between variables. In particular, the concern of the procedure performed is to identify a group of assets whose slopes were significant and stable with respect to the positive or negative signs in all periods analyzed. This framework reflects the periods analyzed and the criterion adopted and it allows us to understand the behaviour of the variables. It is important to highlight that depending on the time frame or selection criteria, other assets could present significant and stable coefficients and thus be defined as pro-risk or safe heavens. However, our procedure can be considered adequate since we use a relevant time horizon.

From this procedure of analyzing assets behaviour in relation to the systemic risk index, we can conduct a classification as described in Table 29. We define as pro-risk assets those that lose value with the increase of systemic risk and vice-versa, that is, that tend to be valued with the decrease of systemic risk. In contrast, safe havens or defensive assets are those that tend to appreciate in times of stress due to the search for quality (flight to quality) and vice versa.

Pro-risk	**Safe havens**
SX_Banks_Euro	CMT_Gold
SX_Banks_FTSE	CORP_AAA
SX_Banks_Nikkei	CORP_BAA
CMT_Agric	CORP_IG_Barc
CMT_Corn	FI_CAN10Y
CMT_Cotton	FI_ESP10Y
CMT_CRB	FI_FRAN10Y
CMT_Oil_WTI	FI_GERM10Y
CMT_Roll_BBG	FI_Japan10Y
CMT_Soybean	FI_Libor_USA1m
CMT_Suggar	FI_Libor_USA6m
FX_BRL	FI_Swiss10y
FX_CLP	FI_UK10Y
FX_DXY	FI_USA_CredGov
FX_IDR	FI_USA10y
FX_INR	FI_USA6m
FX_PHP	FX_CAD
FX_THB	FX_JPY
FX_TRY	MBS_US_Barc
FX_TWD	
SX_DAX	
SX_Nasdaq	
SX_Nikkei	
SX_Russel2000	
SX_Sidney	
SX_SP500	
SX_Stoxx_Small	
SX_Toronto	

Table 29 – Behaviour of assets with regard to general index.

The results indicate that stock indices, commodities, currencies and sector indices of banks can be broadly classified as pro-risk assets, while fixed-income indices, both sovereign and high-rating corporate bonds, can be classified as defensive assets. It is interesting to note that the Canadian dollar and the Japanese yen have also proved to be defensive assets, while the dollar index was placed in the pro-risk assets group. It should be noted that the Canadian dollar is influenced by the behaviour of certain commodities but it is the currency of an economy with a sound banking system and with fewer fiscal uncertainties than the US economy, to which it is closely connected. Even with the problems experienced by the Japanese economy, the yen also appears as a defensive asset. The yen typically depreciates in times of increased risk appetite, in bullish periods, since it is often used to fund carry trades (low-cost borrowing operations that finance the investment in asses with higher expected returns). The reversal of these operations in times of flight to quality causes currency appreciation. The Euro and the British pound, despite being historically strong currencies, also experiencied their particular crises and exhibited oscillating behaviour, presenting characteristics of both pro-risk assets and defensive assets.

Table 29 shows the asset classification in pro-risk assets and safe havens assets. The research reveals whether the behaviour of the asset is stable in relation to the systemic risk indicator elaborated from principal components analysis, as well as the significance of the linear association. These results can also be useful in portfolio management and in the definition of investment strategies because they enable the identification of assets to be included, depending on the systemic risk regime that is expected. It should be noted that the calculated index, even containing the other assets not included in Table 29, does not lose its applicability, since the main interest is in the covariation between the assets. Regardless of the signal of the covariation, the indicator captures its intensity.

Appendix D – Robustness Analysis

D.1 Longer period analysis (1985–2017)

How can one guarantee that in a longer period the regimes would be modelled in the same way? We chose the period since 1994 for the range of important assets that had complete series. However, we perform the modelling with fewer assets in the period 1985-2017 for comparison purposes.

In this longer perspective (1985-2017), working with fewer variables (39) for a 44-day window, the MS estimation results for the different switchings are shown in Tables 30 and 31. These results are compatible with those found for 1994-2017. In addition, the graphs in Figure 20 confirm the stresses in 2003, 2015 and 2016 and the 2007-2013 crisis cluster.

