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Research article

A common risk factor in global credit and equity markets: An exploratory analysis of the subprime and the sovereign-debt crises

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ABSTRACT

This paper investigates the existence of a common risk factor across asset classes and geographical areas, focusing on the crises and post-crisis periods. This factor has important implications for diversification in investor's portfolios. We assess a worldwide sample of assets: Equity, Corporate CDS and Sovereign CDS from fourteen countries across Europe, US and Asia, and focus the analysis to a time window where diversification was crucial: the crises and post-crisis periods. To identify the factors that underlie asset movements and their composition, a Principal Component Analysis (PCA) is applied. We find that there is supporting evidence for the existence of a common risk factor that underlies 86 percent of our sample' assets movements and reflects a global non-diversifiable risk that permeates the financial system. The uncovered risk factor is robust across periods, and it is evenly distributed across assets and countries, with the noticeable exception of Japan, which follows a divergent risk pattern. This is also true, to a lesser extent, for the US, Canada and China. Within the Eurozone financial assets a higher commonality is uncovered. In addition, we confirm that the common risk factor becomes more important in times of crisis. The existence of a common risk factor limits the possibilities of diversification, in particular during turmoil periods when correlations among assets' movements rise. However, the fact that some geographies display a lower commonality can be used to improve the risk profile of diversified portfolios.

1. Introduction

The global economy is deeply interconnected across asset classes and geographical areas, which makes diversification more important and difficult at the same time. In particular, correlations increase in periods of crises, which makes it more difficult to design robust investment strategies. The extent of the connection across markets can be represented by means of a global risk factor that underlies all investments, albeit with different intensities for different investments. As FTSE Russell (2019) state it "factors have become an influential force in investors' decision-making processes."

The search for a common factor to explain risks has been attempted in a myriad of different manners. With examples such as the study of cycles, systematic components in asset prices or systemic contagion, the financial literature is full of empirical and theoretical research pieces addressing this issue (some examples with broad literature review are Longstaff, 2010; Collin-Dufresne et al., 2001; Baele et al., 2010; Schmidt et al., 2019). Factor models are key to understand the risks and relationships between assets in portfolio management and portfolio construction exercises.

Although exploratory in nature, the model introduced in this paper draws heavily on existing mainstream financial research in the area of asset pricing (e.g., Sharpe, 1964; Lintner, 1965; Merton, 1973; Roll and Ross, 1980).

Asset pricing models predict that expected returns should exhibit some sensitivity to one or several fundamental variables that represent a common source of undiversifiable risk. Classical financial theory (Markowitz, 1952; Sharpe, 1964) demonstrates that risks can either be diversified away, by including different assets in the portfolio, or not be diversified away because there is no possibility of eliminating it. This remaining risk which is undiversifiable is the one that should be priced, and it is called market risk or systematic risk, due to factors that affect the overall performance of the financial markets in which the investor is involved.

Factors explain performance, that is, risk and return. Factors can be divided into three main categories: macroeconomic, fundamental or statistical factors (Connor, 1995). Macroeconomic factors are observable

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economic information (e.g., GDP, interest rates, inflation, etc.), fundamental factors refer to observable asset attributes (e.g., industry, market capitalization, price to earnings ratio, etc.), statistical factors are the least intuitive, because they are unobservable factors. The factor we explore in this paper is a statistical factor derived from Principal Component Analysis used for explanatory purposes.

Additionally, in this research, the Merton structural approach is used to provide a link between equity and debt instruments. Merton introduced the structural model (1974) and its extension the Contingent Claim Approach (CCA) to understand the sectors of an economy as interconnected portfolios[1] (Merton et al., 2013), and extend this philosophy to understand the world economy as a single portfolio of assets, liabilities and guarantees. The CCA framework applies option-pricing theory to the valuation of assets. This provides a link between equity and credit risk (Gray et al., 2007) being the credit risk the possibility of a loss resulting from a company's or sovereign's default. The growing interdependence among local economies due to globalization and specifically cross-border financial activity presents the theoretical justification for cross-country and cross-market linkages. Shocks are transmitted through the economies' real sector or through other financial channels (Bratis et al., 2015).

Following these insights, this paper explores how relations proved by two mainstream finance theories work at the intersection: Merton structural approach and international asset pricing models.

Our contribution is twofold: First, finding a global factor that is common to several markets and regions is a rare exercise. However, this underlying factor, which span assets worldwide, if found, is very useful from the point of view of investors. On the one hand, because it can serve as benchmark for evaluating performance of active investments. On the other hand, because, as Pukthuanthong and Roll (2009) and Cotter et al. (2018) have explained, it can be interpreted as a global integration measure across markets based on the explanatory power of a multi-factor model applied to different countries. Being an indicator of markets integration, the risk factor can also be used as a guide for investments (or alternatively for risk diversification). Insights into complexities of factor behavior can help investors to better anticipate how their portfolios might perform in the future (FTSE Russell, 2019).

Second, we use a novel approach to estimate a common underlying risk factor that underlies the global credit and equity markets. The paper seeks to provide an initial framework to help investors with diversification' strategies, by using the information provided in debt and equity instruments. To the extent of our knowledge, this is the first paper to include the information in both markets to this end. As explained by Shahzad et al. (2018) understanding the dynamics of the co-movement of both markets at different horizons as well as primary determinants maybe useful for investors and portfolio managers in order to make better asset allocation, portfolio rebalancing and risk management decisions. Also, industry papers have long recognized these interdependencies: some examples are the papers by Kapadia and Sinder (2017), Invesco (2019).[2]

We consider the information embedded in the prices of three different financial instruments which account for the credit and equity market of a worldwide sample: Sovereign Credit Default Swaps (SCDS hereafter), Corporate Credit Default Swaps (CCDS) and equities, from financial and non-financial companies from 14 countries. We study 135 institutions: 121 companies, financials (54) and non-financials (67) across 14 different countries, through the three financial instruments (SCDS, CCDS and equities) for a long period of 9 years (2007–2015).

We quantify this interdependence among markets and regions by using Principal Component Analysis (PCA). For this reason, our factor is a statistical factor with no direct connection to any macroeconomic variable. The underlying risk factor uncovered should be understood as a systematic factor related to common economic forces, which cannot be diversified away. Its meaning also matches the common systematic component found by Collin-Dufresne et al. (2001) when studying CCDSs and Longstaff et al. (2011) in SCDS, among others.[3]

The paper explores the main features of this systematic risk factor, studies its consistency, its geographical structure and its evolution along the period studied. As robustness check we validate its meaningfulness relating it to the VIX index. The VIX is the Chicago Board Options Exchange (CBOE) Volatility Index. The VIX is widely recognized as an indicator of investors' risk aversion and financial markets' inherent uncertainty, for this reason it affects asset prices (Pukthuanthong and Roll, 2009; Song and Xiu, 2016; Pan and Singleton, 2008). Accordingly, it seems reasonable to believe that changes in the VIX may induce revisions in investors' allocations and risk management strategies affecting the credit and stock market link (Shahzad et al., 2018). As in Longstaff et al. (2011) we relate our common risk factor to the evolution of the VIX index.

The rest of the paper is structured as follows. Next, we explain the theoretical framework. In section 3 we present the data and methodology. Then, in section 4, we, describe and discuss the results. Conclusions can be found at the end of the paper.

2. Theory and evidence

The paper's goal is to extract a common risk factor underlying global credit and equity markets. For this reason, we present our deductive reasoning to link the two markets together. The approach followed relies on both theories: Merton structural approach and international asset pricing models.

Several papers support the rational long run interdependencies between the credit and market risk: by means of the search for long run equilibrium (e.g., Carr and Wu, 2010; Baele et al., 2010; Figuerola-Ferretti and Paraskevopoulos, 2013; Mateev and Marinova, 2019), common fundamentals (e.g., Byström, 2008, 2018; Forte and Lovreta, 2015) or causality links (e.g., Fung et al., 2008; Forte and Pena, 2009; Shahzad et al., 2017).

All corporate issuers have some positive probability of default, which changes with the firm's stock price and thus its leverage. Merton (1974) was the first to demonstrate that a firm's default option could be modeled with the Black and Scholes (1973) methodology. The basic Merton model has been extended in many ways, yielding models that have considerable explanatory power (for a good review see Sundaresan, 2013).

The right-hand side of a company' Balance Sheet (the liabilities) can be thought of as a claim against its left-hand side (the assets). Liabilities are all linked to the same assets, and there are different rules to assign these assets under different conditions. This implies that debt and equity should move together. Equity investors as well as bondholders and CDS buyers should consider default probabilities, recovery rates and relevant accounting ratios. These financial instruments are tied to the same underlying asset value. This links the prices of equity and debt.

These aftermaths corroborate evidence found by Forte and Lovreta (2015) in relation to the stock market's informational dominance versus the CDS market, particularly in times of crisis. It also holds with the

[1] CCA refers to the Corporate Structural Model or Merton Model application to financial institutions and sovereigns.

[2] Industry papers have long recognized the importance of finding diversifying assets for equity risks, these diversifying assets should have insurance properties and show negative correlations with equities. Fixed Income, Commodities, Currencies, Real State, Timberland, have long been considered diversifier' investments.

[3] The risk systematic risk factor studied does not necessarily have a financial root, and in this sense, it is not a systemic risk. Along the literature we find "interconnectedness", "systemic risk" and "macro-financial risks" as synonymous (e.g., Yellen, 2013; Billio et al., 2012; Merton et al., 2013; Longstaff et al., 2011, etc.).

higher sensitivity of equity prices to credit risk related information under worsening credit conditions (Avramov et al., 2009; Carr and Linetsky, 2006; Fung et al., 2008).

Considering that companies are not isolated entities, and risks propagate among them, the sectors of an economy can be viewed as interconnected portfolios of assets, liabilities and guarantees. Structures that look like guarantees cause risk to propagate across the various sectors of the economy in nonlinear ways, both domestically and across geopolitical borders. These interactions generate what Merton et al. (2013) refer to as macrofinancial risks.

How does the household sector relate to governments? For a home mortgage bond, the put option has the value of the house as its underlying; for a corporate bond, the underlying is the value of the corporate assets. For a sovereign bond (and its derivative, the SCDS), the underlying of the put option is the sovereign assets the creditor obtains claim to, including but not limited to taxing power.

How does the banking sector relate to governments? Governments generally act as a guarantee to the banks, formally with deposit insurance and then implicitly even when they are not required to do so. Credit risk propagates among the different sectors, once a shock occurs. Economic balance sheets can be used to demonstrate the interdependence among sectors. There are feedback loops, not only in the domestic markets but also among different countries. For instance, it is common for banks in one country to hold the sovereign debt of another country. However, in this paper, we are also interested in exploring the role in this underlying financial risk of non-financial multinational companies. These companies operate in many different countries, generating professional and business opportunities and threats, and facing complexities that become sources of risk (capital flows, foreign currency exchange risks, credit interactions, etc.).

As Yellen (2013) states, agents within the financial system engage in a diverse array of transactions and relationships that connect them to other participants across geographic and market boundaries.[4] This globalization has created links and interconnectedness among entities and countries. A counterparty failure, whether it is a financial or non-financial company, can result in subsequent defaults that send shock waves through the financial markets.[5]

To view the global economy as a set of inter-related balance sheets allows to extract a measure of the intensity of these connections (or a markets' integration measure) and to observe whether there is a uniform underlying measure. For this reason we analyze jointly our worldwide sample.

In this paper, we develop an empirical analysis across asset classes including equity, corporate and sovereign debt. Asset pricing theory indicates that innovations in macroeconomic variables are risks that are rewarded in the stock market (Chen et al., 1986). We use SCDS as a proxy for macroeconomic risks. SCDS have been widely studied in the literature (e.g., Longstaff, 2010; Acharya et al., 2014; Ang and Longstaff, 2013)[6], since the liquidity of these instruments has provided a good proxy for countries' credit risk. Ang and Longstaff (2013) note that systemic sovereign credit risk is closely related to financial market variables such as stock returns, supporting the view that this risk is rooted in the financial markets connecting these variables. CCDS and SCDS are the financial market variables accounting for credit and equity company risk.

We find a long array of research works connecting CCDS and SCDS, since there is an intimate relationship between sovereign and corporate credit risk (e.g., Ejsing and Lemke, 2011; Arce et al., 2013; Acharya et al., 2014; Bedendo and Colla, 2015), and connecting equity and sovereign risk (e.g., Norden and Weber, 2009; Corzo Santamarí a et al., 2014; Forte and Lovreta, 2015). However, there is limited evidence linking CDS with the corporate structural model. Moreover, works linking the three financial instruments: SCDS, CDS and equities are missing, and for this reason, we will find it useful to motivate our empirical analysis with a visual exploration of the relationship between the three financial variables under consideration, the SCDS, the CCDS and the corporate equity, since the linearities and non-linearities become apparent (next section).

3. Data and methodology

3.1. Data

We have chosen CCDS and SCDS instead of bond prices due to their higher homogeneity and liquidity during the sample period; the literature also shows that CDSs are preferable in terms of information dissemination. Daily 5-year SCDS and CCDSs prices are used together with daily equity closing prices. All data were taken from Bloomberg and were supplied by Credit Market Analytics (CMA) Data Vision.