	Switchings	Mean	Mean and variance	Variance
Regime 1	C	0.227101	0.21008	
	Std. Error	0.000556	0.000516	
	P-value	0.0000		
	log(sigma)	-3.21002	-3.64809	-1.49792
	Std. Error	0.007753	0.01298	0.012942
	P-value	0.0000		
Regime 2	C	0.366302	0.322451	
	Std. Error	0.001226	0.001212	
	P-value	0.0000		
	log(sigma)	-3.21002	-2.81781	-1.07203
	Std. Error	0.007753	0.011823	0.01929
	P-value	0.0000		
	Mean dependent var	0.258687	0.258687	0.258687
	S.E. dependent var	0.070911	0.070911	0.070911
	S.E. of regression	0.040038	0.043438	0.268261
	Sum squared resid	13.51172	15.9028	606.6543
	Durbin-Watson stat	0.049297	0.041513	0.000735
	Log likelihood	14911.15	15536.91	-545.957
	Akaike info criterion	-3.53561	-3.6838	0.130445
	Schwarz criterion	-3.53144	-3.67879	0.133785
	Hannan-Quinn criter.	-3.53419	-3.68209	0.131585

Table 30 – Estimation results of MS model, different switchings. Independent variable: Indicator_1985, constructed with 39 assets, window of 44 working days, period: 3/07/1985 to 6/30/2017, 8432 obs.

Constant transition probabilities	Switchings					
	Mean		Mean and variance		Variance	
Regimes	1	2	1	2	1	2
1	0.99662	0.00338	0.994321	0.005679	0.998909	0.001091
2	0.011745	0.988255	0.007678	0.992322	0.002463	0.997537
Constant expected durations	**Mean**		**Mean and variance**		**Variance**	
	1	2	1	2	1	2
	295.8756	85.14188	176.0973	130.24	916.8921	405.9319

Table 31 – Constant transition probabilities and expected durations according to switchings, dependent variable: index constructed with 39 assets, window of 44 working days, period: 3/07/1985 to 6/30/2017.