The sample range has been selected following a liquidity criterion and considering the global representativeness of the sample, including the maximum number of countries with both a liquid SCDS and companies in that country with liquid CCDS during the study period, 2007–2015.

The CDS-liquidity data was obtained from the 1,000 most liquid CDS in 2015 supplied by DTCC®[7]. For representativeness reasons and considering the investable universe, the sample was designed with the 10 most liquid CCDSs per country, 5 financial and 5 non-financial, in addition to the SCDS. To gain a realistic worldwide data set we selected 10 financial and 10 non-financial companies for the US and for the UK, since the number of liquid CCDS traded for these countries were much higher than for the others. All assets correspond to developed markets. We chose to not include emerging markets due to their more limited liquidity. Illiquidity affects assets' returns because investors require compensation of these costs.[8] Illiquidity affects assets' returns in manners that are not fully understood in the financial literature (Miralles-Quirós et al., 2017), and we chose to isolate our results from liquidity concerns by including only relatively liquid assets in our sample.

The final sample resulted in 14 countries that cope with the requisites of liquidity and representativeness, 7 belonging to the Eurozone (Spain, Germany, France, the Netherlands, Italy, Portugal and Belgium) and 7 countries belonging to the Rest of the World (the US, Australia, Canada, China, Japan, Sweden and the United Kingdom, hereinafter, RoW). A summary of the final sample studied is provided in Table 1, and full sample details with the main descriptive statistics are provided in the Tables 2 and 3.[9]

The sample period starts in January 2007 and ends in December 2015, covering the subprime crisis (2007–2009), the sovereign-debt crisis (January 2010 to June 2011) and the post-crisis years (July 2011 to December 2015).

To enable the joint study of equities and CDS and track the commonalities in their dynamics, we focus on daily log-changes.

For estimation purposes, we have identified the exact previous dates using a rolling VAR. We estimate a company-by-company VAR model with daily observations over a 6-month time frame, with a one-month rolling window. Lead–lag relationships are established based on Granger causality. We identify periods when the p-value for the Granger

[4] The difficult task is to find ways to preserve the benefits of interconnectedness in financial markets while managing the potentially harmful side effects (Yellen, 2013).

[5] A recent attempt to disentangle the interconnectivity of CDS market is the paper by Getmansky et al. (2016); an interesting model for financial networks can be found in Glasserman and Young (2015) as well.

[6] For a review on the wide CDS literature, see Augustin et al. (2016).

[7] DTCC is Depositary Trust and Clearing Corporation. It is an American post-trade financial services company providing clearing and settlement services to the financial markets.

[8] Liquidity is a complex concept. See Amihud et al. (2006) for a complete review on the liquidity effects on asset prices.

[9] Our analysis covers 69 European companies and its notional reaches 36% of the 1000 most liquid European CDS in 2015. Regarding the non-European companies, our study covers 17% of the 1000 most liquid ones (52 companies analyzed).

Table 1. Final sample: Number of companies by country and financial/non-financial classification.

Country	Sovereign CDS	Financial companies	Non Financial companies	Total
Belgium	1	—	1	2
France	1	5	4	10
Germany	1	4	5	10
Italy	1	5	4	10
Netherlands	1	3	3	7
Portugal	1	1	2	4
Spain	1	4	5	10
EURO	**7**	**22**	**24**	**53**
Australia	1	4	6	11
Canada	1	2	5	8
China	1	2	5	8
Japan	1	5	4	10
Sweden	1	4	3	8
United Kingdom	1	6	10	17
USA	1	9	10	20
Rest of the World (RoW)	**7**	**32**	**43**	**82**
CDS	14	54	67	135
Equity	-	54	67	121
RATING A	9	34	12	55
RATING non - A	4	17	52	73
Not Available	1	2	4	7

causality test below 5% and when the direction and significance of the relationship is maintained during more than 6 consecutive rolling periods. Changes in these relationships result in the previous break points.[10]

3.2. Methodology

We use PCA applied to the three previously described financial variables: SCDS, CCDS and equity, following the lines of Roll (2013). For diversification purposes, Roll (2013) demonstrates that factor analysis is a superior method than simple correlation analysis since factors are independent (orthogonal), and asset returns that can be explained by an identical set of common factors do not offer any diversification potential even if they show low correlations among them. In other words, the higher the proportion of asset returns explained by common factors, the less real diversification potential they offer. The common factors should be understood as a sign of market integration.

In addition, PCA has been used by the related literature for different purposes: To decompose the information of several variables into its causes, as in Bühler and Trapp (2009); Longstaff et al. (2011); or Badaoui et al. (2013); to identify variables related to each factor, as in Groba et al. (2013); or Pan and Singleton (2008), which can be used for constructing indexes, identifying the weight each variable should have in the index, as Baker and Wurgler (2006); to identify collinearity among observed variables, with the aim of testing whether the variables are highly interconnected, as in Collin-Dufresne et al. (2001); Billio et al. (2012); or Eichengreen et al. (2012); however, most of them use PCA for various purposes, as do Díaz et al. (2013), who find an important source of commonality among CDS spreads, and decompose the information, using a regression method afterwards. As the main goal of this paper is to find a global factor that is common to several markets and regions, we use PCA to test whether the market variables are highly interconnected with this common risk factor mentioned before.

This paper applies PCA first for the full sample, then, as a robustness check, to the different periods established in the VAR analysis. PCA provides a broad view of the connections among the studied assets and allows us to estimate a factor underlying the movements of these financial instruments and to gauge the value of this underlying financial risk. As explained above, PCA has been the method of choice used recently by Cotter et al. (2018) and Pukthuanthong and Roll (2009) to measure the diversification potential and to assess its reciprocal, the markets' integration condition.

4. Analysis, findings and discussion

This section presents concisely the analyses that were carried out to identify and describe the common risk factor, as well as the main findings that emerged from them and their implications. It has been organized into the following sections:

- First, an Exploratory Data Analysis was carried out to help understand the dynamics of the assets under consideration in the period of study.
- Then, the common risk factor is evidenced through Principal Component Analysis. Later, it is further studied, focusing on three especially relevant aspects:
- The dynamics of this common risk factor,
- Its relationship to VIX,
- The different sources of commonality that the common risk factor reflects: global vs. country-level commonality.

The next paragraphs focus on the first exploratory data analysis, with the rest of the study continuing along the following sections.

4.1. Exploratory data analysis

Given that works linking the three financial instruments used in this paper: SCDS, CDS and equities are missing, we find useful to motivate our

[10] Since our sample contains several countries and companies, we have estimated the rolling VAR for the 5 most liquid CCDS (Santander Bank, Deutsche Bank, Intesa San Paolo, MBIA Insurance Corp and Barclays Bank PLC) and for 4 other CCDS selected randomly (Continental, Peugeot, Credit Agricole and Commonwealth Bank of Australia), obtaining similar results. In the case of the companies that belong to the Eurozone, we have detected the three breakpoints mentioned before. Nevertheless, in the case of the RoW companies, the rolling VAR results do not show any breakpoint, so we have decided to split the sample according to the European results. Detailed rolling VAR results are available upon request.

Table 2. Descriptive statistics for Credit Default Swaps and Stock prices for the Eurozone.

Country	Issuing Country/Company	Rating Moody's 2015	CDS						Stock Price					
			Obs	Min	Max	Mean	Stdev	Stdev/Mean	Obs	Min	Max	Mean	Stdev	Stdev/Mean
Belgium	Sovereign	Aa1	2,233	1.54	306.76	66.39	60.52	0.91	N/A	N/A	N/A	N/A	N/A	N/A
	Solvay	Baa2	2,255	9.95	262.92	85.27	44.15	0.52	2,349	39.48	132.47	88.01	19.59	0.22
France	Sovereign	Aaa	2,304	1.14	190.86	48.68	41.23	0.85	N/A	N/A	N/A	N/A	N/A	N/A
	AXA	A2	2,347	9.10	396.31	125.45	82.27	0.66	2,349	5.74	33.82	17.77	6.02	0.34
	BNP Paribas	A1	2,346	5.70	359.59	98.63	66.40	0.67	2,349	20.78	91.60	51.70	13.67	0.26
	Credit Agricole	A2	2,340	5.84	403.78	119.83	76.91	0.64	2,349	2.88	31.03	11.91	6.23	0.52
	Societe Generale	A2	2,346	6.01	440.27	125.78	85.63	0.68	2,349	15.00	140.55	46.99	26.44	0.56
	Casino Guichard	BB+ (S&P)	2,347	38.35	400.29	134.73	58.06	0.43	2,349	41.50	97.07	68.54	11.59	0.17
	France Telecom	Baa1	2,347	17.40	226.45	78.27	33.87	0.43	2,349	7.10	26.78	15.07	4.54	0.30
	Lafarge	Baa2	2,345	21.20	1,107.77	237.47	179.25	0.75	2,349	23.00	118.08	57.52	22.25	0.39
	Peugeot	Ba3	2,347	17.37	816.33	320.78	203.69	0.63	2,349	3.64	47.34	17.11	10.77	0.63
	Renault	Ba1	2,348	17.90	589.13	227.35	136.65	0.60	2,349	10.57	121.38	54.47	25.25	0.46
Germany	Sovereign	Aaa	2,242	2.08	89–43	26.09	19.68	0.75	N/A	N/A	N/A	N/A	N/A	N/A
	Allianz	Aa3	2,347	6.04	190.81	69.90	34.50	0.49	2,349	46.64	178.64	109.92	30.59	0.28
	Commerzbank	A2	2,347	8.16	353.39	119.38	68.96	0.58	2,349	5.79	224.94	47.53	58.97	1.24
	Deutsche Bank	A3	2,346	9.82	311.60	99.21	45.31	0.46	2,349	14.69	102.66	40.96	19.24	0.47
	Muenchener	Aa3	2,349	6.36	128.24	53.51	20.52	0.38	2,349	79.55	205.85	127.78	26.46	0.21
	BMW	A2	2,345	8.46	512.84	93.82	75.90	0.81	2,349	17.04	122.60	58.69	24.25	0.41
	Continental	Baa1	2,346	36.21	1,522.61	291.62	291.47	1.00	2,349	10.99	231.35	93.68	57.62	0.62
	Daimler	A3	2,347	19.86	538.33	99.53	73.63	0.74	2,349	17.44	95.79	50.54	16.65	0.33
	Deutsche TeleKom	Baa1	2,347	21.05	189.48	76.91	29.80	0.38	2,349	7.71	17.60	11.21	2.42	0.22
	Heildelbergcement	Ba1	2,346	30.13	5,315.85	423.84	690.54	1.63	2,349	18.55	110.79	57.40	23.09	0.40
Italy	Sovereign	Baa2	2,320	4.04	472.86	130.35	103.66	0.80	N/A	N/A	N/A	N/A	N/A	N/A
	Asicurazioni Generali	Baa1	2,347	5.81	451.61	138.71	99.93	0.72	2,349	8.22	33.43	17.81	5.88	0.33
	Banca Monte dei Paschi di Siena	B2	2,347	6.13	883.31	256.97	206.05	0.80	2,349	1.15	90.97	22.73	24.42	1.07
	Banca Popolare di Milano	Ba2	1,964	11.40	839.22	232.97	205.80	0.88	2,349	0.23	4.01	1.15	0.90	0.79
	Intesa San Paolo	A3	2,347	5.76	627.82	155.93	130.40	0.84	2,349	0.87	5.87	2.59	1.23	0.48
	Unicredit	Baa1	2,347	7.48	687.10	180.13	137.04	0.76	2,349	2.29	40.83	11.93	9.87	0.83
	Atlantia	Baa1	2,118	18.13	435.43	130.53	88.85	0.68	2,349	8.07	25.58	16.08	4.33	0.27
	ENEL	Baa2	2,349	11.23	637.91	159.77	115.61	0.72	2,349	2.03	7.54	4.21	1.34	0.32
	ENI	Baa1	2,340	4.78	249.03	81.68	49.37	0.60	2,349	12.17	28.33	18.16	3.29	0.18
	Telecom Italia	Ba1	2,347	33.22	566.30	227.62	119.36	0.52	2,349	0.47	2.42	1.10	0.44	0.41
Netherlands	Sovereign	Aaa	1,860	7.38	105.63	38.11	22.77	0.60	N/A	N/A	N/A	N/A	N/A	N/A
	Aegon	A3	2,347	9.05	608.25	156.73	95.66	0.61	2,349	1.85	16.06	6.39	3.20	0.50
	ING Bank	A1	1,243	58.42	302.50	145.84	55.6	0.38	2,349	1.92	26.64	10.76	5.91	0.55
	Royal Bank of Scotland	Ba1	2,345	4.06	395.94	144.25	86.43	0.60	2,349	103.00	6,026.36	1,060.29	1,554.93	1.47
	K. AHOLD	Baa2	2,349	41.90	339.25	101.66	41.30	0.41	2,349	7.23	20.68	11.85	2.70	0.23
	K. DSM	A3	2,338	21.33	143.14	N/A	19.42	0.34	2,349	15.76	59.75	39.88	9.63	0.24
	K. KPN	Baa3	2,346	31.90	197.89	93.93	37.17	0.40	2,349	1.39	8.15	5.07	2.00	0.40
Portugal	Sovereign	Ba3	2,335	2.95	1,161.71	241.46	249.17	1.03	N/A	N/A	N/A	N/A	N/A	N/A
	Banco Comercial Portugues	B1	2,346	8.15	1,739.05	409.07	398.42	0.97	2,349	0.03	1.32	0.27	0.30	1.11
	EDP	Baa3	2,345	9.15	946.43	236.82	221.80	0.94	2,349	1.66	4.91	3.00	0.67	0.22
	Portugal Telecom	Ba2	2,346	35.51	3,898.00	357.53	359.36	1.01	2,349	1.78	12.60	5.12	2.62	0.51
Spain	Sovereign	Baa2	2,328	1.94	532.28	128.94	109.19	0.85	N/A	N/A	N/A	N/A	N/A	N/A
	BBVA	A3	2,346	7.72	508.82	164,.71	114.96	0.70	2,349	4.43	19.29	9.55	3.35	0.35
	Popular	Ba1	1,197	8.00	538.44	196.58	109.39	0.56	2,349	2.36	43.55	13.14	10.90	0.83
	Sabadell	Baa3	1,568	11.50	855.90	335.99	222.19	0.66	2,349	1.04	6.31	2.67	1.25	0.47
	Santander	A3	2,347	7.62	487.50	157.62	107.51	0.68	2,349	4.00	13.98	8.13	2.66	0.33
	ArcelorMittal	Ba2	1,950	23.10	1,018.64	333.32	170.95	0.51	2,349	2.61	48.70	16.73	10.64	0.64
	Endesa	Baa2	2,347	10.74	623.70	111.55	82.30	0.74	2,349	11.63	40.64	22.74	7.49	0.33
	Iberdrola	Baa1	2,349	12.41	565.70	135.97	90.79	0.67	2,349	2.65	11.90	6.10	1.95	0.32
	Repsol YPF	Baa2	2,349	19.26	537.31	146.88	92.70	0.63	2,349	9.96	30.35	18.94	4.03	0.21
	Telefonica	Baa2	2,346	21.18	570.91	154.02	104.05	0.68	2,349	8.53	23.00	14.55	3.19	0.22

empirical analysis with a visual exploration of the relationship between the three variables under consideration, since the linearities and non-linearities of these relationship become apparent. We use daily closing prices from 2007 to 2015 and graph the three variables together for some companies in our sample, as an illustration of the joint evolution of these variables.

In Figures 1 and 2, we plot the values of the three financial variables we consider (SCDS, CDS and equity) for some specific pairs of companies-countries. This evolution of the joint three main assets studied in a 3D view can also be seen in three videos (Spain SCDS - Santander Equity - Santander CDS, Spain SCDS - Iberdrola Equity - Santander CDS, Germany SCDS - Deutsche Bank Equity - Deutsche Bank CDS).

Supplementary video related to this article can be found at https://doi.org/10.1016/j.heliyon.2020.e03980

We observe how the evolution of the three variables develops in an inclined plane. At the beginning of our sample period, stock prices are high, and the level of risk evidenced by the CDS premium is low. However, as the subprime crisis unfolds, CDSs start to increase and equity prices drop. For European companies, this shift intensifies greatly during the post-subprime-crisis years and the European sovereign crisis, reaching a peak for CDS values in 2012. After that point, we note that CDSs, both sovereign and corporate, return slowly to their lower baseline levels, reflecting a more controlled credit risk environment. We can observe a linear relationship between SCDSs and CCDSs, both representing the credit risk market (see Figure 1 for Iberdrola stock).

However, when CDSs revert, equity prices do not return to pre-crisis levels and instead remain at lower levels (Figure 1 for Iberdrola data, and 2 for Santander and Deustche Bank) depicting a nonlinear movement. This fact can be explained theoretically. Equity prices remain below the high levels that occurred before the crisis period due to the reduction in

Table 3. Descriptive statistics for Credit Default Swaps and Stock prices for countries outside the Eurozone.

Country	Issuing Country/Company	Rating Moody's 2015	CDS						Stock Price					
			Obs	Min	Max	Mean	Stdev	Stdev/Mean	Obs	Min	Max	Mean	Stdev	Stdev/Mean
Australia	Sovereign	Aa3	1,391	21.24	167.40	58.68	24.44	0.42	N/A	N/A	N/A	N/A	N/A	N/A
	ANZ	Aa2	1,714	4.19	241.79	99.92	49.24	0.49	2,349	7.76	33.02	22.83	5.31	0.23
	C.B.A.	Aa2	1,695	4.00	241.82	99.72	48.61	0.49	2,349	15.66	77.52	52.39	13.95	0.27
	N.A.B.	Aa2	1,710	4.35	241.82	100.34	49.46	0.49	2,349	9.67	38.44	25.19	5.20	0.21
	Westpac	Aa2	1,711	4.00	241.80	99.11	49.19	0.50	2,349	9.48	34.86	23.48	5.00	0.21
	BHP BILLITON	A3	1,750	9.44	578.15	90.43	65.93	0.73	2,349	11.70	48.60	30.49	7.31	0.24
	GPT RE	A3	9,510	92.70	391.63	159.48	54.87	0.34	2,349	0.63	14.96	4.71	3.52	0.75
	Qantas	Baa3	1,705	34.57	444.88	194.76	87.68	0.45	2,349	0.92	5.88	2.43	1.16	0.48
	Rio Tinto	Baa1	1,219	56.83	1,062.50	204.33	210.66	1.03	2,349	16.32	117.39	61.16	18.36	0.30
	Telstra	A2	1,705	21.00	192.95	80.39	37.13	0.46	2,349	1.98	5.35	3.77	0.84	0.22
	Woodside Petroleum	Baa1	1,702	18.78	375.48	121.30	68.62	0.57	2,349	18.19	66.36	36.52	8.04	0.22
Canada	Sovereign	N/A	1,961	N/A	133.50	35.49	19.26	0.54	N/A	N/A	N/A	N/A	N/A	N/A
	Brookfield	Baa2	1,019	154.00	906.10	307.23	153.85	0.50	2,349	7.42	38.69	22.10	6.83	0.31
	Fairfax F.H.	Baa3	1,294	52.57	1,305,13	410.75	217.71	0.53	2,349	169.42	587.93	369.41	87.90	0.24
	Agrium	Baa2	2,013	24.93	318.35	95.65	47.86	0.50	2,349	23.38	116.52	76.52	22.73	0.30
	Barrick Gold	Baa3	2,043	22.76	465.00	145.93	80.10	0.55	2,349	5.93	55.68	32.09	13.41	0.42
	Bombardier	B2	1,901	94.57	1,043.94	332.81	153.75	0.46	2,349	0.82	8.76	4.26	1.47	0.34
	C.N.R.	Baa3	1,806	36.62	701.16	143.08	112.80	0.79	2,349	13.67	53.93	33.12	7.00	0.21
	Encana	Ba2	1,920	16.76	551.07	144.91	96.86	0.67	2,349	4.68	51.34	24.68	8.69	0.35
China	Sovereign	Baa3	2,094	10.00	276.30	84.45	43.66	0.52	N/A	N/A	N/A	N/A	N/A	N/A
	Bank of China	A1	1,258	15.75	413.77	135.44	89.77	0.66	2,349	0.21	0.72	0.46	0.08	0.17
	Oversea-Chinese Banking	Aa1	1,148	5.75	292.25	63.84	45.52	0.71	2,349	0.50	1.41	1.12	0.17	0.15
	Cnooc	Aa3	1,211	10.75	327.75	83.55	59.66	0.71	2,349	0.55	2.68	1.64	0.42	0.26
	Hutchison Whampoa	A3	1,664	17.62	665.85	110.25	79.91	0.72	2,349	4.40	15.21	10.21	2.64	0.26
	Noble	Ba3	8,730	93.37	1924.78	282.29	223.88	0.79	2,349	0.04	0.30	0.16	0.06	0.37
	Pccw-Hkt Telephone	RWR	1,075	40.49	773.22	170.68	133.73	0.78	2,349	0.22	0.72	0.45	0.12	0.27
	Swire Pacific	A3	1,220	12.03	654.06	112.62	91.10	0.81	2,349	4.64	15.32	11.01	1.94	0.18
Japón	Sovereign	Aaa	2,214	2.13	157.21	57.10	33.40	0.58	N/A	N/A	N/A	N/A	N/A	N/A
	ACOM CO.	RWR	2,327	0.20	12.65	2.44	2.21	0.91	2,349	0.98	5.69	2.73	0.98	0.36
	Bank of Tokyo-Mitsubishi	A1	2,168	6.10	197.50	77.30	37.18	0.48	2,349	3.85	12.74	6.40	2.00	0.31
	Mizuho Bank	A1	2,274	6.45	238.40	91.53	44.09	0.48	2,349	1.26	7.51	2.62	1.55	0.59
	Orix	N/A	2,322	0.15	25.85	2.71	3.85	1.42	2,349	1.92	29.68	12.62	5.52	0.44
	Sumitomo Mitsui Bank.	A1	2,264	6.39	222.16	79.78	40.84	0.51	2,349	26.14	105.46	45.68	19.29	0.42
	Nippon Steel	Baa1	2,323	0.09	3.20	0.84	0.66	0.78	2,349	17.84	79.11	35.52	14.07	0.40
	Panasonic	Baa1	2,316	0.02	6.15	0.82	0.89	1.09	2,349	4.83	23.94	13.05	4.30	0.33
	Ricoh	RWR	2,310	0.04	2.83	0.55	0.49	0.89	2,349	6.38	24.05	12.87	3.80	0.30
	Sony	Ba1	2,322	0.07	6.03	1.28	1.15	0.90	2,349	9.57	58.82	27.90	11.84	0.42
Sweden	Sovereign	Aa2	1,892	1.63	156.36	33.48	25.49	0.76	N/A	N/A	N/A	N/A	N/A	N/A
	Nordea Bank	Aa3	1,300	37.47	274.51	128.61	43.31	0.34	2,349	3.50	14.97	10.83	2.24	0.21
	Skandinaviska Enskilda	Aa3	1,668	10.03	330.11	148.83	74.00	0.50	2,349	1.73	19.10	9.78	3.75	0.38
	Svenska Handelsbanken	Aa2	1,454	48.11	215.57	105.56	38.08	0.36	2,349	3.38	17.66	11.25	3.22	0.29
	Swedbank	Aa3	8,660	107.95	332.77	170.32	55.96	0.33	2,349	1.66	33.25	18.64	7.56	0.41
	A. Electrolux	RWR	2,348	31.92	274.00	104.99	47.94	0.46	2,349	6.23	33.62	22.08	5.90	0.27
	A. Volvo	Baa2	2,349	26.92	881.16	209.96	147.53	0.70	2,349	3.30	22.86	12.79	3.54	0.28
	Svenska Cellulosa	Baa1	1,793	29.87	494.05	125.73	68.76	0.55	2,349	6.19	30.88	18.48	6.12	0.33

(continued on next page)

Table 3 (*continued*)