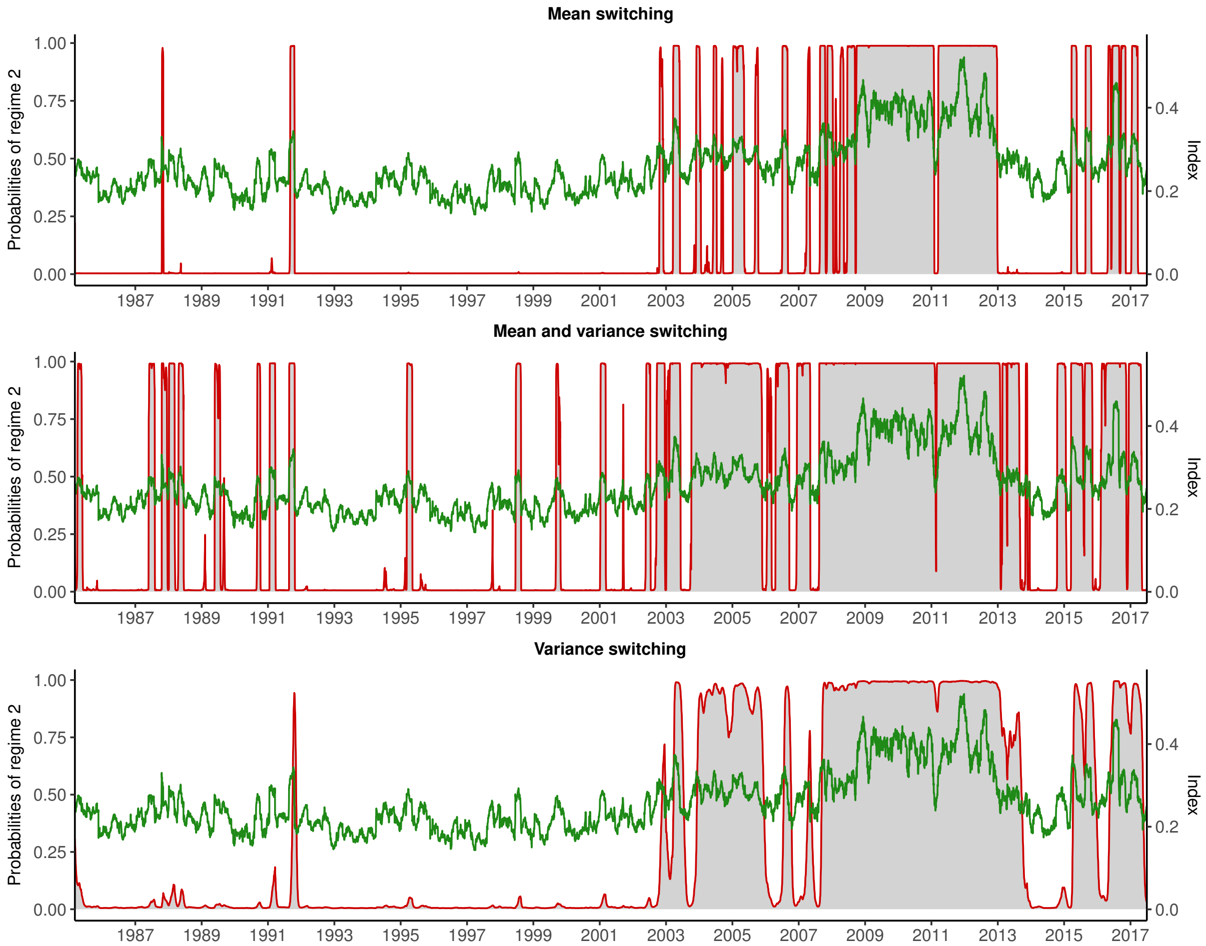

Figure 20 – General index plotted with probabilities of regime 2 according to MS model, switchings in mean, both mean and variance, and variance. Period: 3/07/1985 to 6/30/2017

D.2 Analysis of the sample in two subperiods

Let us now see what happens if we divide the period 1994–2017 into two subperiods to estimate the regimes. For 1994–2006, the estimation results are shown in Tables 32 and 33 and the probabilities of the stress regime are shown in Figure 21.

	Switchings	Mean	Mean and variance	Variance
Regime 1	C	0.175617	0.173922	
	Std. Error	0.000936	0.000503	
	P-value	0.0000	0.0000	
	log(sigma)	-3.72687	-3.96551	-1.66677
	Std. Error	0.012394	0.017144	0.016154
	P-value	0.0000	0.0000	0.0000
Regime 2	C	0.236292	0.233639	
	Std. Error	0.001389	0.000903	
	P-value	0.0000	0.0000	
	log(sigma)	-3.72687	-3.51175	-1.36806
	Std. Error	0.012394	0.018996	0.039789
	P-value	0.0000	0.0000	0.0000
	Mean dependent var	0.199007	0.199007	0.199007
	S.E. dependent var	0.038102	0.038102	0.038102
	S.E. of regression	0.023751	0.024057	0.202681
	Sum squared resid	1.885793	1.934174	137.37
	Durbin-Watson stat	0.093113	0.087286	0.000956
	Log likelihood	7588.875	7746.244	627.3395
	Akaike info criterion	-4.5331	-4.62657	-0.37259
	Schwarz criterion	-4.52396	-4.6156	-0.36528
	Hannan-Quinn criter.	-4.52983	-4.62264	-0.36997

Table 32 – Estimation results of MS model, different switchings. Independent variable: general index, period: 3/04/1994 to 12/29/2006, 3346 obs.

Constant transition probabilities	**Switchings**					
	Mean		**Mean and variance**		**Variance**	
Regimes	1	2	1	2	1	2
1	0.990344	0.009656	0.990014	0.009986	0.998352	0.001648
2	0.015228	0.984772	0.013679	0.986321	0.007561	0.992439
Constant expected durations	**Mean**		**Mean and variance**		**Variance**	
	1	2	1	2	1	2
	103.561	65.66827	100.1399	73.10245	606.7754	132.2505

Table 33 – Constant transition probabilities and expected durations according to switchings. Independent variable: general index, period: 3/04/1994 to 12/29/2006