Country	Issuing Country/Company	Rating Moody's 2015	CDS						Stock Price					
			Obs	Min	Max	Mean	Stdev	Stdev/Mean	Obs	Min	Max	Mean	Stdev	Stdev/Mean
U.K.	Sovereign	A1	1,868	14.59	164.79	52.93	29.04	0.55	N/A	N/A	N/A	N/A	N/A	N/A
	Aviva	A3	2,346	7.71	640.39	157.26	89.09	0.57	2,349	230.14	1,679.03	772.03	319.05	0.41
	Barclays Bank	A2	2,346	7.19	378.82	148.37	78.62	0.53	2,349	65.27	1,394.90	498.83	283.35	0.57
	Experian Finance	Baa1	2,328	37.71	239.78	76.27	25.26	0.33	2,349	442.87	2,036.96	1,297.84	416.75	0.32
	HSBC	Aa2	2,346	6.44	244.18	102.52	46.80	0.46	2,349	419.02	1,723.50	1,072.42	246.32	0.23
	Lloyds TSB Bank	A1	2,341	4.84	512.22	173.69	116.48	0.67	2,349	28.23	595.53	167.73	157.42	0.94
	Royal Bank of Scotland	Ba1	2,345	5.27	525.22	192.99	115.58	0.60	2,349	143.50	11,684.52	1,988.58	3,142.99	1.58
	Anglo American	Ba3	2,320	19.06	1,120.36	229.53	162.26	0.71	2,349	392.74	7,682.17	3,535.32	1,561.71	0.44
	Bae Systems	Baa2	2,343	18.22	414.35	122.79	64.41	0.52	2,349	389.61	1,073.82	651.11	159.69	0.25
	BP	A2	2,340	4.83	753.39	95.55	78.16	0.82	2,349	456.28	1,322.45	806.15	180.76	0.22
	British Airways	Baa3	1,815	88.39	1,156.30	615.30	272.67	0.44	2,349	165.63	1,133.42	498.85	243.84	0.49
	British American Tobacco	A3	2,347	26.31	226.63	75.40	32.02	0.42	2,349	2,196.25	6,183.13	4,323.34	1,077.87	0.25
	British Telecom.	Baa1	2,347	38.05	343.90	126.86	56.64	0.45	2,349	99.05	751.36	427.26	184.93	0.43
	Centrica	Baa1	2,055	18.46	220.28	89.64	33.43	0.37	2,349	303.02	718.84	500.87	89.89	0.18
	Dixons Retail	RWR	2,331	44.39	2,564.00	638.26	500.71	0.78	2,349	10.45	2,866.62	73.52	60.14	0.82
	GKN Holdings	Baa3	2,055	49.91	1,407.08	282.97	214.01	0.76	2,349	52.77	691.80	375.16	153.71	0.41
	Glencore	Baa3	2,035	49.34	2,303.99	300.03	303.94	1.01	2,349	410.92	4,875.62	1,959.59	919.12	0.47
USA	Sovereign	Aa1	1,568	16.72	93.35	43.61	17.68	0.41	N/A	N/A	N/A	N/A	N/A	N/A
	Bank of America	Baa1	2,328	8.59	483.06	134.37	87.90	0.65	2,349	3.14	54.05	19.14	12.91	0.67
	Berkshire Hathaway	Aa2	1,923	18.26	519.98	129.47	80.42	0.62	2,349	46.00	152.67	93.37	26.37	0.28
	Citigroup	Baa1	2,335	7.44	665.53	150.19	104.70	0.70	2,349	10.20	557.00	107.47	143.02	1.33
	General Electric	A1	2,220	11.51	1,000.26	153.55	143.37	0.93	2,349	6.66	42.12	23.43	7.46	0.32
	Goldman Sachs	A3	2,292	20.90	545.14	144.01	83.36	0.58	2,349	52.00	247.92	158.23	36.99	0.23
	JPMorgan Chase	A3	2,339	14.49	232.30	85.09	35.46	0.42	2,349	15.90	70.08	46.19	10.30	0.22
	MBIA Inc.	Ba1	1,976	18.32	3,316.75	891.30	521.36	0.58	2,349	2.29	73.06	14.64	16.57	1.13
	MGIC	B1	2,003	27.73	2,315.74	770.78	542.06	0.70	2,349	0.84	70.09	11.40	14.15	1.24
	Radian Group	Ba3	1,921	29.00	5,392.32	983.28	836.50	0.85	2,349	0.77	66.51	12.25	13.03	1.06
	H-Packard	Baa2	2,210	7.84	374.41	95.62	74.74	0.78	2,349	5.32	24.75	16.10	4.69	0.29
	Sprint Nextel	B3	1,893	83.42	1,474.51	480.37	232.73	0.48	0,649	3.10	10.79	6.14	1.85	0.30
	Alcoa	Ba1	2,111	15.51	1,082.08	254.09	161.29	0.63	2,349	5.22	47.35	16.28	10.02	0.61
	Caterpillar	A2	2,229	11.07	426.85	79.67	54.30	0.68	2,349	22.17	116.20	78.41	20.06	0.26
	CenturyLink	Ba2	2,232	36.84	548.53	184.59	87.29	0.47	2,349	21.81	49.52	36.42	5.51	0.15
	Darden Rest.	Baa3	1,898	47.73	438.30	148.93	52.28	0.35	2,349	12.12	67.08	40.84	9.84	0.24
	J. C. Penney	B3	1,727	29.77	1,827.48	432.20	382.52	0.89	2,349	5.08	86.35	27.89	18.78	0.67
	Macy's	Baa2	2,202	44.23	1,036.90	170.75	153.49	0.90	2,349	5.68	72.80	35.45	16.62	0.47
	PulteGroup	Ba1	1,826	39.86	655.14	278.09	114.17	0.41	2,349	3.54	35.10	14.56	6.13	0.42
	Safeway	B3	2,180	30.18	495.04	174.64	114.44	0.66	2,349	13.43	35.34	24.60	6.97	0.28

firm value, which leads to a reduction in stock price according to the structural model (Merton, 1974). Credit risk exposure represents a nonlinear exposure to the value of the firm.

These figures help our understanding of the connectedness between these financial variables and how information is incorporated in them.

Tables 2 and 3 summarize the explanatory variables and their main descriptive statistics split by country and company/sovereign. Such descriptive statistics show that there is wide dispersion within the sample, among all the companies, both in the Eurozone and in the RoW, for SCDS, CCDS and equities. The data are, however, more homogenous in the Eurozone than in the RoW. We can find an average of 0.55 basis points (bps) for the Japanese Ricoh CCDS and an average of 983.28 bps for the American Radian Group CCDS. Nevertheless, we find lower dispersion when observations of the same company are analyzed. The standard-deviation- to-mean ratio is below 1 for almost all the companies and sovereigns analyzed. The values of skewness and kurtosis indicate asymmetry within the variables.[11] Thus, we test normality using the Kolmogorov-Smirnov test. Table 4 shows very low evidence of normality both for the Eurozone and for the RoW variables. Full-sample analysis rejects normality for all variables, and only during the European sovereign crisis period do we find some variables (39%) distributed according to a Gaussian distribution. This means that the application of PCA will not guarantee that the components obtained will be independent factors, but they will be uncorrelated. This means we can still assess the issue of market integration which is the main focus of this paper.

At the sovereign level, Table 5 shows the Spearman correlations of log-changes in SCDSs.[12]9 All SCDSs are correlated: we find that all correlations are positive and statistically significant at the 1% level. The overall average correlation amounts to +0.35. Correlations were at their

[11] Skewness and Curtosis are not presented in Tables 2 and 3, but they are available upon request.

[12] Comparing the 14 SCDS spreads, we find a large correlation as Longstaff et al. (2011) did, with many companies exhibiting correlations over 50% and even over 80%. In fact, 31% of the 91 total CCDS and SCDS pairs present a correlation higher than 80%, and 82% higher than 50%. The average pairwise correlation taken over all countries is approximately 67%, while Longstaff et al. (2011) found a 62%. These results are even larger when considering different sub-periods, finding that the first and third periods present approximately 80% of the pairwise correlations above 80%, and approximately 90% of the pairs above 50%.

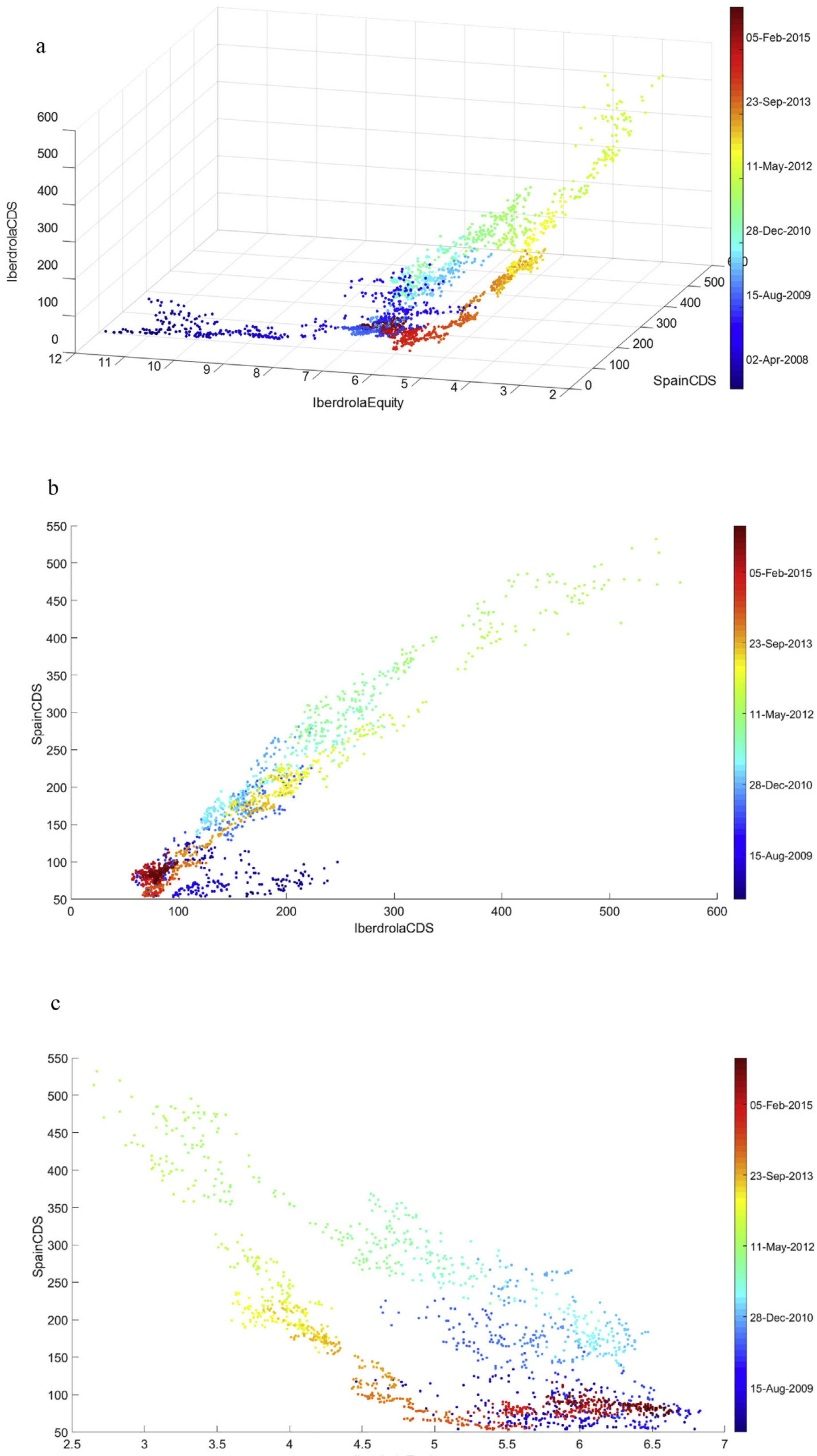
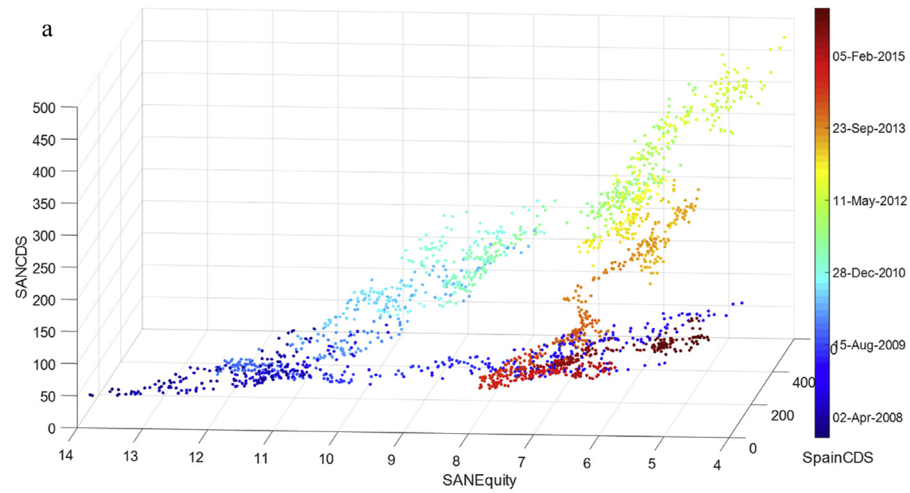


Figure 1. Daily evolution of Spanish Sovereign CDS versus Iberdrola Company CDS and Iberdrola stock during the period 2007–2015. We first plot the three variables together (panel a); second, we plot them by twos (panels b and c). In dark blue are year 2007 observations; colors lighten up as we approach more recent dates. In bright red are year 2015 observations. a) Joint evolution of the thee variables: Spanish Sovereign CDS vs. Iberdrola CDS and Iberdrola Stock. b) Joint evolution of the Spanish Sovereign CDS and Iberdrola CDS. c) Joint evolution of the Spanish Sovereign CDS vs. Iberdrola Equity.



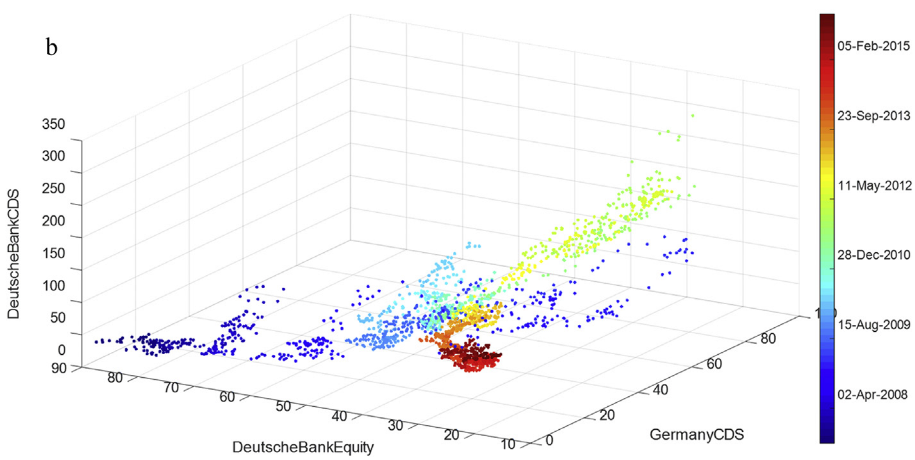


Figure 2. Daily evolution of Deustche Sovereign CDS, Deustche Bank CDS and equity (panel a); and Spanish Sovereign CDS, Banco Santander CDS and equity (panel b), during the period 2007–2015. In dark blue are year 2008 observations; colors lighten up as we approach more recent dates. In bright red are year 2015 observations. a) Evolution of Deustche Sovereign CDS, Deustche Bank CDS and Deutsche Bank Equity. b) Evolution of Spanish Sovereign CDS, Banco Santander CDS and Banco Santander Equit.

highest during the Sovereign crisis (2010–June 2011), with eight countries having correlations above +0.5. This confirms the commonly held assumption that correlations tend to increase during periods of financial crisis (Ang and Bekaert, 2002). After the crises, correlations decrease. The final period (July 2011 to December 2015) is the one with the lowest total average correlation: +0.31.

In Tables 6 and 7, we report Spearman correlations between SCDS- and CCDS- spread log-changes, and SCDS and equity log-changes for each country. As expected, we find positive correlations between SCDS and CCDS movements and negative correlations between SCDS and equities. In all countries, correlations are higher for CCDS than for stocks. On average, correlations are larger for Eurozone countries than for countries outside the Eurozone. For the Eurozone, CCDS movements correlate an average of +0.4 with their sovereign, and the companies' equity correlates at an average of -0.3. Outside the Eurozone, the averages are +0.25 and -0.18 respectively. Nevertheless, Australia is the country with the highest correlations between SCDS and CCDS, +0.5, and Canada presents the lowest ones at +0.1. Italy presents the highest correlations between SCDS and equities in absolute terms, -0.36, while the US shows the lowest: -0.04, being almost independent. These results already offer very interesting insights from a diversification point of view and foretell what we will find in the analysis of the underlying financial risk factor. Again, we find maximum correlations during the Sovereign Crisis.

4.2. The common risk factor

This section measures the underlying risk and presents its main features and evolution. A complementary study has been done to check not only the commonality worldwide but also commonalities inside each country, and their relationships.

As Longstaff (2010) notes, "contagion, however, is possible in virtually any set of financial markets". He finds strong evidence of contagion in stock returns, Treasury and corporate bond-yield changes. Collin-Dufresne et al. (2001) could not find "any set of variables that can explain

Table 4. Results for the Kolmogorov-Smirnov test of normality. The table displays the percentage of financial variables, in log-changes, that fulfill the normality distribution at a 5% of significance.

	Eurozone	RoW	TOTAL
Full sample period 01/01/2007-12/31/2015	0%	0%	0%
01/01/2007-12/31/2009	0%	1%	1%
01/01/2010-06/30/2011	39%	38%	39%
07/01/2011-12/31/2015	2%	4%	3%

Table 5. Correlation (Spearman) between SCDS log-changes. Total sample period and sub periods. ** and * represent significance at the 1%, and 5% levels, respectively.

Total Period	Australia	Belgium	Canada	China	France	Germany	Italy	Japon	Netherlands	Portugal	Spain	Sweden	UK	USA
Australia	1													
Belgium	0.284**	1												
Canada	0.143**	0.225**	1											
China	0.489**	0.246**	0.096**	1										
France	0.304**	0.595**	0.245**	0.269**	1									
Germany	0.293**	0.556**	0.238**	0.267**	0.585**	1								
Italy	0.322**	0.617**	0.234**	0.309**	0.608**	0.533**	1							
Japon	0.391**	0.170**	0.075**	0.290**	0.168**	0.155**	0.212**	1						
Netherlands	0.272**	0.636**	0.249**	0.266**	0.586**	0.584**	0.558**	0.206**	1					
Portugal	0.250**	0.545**	0.202**	0.266**	0.512**	0.443**	0.660**	0.160**	0.478**	1				
Spain	0.274**	0.595**	0.211**	0.281**	0.576**	0.483**	0.759**	0.140**	0.540**	0.688**	1			
Sweden	0.287**	0.476**	0.214**	0.243**	0.453**	0.459**	0.451**	0.151**	0.539**	0.379**	0.436**	1		
UK	0.268**	0.545**	0.204**	0.258**	0.483**	0.485**	0.496**	0.193**	0.509**	0.417**	0.469**	0.503**	1	
USA	0.168**	0.180**	0.249**	0.101**	0.189**	0.222**	0.192**	0.117**	0.193**	0.168**	0.183**	0.212**	0.239**	1
2007–2009	Australia	Belgium	Canada	China	France	Germany	Italy	Japon	Netherlands	Portugal	Spain	Sweden	UK	USA
Australia	1													
Belgium	0.202**	1												
Canada	0.051	0.084	1											
China	0.333**	0.287**	0.102*	1										
France	0.219**	0.458**	0.132**	0.305**	1									
Germany	0.222**	0.468**	0.141**	0.325**	0.448**	1								
Italy	0.273**	0.556**	0.096*	0.314**	0.559**	0.528**	1							
Japon	0.236**	0.141**	0.049	0.178**	0.111**	0.073	0.165**	1						
Netherlands	0.231**	0.791**	0.089	0.403**	0.683**	0.702**	0.788**	0.252**	1					
Portugal	0.182**	0.520**	0.085	0.278**	0.484**	0.444**	0.635**	0.106**	0.762**	1				
Spain	0.193**	0.523**	0.100*	0.286**	0.474**	0.408**	0.594**	0.062	0.737**	0.699**	1			
Sweden	0.204**	0.484**	0.154**	0.275**	0.394**	0.451**	0.485**	0.083	0.649**	0.448**	0.440**	1		
UK	0.226**	0.680**	0.090	0.421**	0.573**	0.579**	0.688**	0.226**	0.676**	0.626**	0.651**	0.619**	1	
USA	0.305*	0.382*	0.196	0.074	0.157	0.380*	0.476**	0.179	0.306*	0.410**	0.415**	0.409**	0.534**	1
2010–06 2011	Australia	Belgium	Canada	China	France	Germany	Italy	Japon	Netherlands	Portugal	Spain	Sweden	UK	USA
Australia	1													
Belgium	0.326**	1												
Canada	0.133**	0.375**	1											
China	0.573**	0.298**	0.101	1										
France	0.354**	0.727**	0.377**	0.327**	1									
Germany	0.304**	0.738**	0.427**	0.280**	0.750**	1								
Italy	0.318**	0.834**	0.363**	0.294**	0.693**	0.721**	1							
Japon	0.411**	0.221**	0.082	0.338**	0.220**	0.213**	0.217**	1						
Netherlands	0.307**	0.717**	0.407**	0.305**	0.674**	0.749**	0.733**	0.234**	1					
Portugal	0.249**	0.784**	0.363**	0.258**	0.678**	0.690**	0.805**	0.151**	0.666**	1				
Spain	0.255**	0.809**	0.323**	0.248**	0.727**	0.711**	0.836**	0.116*	0.684**	0.813**	1			
Sweden	0.301**	0.607**	0.258**	0.282**	0.555**	0.608**	0.594**	0.211**	0.647**	0.548**	0.579**	1		
UK	0.307**	0.751**	0.304**	0.294**	0.619**	0.642**	0.733**	0.190**	0.631**	0.645**	0.659**	0.589**	1	
USA	0.248**	0.425**	0.468**	0.181**	0.413**	0.489**	0.449**	0.279**	0.482**	0.472**	0.408**	0.440**	0.414**	1

the bulk of this common systematic factor", so if the systematic factor does not correlate with any specific firm proxy, it is because it seems to be a non-firm-specific factor, but a generic systematic risk that has an effect that extends across companies.

Thus, according to recent financial literature there is a common factor affecting sovereign credit risk, and debt and equity markets, in most of the companies and countries, through time and across geographical areas. We call this factor the *Common Risk Factor*.

We use PCA to derive the common sources of risk in the sample. Table 8 and Figure 3 show the main PCA results run for the full sample across all countries. Due to a large amount of missing data, 17 financial assets have been removed from the original database. Table 9 presents such assets. The first five principal components capture more than 51% of the total variance explained, showing that the first principal component, which represents the common risk factor, captures almost the 36% of the variance. There are 38 principal factors with eigenvalue higher than 1, and a very strong average commonality of 74% has been detected among 38 such factors. According to the Kaiser-Meyer-Olkin, and Bartlett's Test of Sphericity, we can perform efficiently PCA on our dataset.[13]

We find positive loading of each equity onto the first factor and negative loading for each CDS. This agrees with the negative correlation displayed by both assets' types as explained above. Across the crises and post-crisis periods, we find a very high absolute loading of 57% for all financial assets onto the common risk factor.

[13] The aim of both statistical tools is to detect whether summarizing the information of the original variables in a few number of factors is recommended. The lower the Bartlett's Test of Sphericity is, the more efficient using the PCA is. However, the closer to 1 is the KMO, more recommended using the PCA is.

Table 6. Correlation (Spearman) between log changes in Sovereign Credit Default Swaps and in Company Credit Default Swaps spreads, and between log changes in Sovereign Credit Default Swaps spreads and in Company Stock prices. Eurozone countries. ** and * represent significance at the 1%, and 5% levels, respectively.

Country	Sector	Issuing Country/Company	FULL SAMPLE		01/01/2007–12/31/2009		01/01/2010–06/30/2011		07/01/2011–12/31/2015	
			ρ_s (SCDS, CCDS)	ρ_s (SCDS, REq)	ρ_s (SCDS, CCDS)	ρ_s (SCDS, REq)	ρ_s (SCDS, CCDS)	ρ_s (SCDS, REq)	ρ_s (SCDS, CCDS)	ρ_s (SCDS, REq)
Belgium		Solvay	0.313**	-0.242**	0.244**	-0.173**	0.418**	-0.297**	0.321**	-0.268**
France	FIN	BNP Paribas	0.401**	-0.285**	0.273**	-0.126**	0.541**	-0.404**	0.434**	-0.361**
		AXA	0.356**	-0.284**	0.200**	-0.168**	0.514**	-0.374**	0.412**	-0.337**
		Societe Generale	0.393**	-0.309**	0.223**	-0.189**	0.567**	-0.395**	0.434**	-0.362**
		Credit Agricole	0.395**	-0.301**	0.233**	-0.178**	0.544**	-0.369**	0.446**	-0.369**
	NO FIN	Lafarge	0.343**	-0.277**	0.206**	-0.189**	0.457**	-0.326**	0.392**	-0.326**
		Casino Guichard	0.337**	-0.215**	0.260**	-0.121**	0.412**	-0.182**	0.373**	-0.298**
		France Telecom	0.336**	-0.198**	0.204**	-0.094**	0.461**	-0.288**	0.394**	-0.246**
		Peugeot	0.349**	-0.220**	0.270**	-0.144**	0.460**	-0.276**	0.362**	-0.256**
		Renault	0.371**	-0.256**	0.293**	-0.175**	0.453**	-0.294**	0.396**	-0.306**
Germany	FIN	Allianz	0.352**	-0.271**	0.264**	-0.212**	0.539**	-0.369**	0.338**	-0.275**
		Deutsche Bank	0.367**	-0.267**	0.313**	-0.148**	0.535**	-0.352**	0.326**	-0.321**
		Commerzbank	0.356**	-0.269**	0.283**	-0.190**	0.515**	-0.365**	0.332**	-0.295**
		Muenchener	0.317**	-0.222**	0.240**	-0.120**	0.496**	-0.338**	0.302**	-0.254**
	NO FIN	Continental	0.309**	-0.203**	0.220**	-0.162**	0.437**	-0.260**	0.326**	-0.208**
		Daimler	0.334**	-0.214**	0.323**	-0.186**	0.413**	-0.246**	0.307**	-0.226**
		BMW	0.340**	-0.194**	0.331**	-0.148**	0.440**	-0.219**	0.308**	-0.220**
		Deutsche TeleKom	0.323**	-0.161**	0.254**	-0.094**	0.480**	-0.171**	0.314**	-0.201**
		Heildelbergcement	0.296**	-0.238**	0.192**	-0.182**	0.418**	-0.263**	0.325**	-0.269**
Italy	FIN	Intesa San Paolo	0.560**	-0.412**	0.373**	-0.236**	0.702**	-0.507**	0.637**	-0.482**
		Asicurazioni Generali	0.481**	-0.411**	0.278**	-0.292**	0.598**	-0.469**	0.584**	-0.464**
		Unicredit	0.532**	-0.407**	0.310**	-0.232**	0.648**	-0.484**	0.643**	-0.491**
		Banca Monte dei Paschi di Siena	0.513**	-0.344**	0.308**	-0.228**	0.659**	-0.418**	0.606**	-0.391**
		Banca Popolare di Milano	0.390**	-0.352**	0.256**	-0.202**	0.417**	-0.463**	0.522**	-0.402**
	NO FIN	ENI	0.424**	-0.341**	0.248**	-0.258**	0.509**	-0.376**	0.515**	-0.390**
		ENEL	0.535**	-0.340**	0.326**	-0.221**	0.688**	-0.391**	0.613**	-0.398**
		Atlantia	0.413**	-0.316**	0.265**	-0.167**	0.412**	-0.355**	0.529**	-0.399**
		Telecom Italia	0.505**	-0.289**	0.337**	-0.193**	0.639**	-0.347**	0.569**	-0.331**
Netherlands	FIN	ING Bank	0.415**	-0.319**	0.376**	-0.286**	0.423**	-0.432**	0.435**	-0.288**
		Royal Bank of Scotland	0.383**	-0.245**	0.383**	-0.204**	0.586**	-0.301**	0.306**	-0.236**
		Aegon	0.384**	-0.278**	0.437**	-0.229**	0.553**	-0.379**	0.307**	-0.259**
	NO FIN	K. AHOLD	0.346**	-0.104**	0.440**	-0.050**	0.442**	-0.147**	0.282**	-0.110**
		K. DSM	0.297**	-0.243**	0.326**	-0.334**	0.395**	-0.259**	0.244**	-0.196**
		K. KPN	0.338**	-0.119**	0.355**	-0.031**	0.452**	-0.253**	0.290**	-0.112**
Portugal	FIN	Banco Comercial Portugues	0.407**	-0.311**	0.290**	-0.175**	0.615**	-0.520**	0.421**	-0.336**
	NO FIN	EDP	0.455**	-0.267**	0.249**	-0.178**	0.706**	-0.386**	0.492**	-0.292**
	NO FIN	Portugal Telecom	0.433**	-0.264**	0.273**	-0.162**	0.655**	-0.354**	0.463**	-0.301**
Spain	FIN	Santander	0.507**	-0.403**	0.333**	-0.223**	0.647**	-0.520**	0.581**	-0.495**
		BBVA	0.517**	-0.409**	0.342**	-0.244**	0.654**	-0.537**	0.593**	-0.482**
		Popular	0.321**	-0.367**	0.274**	-0.220**	0.385**	-0.460**	0.326**	-0.436**
		Sabadell	0.327**	-0.378**	0.174**	-0.224**	0.481**	-0.481**	0.408**	-0.442**
	NO FIN	Telefonica	0.470**	-0.369**	0.299**	-0.194**	0.611**	-0.468**	0.542**	-0.469**
		Iberdrola	0.466**	-0.347**	0.248**	-0.151**	0.606**	-0.479**	0.567**	-0.461**
		Repsol YPF	0.426**	-0.328**	0.245**	-0.216**	0.599**	-0.406**	0.492**	-0.385**
		Endesa	0.373**	-0.287**	0.276**	-0.150**	0.523**	-0.362**	0.390**	-0.356**
		ArcelorMittal	0.426**	-0.290**	0.217**	-0.234**	0.484**	-0.264**	0.476**	-0.356**