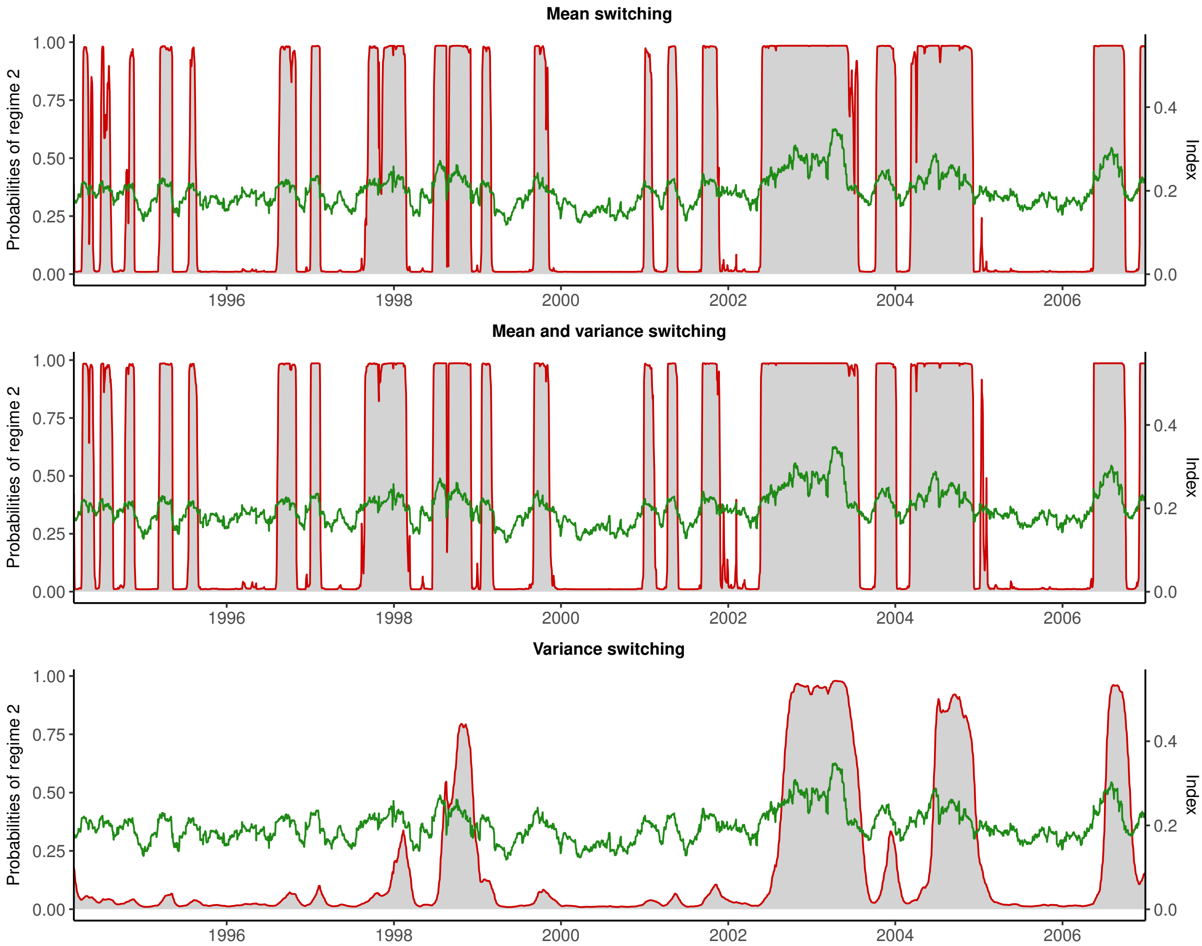

Figure 21 – General index plotted with probabilities of regime 2 according to MS model, switchings in mean, both mean and variance, and variance, period: 3/04/1994 to 12/29/2006, 3346 obs.

For 2007–2017, the estimation results are shown in Tables 34 and 35 and the probabilities of the stress regime are shown in the graphs in Figure 22.