As indicated, we have also considered the variables by countries and groups. Table 10 and Figure 4 show the results of this study. We document a very large variation by country.

We observe that the companies and Sovereigns with higher loading are European: France, Germany and Spain loadings are above 70%. In contrast, Japanese variables present the lowest loading: 20%, and Chinese and Canadian variables are just above 40%. These findings will be corroborated with posterior results.

Considering different assets' characteristics, we find that, by rating, A-rated companies present a slightly higher loading onto the first factor than the rest: 59.5% against 55%. By sector, financial companies' show a higher loading, 59.4%, vs. non-financial ones, 55%.

Most of the factors permeate almost every asset. For instance, Santander stock returns correlate 76% with the common risk factor; 27.5% with the second factor, -24.2% with the third factor, 12% with the sixth factor, and so on. By examining the factor loading of each variable, we can identify which assets are connected more intensely to each factor. If we place each variable in the factor with higher loading, we find that most financial assets, 206 (86%), are included in the first, and all of them (239) can be associated with 15 factors. In addition to the common risk

Table 7. Correlation (Spearman) between log changes in Sovereign Credit Default Swaps and Company Credit Default Swaps spreads, and between log changes in Sovereign Credit Default Swaps spreads and Company Stock prices. Rest of the World Countries. ** and * represent significance at the 1%, and 5% levels, respectively.

Country		Issuing Country/Company	FULL SAMPLE		01/01/2007–12/31/2009		01/01/2010–06/30/2011		07/01/2011–12/31/2015	
			ρ_s (RSCDS, RCDS)	ρ_s (RSCDS, REq)	ρ_s (RSCDS, RCDS)	ρ_s (RSCDS, REq)	ρ_s (RSCDS, RCDS)	ρ_s (RSCDS, REq)	ρ_s (RSCDS, RCDS)	ρ_s (RSCDS, REq)
Australia	FIN	ANZ	0.561**	-0.337**	0.363**	-0.199**	0.579**	-0.390**	0.683**	-0.388**
		C.B.A.	0.585**	-0.326**	0.386**	-0.170**	0.637**	-0.379**	0.691**	-0.396**
		N.A.B.	0.560**	-0.324**	0.343**	-0.170**	0.579**	-0.377**	0.697**	-0.395**
		Westpac	0.578**	-0.324**	0.419**	-0.143*	0.577**	-0.385**	0.687**	-0.393**
	NO FIN	GPT RE	0.544**	-0.286**	0.281**	-0.233**	0.546**	-0.349**	0.599**	-0.289**
		BHP BILLITON	0.489**	-0.394**	0.401**	-0.263**	0.408**	-0.444**	0.607**	-0.441**
		Rio Tinto	0.436**	-0.400**	0.244**	-0.289**	0.440**	-0.46**	0.536**	-0.436**
		Telstra	0.478**	-0.198**	0.276**	0.013	0.495**	-0.264**	0.589**	-0.280**
		Qantas	0.456**	-0.305**	0.337**	-0.322**	0.467**	-0.337**	0.537**	-0.281**
		Woodside Petroleum	0.445**	-0.343**	0.282**	-0.266**	0.453**	-0.393**	0.549**	-0.367**
Canada	FIN	Fairfax F.H.	0.042	-0.024	-0.068	0.011	0.064	-0.026	0.100*	-0.052
		Brookfield	0.101**	-0.044	-0.021	-0.010	0.173**	-0.051	0.081	-0.046
	NO FIN	Barrick Gold	0.124**	-0.029	0.113*	-0.068	0.135*	0.028	0.122**	-0.032
		Bombardier	0.122**	-0.080**	0.062	-0.026	0.131*	-0.093	0.139**	-0.088**
		Encana	0.125**	-0.081**	0.094	0.017	0.142*	-0.068	0.132**	-0.121**
		C.N.R.	0.116**	-0.094**	0.064	-0.027	0.090	-0.067	0.131**	-0.123**
		Agrium	0.086**	-0.074**	0.103	-0.031	0.078	-0.089	0.088**	-0.091**
China	FIN	Bank of China	0.447**	-0.372**	0.445**	-0.342**	0.480**	-0.398**	0.340**	-0.409**
		Oversea-Chinese Banking	0.219**	-0.338**	0.251**	-0.370**	0.115*	-0.316**	0.091	-0.311**
	NO FIN	Hutchison Whampoa	0.560**	-0.307**	0.583**	-0.349**	0.564**	-0.327**	0.488**	-0.248**
		Cnooc	0.444**	-0.360**	0.437**	-0.336**	0.501**	-0.389**	0.285**	-0.385**
		Noble	0.300**	-0.334**	0.300**	-0.346**	0.295**	-0.395**	0.244*	-0.300**
		Pccw-Hkt Telephone	0.408**	-0.159**	0.412**	-0.153**	0.475**	-0.183**	0.060	-0.158**
		Swire Pacific	0.354**	-0.304**	0.357**	-0.327**	0.371**	-0.336**	0.280**	-0.275**
Japan	FIN	Mizuho Bank	0.202**	-0.167**	0.160**	-0.164**	0.226**	-0.092	0.248**	-0.205**
		Bank of Tokyo-Mitsubishi	0.204**	-0.202**	0.166**	-0.176**	0.181**	-0.114*	0.258**	-0.256**
		Sumitomo Mitsui Bank.	0.205**	-0.204**	0.159**	-0.186**	0.216**	-0.099	0.266**	-0.255**
		ACOM CO.	0.187**	-0.138**	0.131**	-0.141**	0.268**	-0.047	0.240**	-0.166**
		Orix	0.227**	-0.199**	0.148**	-0.158**	0.311**	-0.166**	0.290**	-0.260**
	NO FIN	Nippon Steel	0.291**	-0.217**	0.210**	-0.162**	0.349**	-0.202**	0.360**	-0.271**
		Panasonic	0.217**	-0.206**	0.176**	-0.178**	0.128*	-0.199**	0.305**	-0.242**
		Ricoh	0.114**	-0.199**	0.034	-0.220**	0.152**	-0.192**	0.187**	-0.195**
		Sony	0.276**	-0.183**	0.184**	-0.178**	0.330**	-0.165**	0.360**	-0.195**
Sweden	FIN	Nordea Bank	0.268**	-0.221**	0.317**	-0.165**	0.126*	-0.282**	0.318**	-0.248**
		Svenska Handelsbanken	0.208**	0.210**	0.281**	-0.154**	0.085	-0.279**	0.227**	-0.240**
		Skandinaviska Enskilda	0.177**	-0.23**	0.122**	-0.153**	0.074	-0.291**	0.291**	-0.266**
		Swedbank	0.242**	-0.218**	N/A	-0.164**	0.105	-0.280**	0.302**	-0.249**
	NO FIN	A. Volvo	0.280**	-0.234**	0.261**	-0.190**	0.366**	-0.242**	0.262**	-0.280**
		A. Electrolux	0.172**	-0.196**	0.194**	-0.164**	0.176**	-0.224**	0.163**	-0.218**
		Svenska Cellulosa	0.218**	-0.218**	0.218**	-0.196**	0.230**	-0.265**	0.214**	-0.233**
U.K.	FIN	Barclays Bank	0.372**	-0.246**	0.455**	-0.219**	0.500**	-0.338**	0.294**	-0.219**
		Lloyds TSB Bank	0.360**	-0.233**	0.461**	-0.149**	0.435**	-0.318**	0.298**	-0.234**
		Royal Bank of Scotland	0.350**	-0.245**	0.411**	-0.230**	0.475**	-0.336**	0.282**	-0.210**
		Aviva	0.335**	-0.287**	0.371**	-0.323**	0.465**	-0.358**	0.280**	-0.239**
		HSBC	0.293**	-0.238**	0.390**	-0.238**	0.358**	-0.334**	0.240**	-0.205**
		Experian Finance	0.185**	-0.226**	0.288**	-0.246**	0.156**	-0.339**	0.157**	-0.181**
	NO FIN	Anglo American	0.322**	-0.212**	0.382**	-0.212**	0.416**	-0.346**	0.270**	-0.172**
		Glencore	0.340**	-0.235**	0.363**	-0.285**	0.419**	-0.329**	0.300**	-0.179**
		Bae Systems	0.271**	-0.193**	0.329**	-0.142**	0.258**	-0.285**	0.257**	-0.180**
		BP	0.216**	-0.209**	0.276**	-0.203**	0.232**	-0.252**	0.186**	-0.194**
		British Airways	0.325**	-0.229**	0.267**	-0.227**	0.366**	-0.346**	0.331**	-0.185**
		British American Tobacco	0.206**	-0.133**	0.358**	-0.135*	0.119*	-0.228**	0.179**	-0.101**
		British Telecom.	0.277**	-0.198**	0.287**	-0.220**	0.362**	-0.213**	0.249**	-0.180**
		Centrica	0.280**	-0.139**	0.324**	-0.093	0.257**	-0.210**	0.268**	-0.138**
		Dixons Retail	0.195**	-0.182**	0.194**	-0.167**	0.171**	-0.240**	0.201**	-0.162**
		GKN Holdings	0.360**	-0.241**	0.411**	-0.273**	0.405**	-0.322**	0.299**	-0.193**

(continued on next page)

Table 7 (*continued*)

Country		Issuing Country/Company	FULL SAMPLE		01/01/2007–12/31/2009		01/01/2010–06/30/2011		07/01/2011–12/31/2015	
			ρ_s (RSCDS, RCDS)	ρ_s (RSCDS, REq)	ρ_s (RSCDS, RCDS)	ρ_s (RSCDS, REq)	ρ_s (RSCDS, RCDS)	ρ_s (RSCDS, REq)	ρ_s (RSCDS, RCDS)	ρ_s (RSCDS, REq)
USA	FIN	MBIA Inc.	0.136**	-0.048	0.280	0.041	0.143**	-0.06	0.128**	-0.047
		General Electric	0.094**	-0.034	0.175	-0.212	0.178**	-0.102*	0.063*	-0.003
		Bank of America	0.114**	-0.069**	0.329*	-0.177	0.211**	-0.088	0.073*	-0.059*
		Berkshire Hathaway	0.110**	0.000	0.037	-0.208	0.111*	0.005	0.110**	0.007
		JPMorgan Chase	0.123**	-0.05*6	0.030	-0.058	0.274**	-0.076	0.068*	-0.048
		Radian Group	0.115**	-0.063*	0.266	0.025	0.174**	-0.081	0.085*	-0.062*
		Goldman Sachs	0.127**	-0.054*	0.252	-0.068	0.221**	-0.085	0.089**	-0.043
		Citigroup	0.133**	-0.098**	0.089	-0.216	0.252**	-0.152**	0.095**	-0.073*
		MGIC	0.121**	-0.046	0.155	0.061	0.136**	-0.065	0.114**	-0.044
	NO FIN	H-Packard	0.095**	-0.051*	0.204	-0.187	0.200**	-0.076	0.063*	-0.041
		Sprint Nextel	0.105**	0.037	0.148	N/A	0.204**	N/A	0.073*	0.037
		Alcoa	0.124**	-0.061*	0.204	-0.178	0.218**	-0.034	0.086**	-0.066*
		Caterpillar	0.068**	-0.053*	0.091	-0.171	0.098	-0.085	0.063*	-0.036
		CenturyLink	0.104**	-0.017	0.166	-0.223	0.145**	-0.085	0.090**	0.010
		Darden Rest.	0.077**	-0.025	0.233	-0.107	0.229**	-0.061	0.031	-0.010
		J. C. Penney	0.144**	-0.018	0.456**	-0.160	0.210**	-0.024	0.101**	-0.015
		PulteGroup	0.140**	-0.054*	0.279	-0.149	0.189**	0.001	0.112**	-0.068*
		Safeway	0.121**	-0.029	0.138	-0.154	0.214**	0.074	0.090**	-0.066*
		Macy's	0.118**	-0.006	0.254	-0.047	0.242**	0.001	0.076*	-0.004

Table 8. PCA World main features.

N	536
Variables	239[15]
Common Risk Factor (1st principal component)	36%
5 principal component	52%
Factor number with Eigenvalue >1	38
Average Commonality	74%
Kaiser-Meyer-Olkin (Bartlett's Test of Sphericity)	0.968 (0.000)

factor, the remaining 14 factors include 33 financial assets, 14% of total sample. Figure 5 and Figure 6 present the number of assets placed on each factor, showing how the common factor relates primarily to financial assets, while other factors relate primarily to only a few assets: the second factor is linked to 8 assets (3.3%), the third factor to 6 (2.5%), and the rest below 2%. Furthermore, there are seven financial variables that represent factors in themselves.

Examining those isolated assets not included in the first factor, we find that US and Canada SCDS are not included in this first factor. Only one asset of the Eurozone (the equity of KKPN, Netherlands) is not included either, while the other 32 assets in this category belong to the rest of the world, mainly to Japanese companies. Interestingly, only one Japanese financial variable contributes to this first factor: Japan SCDS. The remaining Japanese financial assets are distributed among 7 different factors. These results suggest a high dispersion for Japan and a very low commonality exhibited by Japanese companies with the rest of the word. Jitmaneeroj and Ogwang (2016), Mullen and Berrill (2017) and Cotter et al. (2018) provide aligned evidence in relation to Japan.

Considering financial activity, we find that financial companies are more closely related to the common risk factor than non financials (17 vs. 14), suggesting a tighter integration for the latter. Finally, there are more CDS than stocks out of the first factor (18/15), pointing to a higher integration for stocks.

Other than the first factor, it is not easy to identify specific patterns in the rest. Nonetheless, we have tried to name them on the basis of the assets included. For instance, we can find that factor 3 includes Japanese

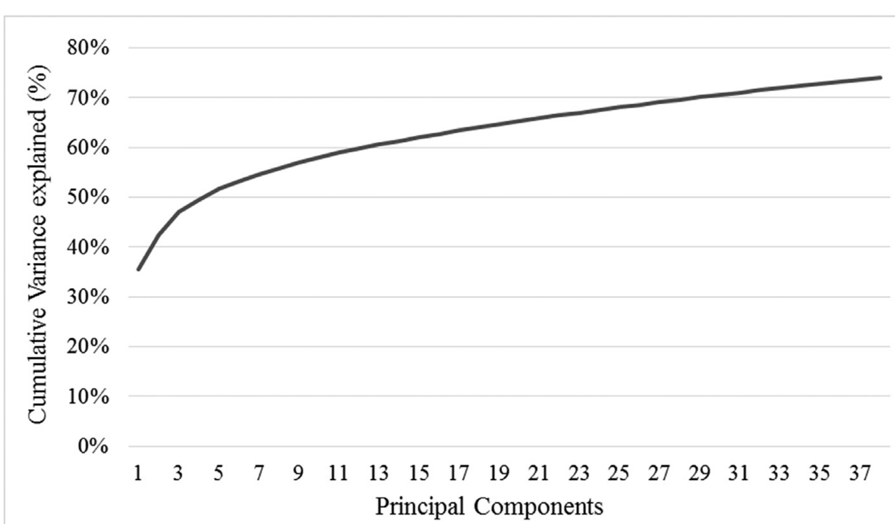


Figure 3. Cumulative variance explained by factors. This figure presents the cumulative variance explained by 38 factors with eigenvalue above 1. The first factor explains 36% of the variance of the 239 financial assets in the sample, and 38 factors together explain 74% of the 239 assets' variance.

Table 9. Financial assets removed from the original database for PCA estimations.

Financial asset	Missing data
CDS Popular	1,253
CDS Sabadell	835
CDS ING Bank	1,154
Equity Sprint Nextel	1,700
CDS GPT RE	1,405
CDS Rio Tinto	1,212
CDS Fairfax F.H.	1,087
CDS Brookfield	1,389
CDS Bank of China	1,110
CDS Oversea-Chinese Banking	1,248
CDS Cnooc	1,156
CDS Noble	1,521
CDS Pccw-Hkt Telephone	1,306
CDS Swire Pacific	1,153
CDS Nordea Bank	1,089
CDS Svenska Handelsbanken	928
CDS Swedbank	1,501

companies' stocks, either financial or non-financial, but all of them with rating non-A, but it also includes the CDS of an Australian company. We name this factor as Equity Japan Non-A, because most of the assets (5 of 6) fulfill this requirement. Factor 2 includes 8 different assets, CCDS and Equities; from the US, Australia and Japan; financial and non-financial companies; with rating A and Non-A. Then, we decide to name this Factor as *fuzzy*, due to the absence of an evident pattern. Other factors include only one or two assets, except for factor 7, which includes CDS of 4 Japanese companies rating Non-A.

Finally, if we consider only the 206 variables (86%) contributing to the first factor and recalculate the PCA, we find that the average loading of the assets onto the common risk factor increases from the 57% previously reported to 62%. In this case, Skandinaviska CDS presents the lowest loading factor at 33%.

All these results indicate a strong source of commonality, a single principal component which explains approximately 57% of all the assets' movements. This factor is a good measure of economy-wide variation due to its large influence in the markets worldwide, as noted by Hilscher and Wilson (2016).

In addition, we find interesting insights from a global diversification perspective. Japanese companies as well as some Canadian and American companies behave diverse behavior and can be considered from a global investor point of view as potential global risk mitigators.

Next, we perform some robustness checks to understand the behavior and properties of the common risk factor. Assessing its dynamics helps in gaining a better understanding of the fragility and potential contagions as well as the different countries exposures and the potential for geographical diversification.

4.3. Dynamics of the common risk factor

We proceed to explore the factor' dynamics, by means of an annual analysis using a semester rolling window, as in Billio et al. (2012). We observe in Figure 7 that the factor' performance goes from 25% (in 2013/14) to near 45% in 2011 and 2011/12.[14] In addition, we also explore the evolution of the average correlation between all the financial assets and the factor. In this case, our findings show 2013/14 as the less uniform period (correlation average of 45.6%) and 2011/12 as the highest correlation period (63.4%).

According to the literature, these results are very similar to other PCA studies. We identify lower results when using stocks than CDS. Billio et al. (2012) found a peak of 37% variance explained by the first component over the financial crisis 2007–2009, analyzing the stock return variation of 25 financial institutions (banks, insurances, hedge funds and broker/dealers firms) from 1994 to 2008; Longstaff et al. (2011) found 46–61% during 2000–2010, with stock indexes returns. For CDS, Eichengreen et al. (2012) found a 40–65% variance explanation, analyzing CDS weekly spreads of 45 banking institutions; Collin-Dufresne et al. (2001) found 40–75% considering 688 bonds of 261 issuers from 1988 to 1987; Longstaff et al. (2011) found 64%–74% for 26 SCDS spreads; Groba et al. (2013) found 61–75% in 14 European SCDS 2008–2012; and Díaz et al. (2013) found 88% in 85 European CDS firms.

Our study uses a wider coverage sample with a non-homogeneous type of financial instruments and different geographical locations, which justifies that the results found are somehow in between, but generally aligned with the previous findings.

Table 10. Average loading of all variables onto the common risk factor, classified by countries and by groups. Loading average indicates the mean of the loadings or correlations among the common risk factor and the set of financial assets included in each country or group.

By Countries	Financial Assets (SCDS, CCDS, stocks)	Loading Average
France	19	76.2%
Germany	19	72.0%
Spain	17	71.0%
Belgium	3	68.2%
Italy	19	68.2%
Netherlands	12	65.7%
UK	33	61.7%
Sweden	12	60.9%
Portugal	7	56.7%
USA	38	48.9%
Australia	19	48.5%
Canada	13	43.6%
China	9	41.6%
Japan	19	20.0%
	239	
By asset type	**Financial Assets (SCDS, CCDS, stocks)**	**Loading Average**
SCDS	14	55.3%
CDS	105	57.2%
Equity	120	56.6%
	239	
By Rating		
Rat A	94	59.5%
Rat Non A	145	55.0%
	239	
By Sector		
Fin	96	59.4%
Non Fin	129	55.0%
SCDS	14	55.3%
	239	

TOTAL SAMPLE AVERAGE: 57%.
Max loading: Axa Equity Return: 84%.
Min loading: The Bank of Tokyo-Mitsubishi UFJ, Ltd, CDS, 6.7%.

[14] Due to the large amount of missing data over several years, we need to reduce the sample, removing some variables from the original 239. Depending on the year, the sample includes from 193 assets (2007 and 2008) to 198 (2009–2013). However, these sample sizes are still large enough to run the PCA study.

[15] Due to a large amount of missing data, 17 financial assets have been removed from the original database. Such removed assets are available upon request.

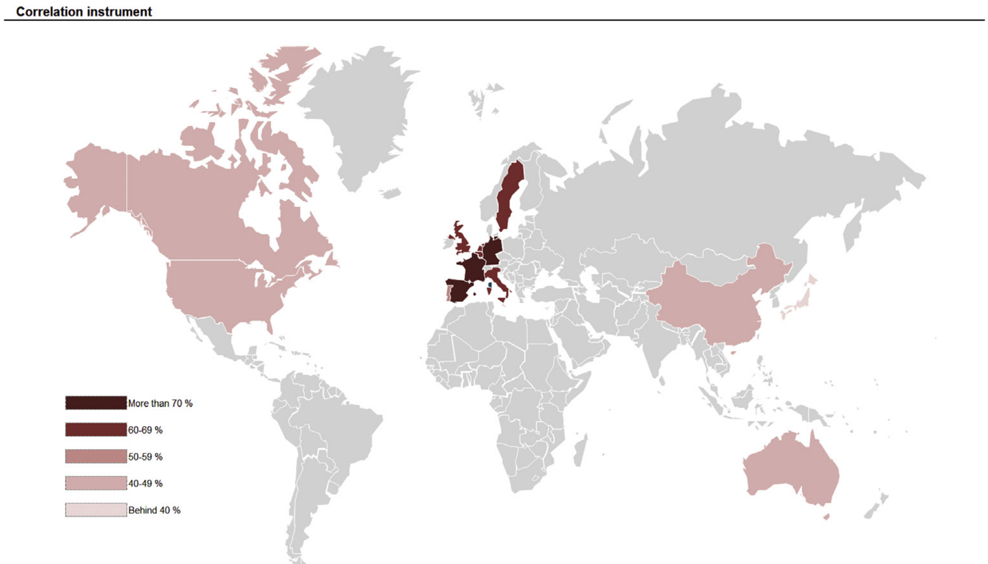


Figure 4. Map of average countries' correlations with the common risk factor.

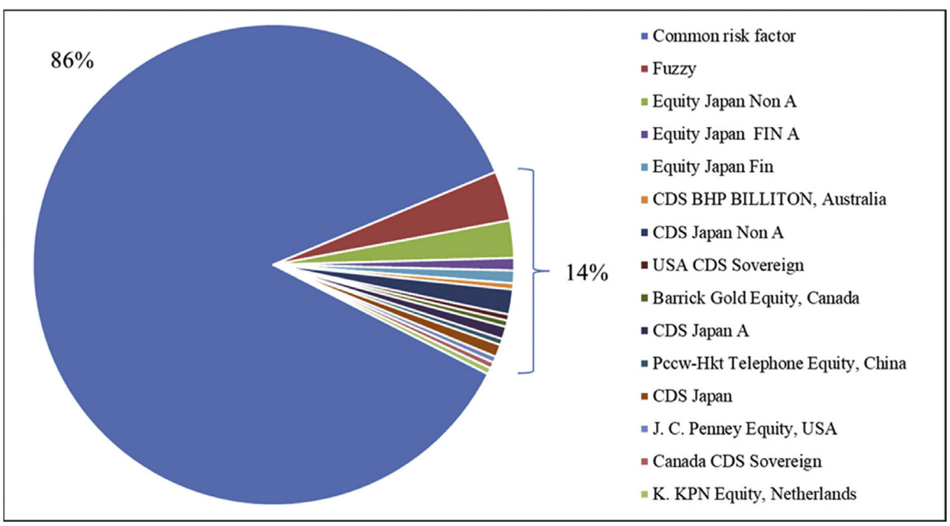


Figure 5. World factors and assets directly related with them. The figure shows the name of each factor given by its largest loading.