	Switchings	Mean	Mean and variance	Variance
Regime 1	C	0.237277	0.231834	
	Std. Error	0.001148	0.00094	
	P-value	0.0000	0.0000	
	log(sigma)	-3.271139	-3.48081	-1.4482
	Std. Error	0.013694	0.021171	0.023562
	P-value	0.0000	0.0000	0.0000
Regime 2	C	0.359588	0.351834	
	Std. Error	0.00123	0.001245	
	P-value	0.0000	0.0000	
	log(sigma)	-3.271139	-3.11371	-1.05396
	Std. Error	0.013694	0.019119	0.019831
	P-value	0.0000	0.0000	0.0000
	Mean dependent var	0.29466	0.29466	0.29466
	S.E. dependent var	0.071895	0.071895	0.071895
	S.E. of regression	0.038099	0.038693	0.303412
	Sum squared resid	3.972917	4.09625	252.0565
	Durbin-Watson stat	0.092988	0.087904	0.000996
	Log likelihood	4966.597	5022.422	-542.944
	Akaike info criterion	-3.621604	-3.66162	0.399229
	Schwarz criterion	-3.610809	-3.64867	0.407865
	Hannan-Quinn criter.	-3.617703	-3.65694	0.40235

Table 34 – Estimation results of MS model, different switchings. Independent variable: general index, period: 1/01/2007 to 6/30/2017.

Constant transition probabilities	**Switchings**					
	Mean		**Mean and variance**		**Variance**	
Regimes	1	2	1	2	1	2
1	0.990961	0.009039	0.991779	0.008221	0.996744	0.003256
2	0.010918	0.989082	0.007999	0.992001	0.003247	0.996753
Constant expected durations	**Mean**		**Mean and variance**		**Variance**	
	1	2	1	2	1	2
	110.6371	91.59574	121.6334	125.019	307.1572	307.964

Table 35 – Constant transition probabilities and expected durations according to different switchings. Independent variable: general index, period: 1/01/2007 to 6/30/2017.

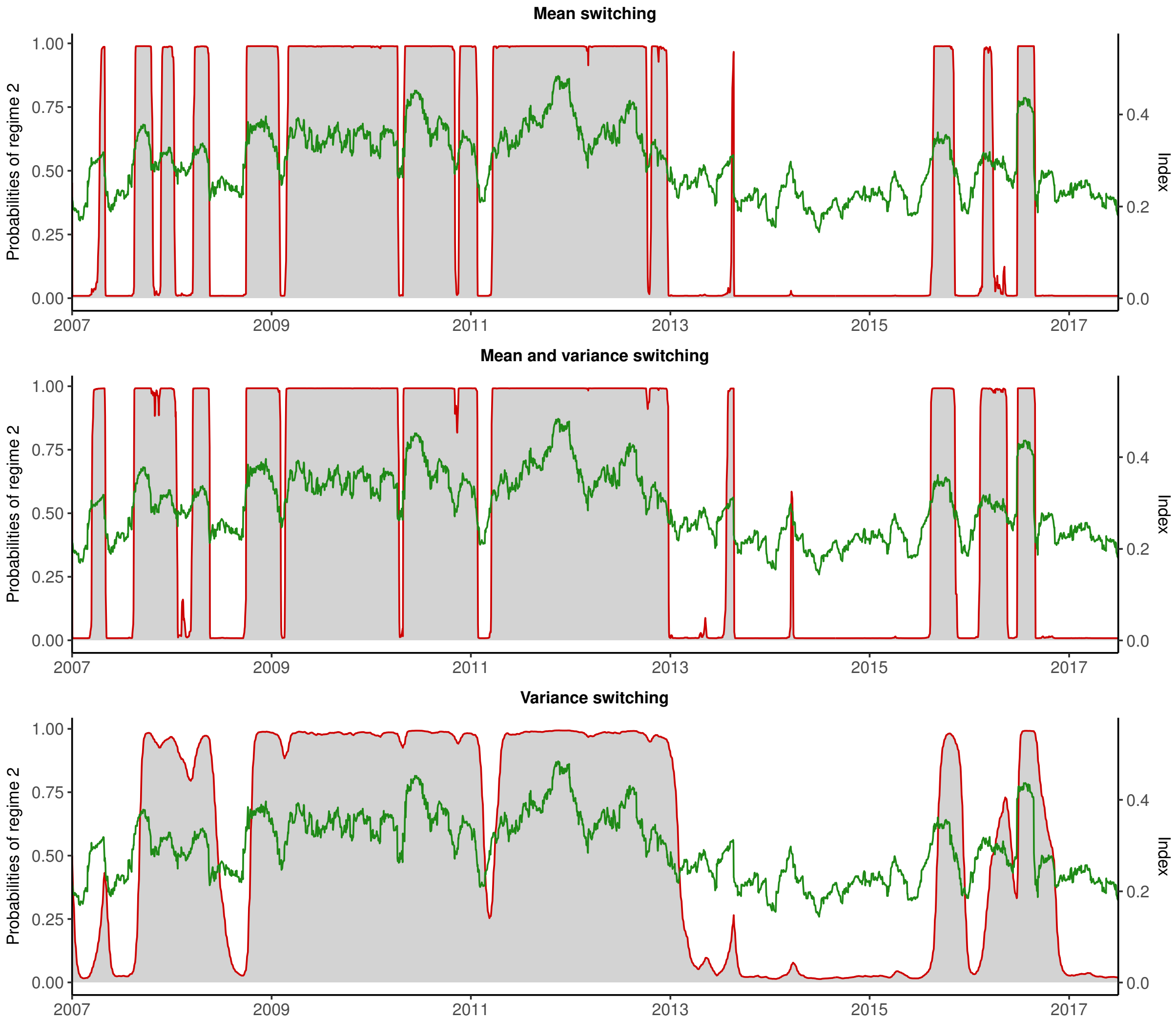

Figure 22 – General index plotted with probabilities of regime 2 according to MS model, different switchings, period: 1/01/2007 to 6/30/2017.

As in the first period (1994–2006), there were fewer moments of stress. The model assigns to regime 2 (stress) part of the sample that would have been in the normal regime when modelling with the whole sample, since the mean and variance now calculated for the stress regime are much lower. The graphs for the second subperiod (2007–2017), in which the occurrence of the two regimes occurred more frequently, became much more adherent to this period in the original graph (with the whole sample). From what we can conclude that the effective occurrence of stress periods in the sample impacts positively the index accuracy, as was the case of our original series.

Appendix E – Indicator constructed with 93 assets, window of 65 days

For comparison purposes, we show in Tables 36 and 37 and in Figure 23 the results of MS analysis for a different window (65 working days) for the indicator calculated with PCA. The differences are not very marked. The larger window provides an indicator a little more parsimonious, as expected.

	Switchings	**Mean**	**Mean and variance**	**Variance**
Regime 1	C	0.194605	0.186064	
	Std. Error	0.000619	0.000568	
	P-value	0.0000	0.0000	
	log(sigma)	-3.32279	-3.674135	-1.654525
	Std. Error	0.009124	0.015755	0.013581
	P-value	0.0000	0.0000	0.0000
Regime 2	C	0.332883	0.311308	
	Std. Error	0.001082	0.001469	
	P-value	0.0000	0.0000	
	log(sigma)	-3.32279	-2.92429	-1.145252
	Std. Error	0.009124	0.016078	0.016413
	P-value	0.0000	0.0000	0.0000
Common	Mean dependent var	0.234961	0.234961	0.234961
	S.E. dependent var	0.072473	0.072473	0.072473
	S.E. of regression	0.035783	0.038252	0.245923
	Sum squared resid	7.76171	8.868733	366.6798
	Durbin-Watson stat	0.038672	0.032161	0.000479
	Log likelihood	11455.56	11778.6	261.4888
	Akaike info criterion	-3.77595	-3.882144	-0.08491
	Schwarz criterion	-3.77041	-3.875506	-0.080484
	Hannan-Quinn criter.	-3.77403	-3.87984	-0.083374

Table 36 – Estimation results of MS model, different switchings. Independent variable: index constructed with 93 assets, window of 65 working days, period: 4/04/1994 to 6/30/2017, 6065 obs.

Constant transition probabilities	**Switchings**					
	Mean		**Mean and variance**		**Variance**	
Regimes	1	2	1	2	1	2
1	0.997863	0.002137	0.996341	0.003659	0.999163	0.000837
2	0.005499	0.994501	0.006029	0.993971	0.001715	0.998285
Constant expected durations	**Mean**		**Mean and variance**		**Variance**	
	1	2	1	2	1	2
	467.967	181.8561	273.3039	165.8699	1195.017	583.0858

Table 37 – Constant transition probabilities and constant expected durations according to different switchings. Independent variable: Index constructed with 93 assets, window of 65 working days, period: 4/04/1994 to 6/30/2017.

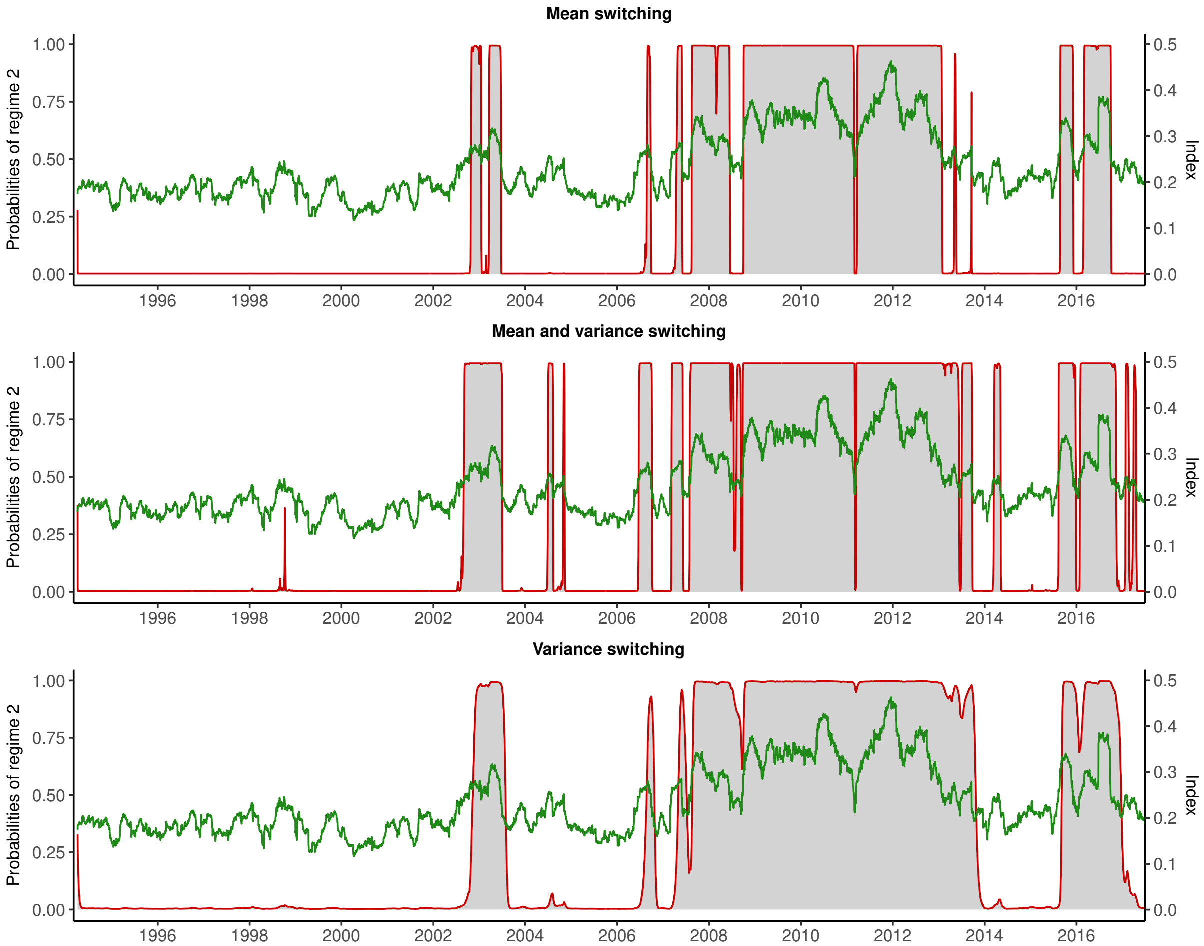

Figure 23 – Indicator calculated with 93 assets, window of 65 working days, plotted with the probabilities that series is in regime 2, according to different switchings, period: 4/04/1994 to 6/30/2017.