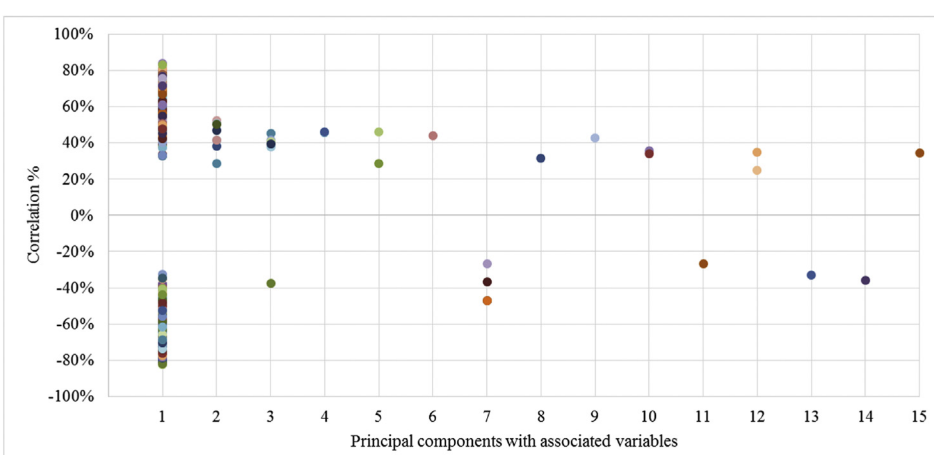


Figure 6. Number of financial variables with largest loading included in each World factor. We show for each factor, the number of variables directly related with it, and its pairwise correlation.

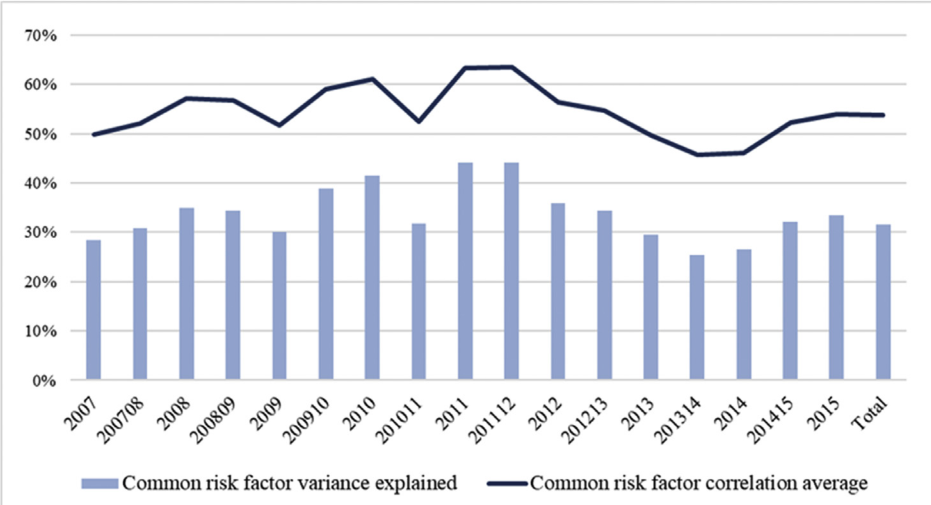


Figure 7. Evolution of the common risk factor using a six-month rolling window. The figure shows the evolution of common risk factor in terms of two features of the data: evolution of total variance explained in columns and evolution of the average of the financial asset correlation with the factor (absolute value) by a line. For example, in 2011, all the worldwide financial assets, correlated with it in an average of 63.4%, and the common risk factor explained 44.2% of the variance. KMO is larger than 0.8 in every rolling year analyzed, indicating an exceptional adequacy for using PCA.

Table 11. Evolution of common risk factor and VIX Correlation.

	2007–2015	2007–2009	2010–06 2011	07 2011–2015
Coef. Correl.	-0.47**	-0.52*	-0.49**	-0.46**

4.4. The common risk factor and VIX

As commented in the Introduction it is advisable to validate the common risk factor's meaningfulness relating it to the VIX index. The VIX is the Chicago Board Options Exchange (CBOE) Volatility Index, and it is widely recognized as an indicator of investors' risk aversion and financial markets' inherent uncertainty, for this reason it affects asset prices (Pukthuanthong and Roll, 2009; Song and Xiu, 2016; Pan and Singleton, 2008). Accordingly, it seems reasonable to believe that changes in the VIX may induce revisions in investors' allocations and risk management strategies affecting the credit and stock market link (Shahzad et al., 2018). As in Longstaff et al. (2011) we relate our common risk factor to the evolution of the VIX index.

Additionally, in the finance literature, for a common factor to be relevant for asset prices, it must be related to the stochastic discount factor (also called pricing kernel in the literature). The term stochastic discount factor extends concepts from economics and finance to include adjustments for risk (Hansen and Renault, 2009). The literature indicates that the discount factor must be noticeably higher during and immediately after recessions and financial crises, when economic theory suggests the stochastic discount factor is higher (Harrison and Kreps, 1979; Hansen and Jagannathan, 1997).

Since VIX has been proved to be a successful stochastic discount factor, e.g., Song and Xiu (2016) and Pan and Singleton (2008), we relate our common risk factor to the evolution of the VIX index in the way Longstaff et al. (2011) did with the first principal component obtained from 26 SCDS spreads.

We study this relation calculating the correlation coefficient and its significance, and by means of a lead-lag analysis. The correlation between the two variables is -0.47 for the full period, being the highest during the subprime crisis period, where it peaks at -0.52. During the post-crisis period, correlations drop to -0.46. Once again, we confirm the tendency of correlations to increase during crisis periods (see Table 11 below).

Table 12. Different groups' PCA main features.

	Obs.	Vbles	1st PC	1st and 2 nd PC	PC Number	Average Loading	Standard Deviation	KMO
World	536	239	35,6%	42,4%	38	56,8%	0,18	0,968
EUR	1.301	96	48,4%	56,3%	8	68,7%	0,11	0,988
RoW	541	141	28,1%	37,2%	25	50,5%	0,16	0,958
FIN	576	110	39,5%	46,9%	16	59,4%	0,21	0,972
NO FIN	604	143	35,1%	41,9%	21	56,9%	0,17	0,974
RAT A	593	94	39,9%	48,0%	14	60,4%	0,19	0,973
RAT no A	949	145	32,1%	39,0%	24	53,8%	0,18	0,974
H VOLATILITY	585	123	35,6%	42,2%	19	56,8%	0,18	0,970
L VOLATILITY	592	129	36,3%	43,9%	19	57,4%	0,18	0,973
EUR FIN	1.452	46	53,1%	63,8%	5	72,3%	0,09	0,979
EUR NO FIN	1.484	57	43,6%	51,7%	6	65,1%	0,11	0,980
ROW FIN	577	64	30,3%	40,6%	12	51,9%	0,18	0,947
ROW NO FN	608	86	28,3%	36,9%	14	51,3%	0,14	0,958

This table document the results of Principal Component Analysis considering different variables classifications. Obs. includes the number of observations for each variable in each group; Vbles, the number of financial Assets; 1st PC, the variance explained by the first factor in each group, in %; 1st and 2nd PC, the variance explained by the two main factors; PC number, the number of factors with eigenvalue larger than 1. Correlation Average, the loading average of all the assets onto its Group first factor. Standard deviation and Kaiser-Meyer-Olkin Measure of Sampling Adequacy are also provided.

Table 13. Different countries' PCA main features.

	Obs.	Vbles	1st PC	1st and 2 nd PC	PC Number	Average Loading	Standard Deviation	KMO
Australia	1,176	19	47.3%	64.1%	2	68.0%	0.10	0.940
Belgium	2,129	3	49.7%	N.a.	1	70.2%	0.08	0.583
Canada	1,234	13	32.5%	48.6%	3	53.6%	0.20	0.859
China	1,526	9	47.2%	59.1%	2	66.5%	0.18	0.864
France	2,282	19	50.5%	62.1%	2	69.9%	0.13	0.948
Germany	2,215	19	46.0%	58.9%	2	67.0%	0.11	0.935
Italy	1,852	19	47.1%	59.9%	2	68.2%	0.08	0.955
Japan	1,971	19	33.9%	48.5%	4	55.9%	0.17	0.908
Netherlands	1,828	12	40.5%	51.9%	3	62.3%	0.14	0.898
Portugal	2,324	7	44.5%	59.5%	2	66.2%	0.09	0.829
Spain	1,926	17	53.0%	65.5%	2	72.2%	0.10	0.939
Sweden	1,489	12	47.6%	62.8%	2	62.2%	0.31	0.915
U.K.	1,322	33	39.4%	52.7%	4	62.3%	0.08	0.959
USA	889	38	35.9%	46.1%	6	58.3%	0.14	0.954

This table documents each country's PCA. Obs. includes the number of observation taken in each country for each variable; Vbles, the number of financial assets; 1^{st} PC, the variance explained by the first factor in each country, in %; 1^{st} and 2^{nd} PC, the variance explained by the two first factors; PC number, the number of factors with eigenvalue higher than 1. Correlation average is the loading average of all the assets onto its country's first factor. Standard deviation and Kaiser-Meyer-Olkin Measure of Sampling Adequacy are also provided.

The correlation sign found is negative given that factor' loadings are positive for equities and negative for CDS, which is consistent with Longstaff et al. (2011), who find a positive +0.61 correlation between their first factor (calculated only with SCDS) and VIX changes, but a negative correlation of -0.75 between the stock market returns and changes in the VIX index.

We also performed a lead-lag analysis between the common risk factor and the VIX log-changes with daily data. The optimal lag length turns out to be 3. We find a strong bidirectional relationship with feedback loops. VIX index Granger causes common risk factor at a 3% significance level, while common risk factor Granger causes VIX movements at 9% significance level. These relations and feedback loops confirm the common risk factor soundness.

4.5. Global and country commonality

Given the evidence of common pattern in the securities studied, next we pursue an alternative way of looking at the first factor, and perform a PCA study for each country and group class.

We find higher commonality in financial companies than non-financial ones (see Table 12); in Eurozone countries rather than in RoW countries; and in rating A rather than in non-A rating companies. In fact, financial European companies present the highest commonality level, where its first principal component accumulates 53% of the explained variance, with an average of 72% variables loading onto its first factor. However, non-financial companies of RoW present a very low commonality, with a 28% of variance explained by the first factor and a loading of 52%. Volatility results do not discriminate across groups.

Most likely due to the European Sovereign and Bank crisis, European movements have turned out to be more coordinated. We observe more commonality within the Eurozone than for RoW. Along this line, an associated result by Ang and Longstaff (2013) already shows a higher systemic risk in the Eurozone than in the US, and they find that this risk is strongly related to financial market variables backing up our results (note that we use stock prices in this study). Due to this shared risk structure, we find a lower potential for diversification inside the Eurozone than outside it.

When we look at countries' PCA performance, we find the highest level of commonality in Spain, followed by France, with both over 50% of variance explained with an average correlation with the Common Risk Factor of 72% and 70%, respectively. However, Canada and Japan present the lowest level of variance explained by the first factor, below 35%, with correlation level below 60%. Interestingly, the ranking of countries in Table 10 almost perfectly parallels the ranking in Table 13; Japan is the country with the lowest loading factor in the common risk factor and is also the country with the second to the lowest level of commonality inside. The results for Canada and the US also indicate a very low level of

Table 14. Granger causality tests and correlations between common risk factor and countries' first factor.

	Country	GC test p-value	Lags	CRF and First Factor Correlation
Leaders	Canada	0.002	1	75.45%
	USA	0.000	2	80.70%
CRF leads	Belgium	0.004	1	85.54%
	German	0.030	1	96.74%
	Netherlands	0.025	1	95.73%
	Australia	0.000	1	68.62%
	China	0.000	1	63.58%
	Japan	0.000	1	34.43%
Comovement	France	CRF leads 0.001 France leads 0.004	1	96.90%
	United Kingdom	CRF leads 0.000 U.K. leads 0.037	1	95.54%
No casual relationship found	Italy	N/A	1	90.98%
	Portugal	N/A	1	78.38%
	Spain	N/A	2	90.93%
	Sweden	N/A	1	85.27%

commonality, pointing to a good diversification opportunity for global investors (see Table 14).

Again, Japan is found to have the lowest correlation with the common risk factor: Approximately 34%, but the direction of the causal relationship suggests that the common risk factor is a driver of Japanese movements.

5. Conclusions

Evidence of high cross-country and cross-market integration is growing in the financial literature in accordance to the claimed reduction in diversification potential among all assets classes.

To assess the level of commonality present in a worldwide sample of developed countries and companies, we have studied the main common risk factor underlying financial assets changes representing 121 companies and 14 sovereigns. Although exploratory in nature our model draws heavily on existing mainstream economic research in the area of asset pricing.

Finding a global factor that is common to several markets and regions is a rare exercise. However, this underlying factor, which span assets worldwide, is very useful from the investors' point of view, because it can serve as benchmark for evaluating performance of active investments, it can be interpreted as a global integration measure across markets, and, as a guide for investments (or alternatively as a guide for risk diversification).

We find a global systematic risk factor that underlies 86% of our sample assets' movements. Moreover, the three different asset types studied (SCDS, CCDS and stocks), which consider corporates and countries risks, are highly represented in this risk factor, supporting the assumption of high cross-markets integration. This factor corresponds to a systematic risk that cannot be avoided by diversification. The uncovered risk factor is robust across periods, and it is evenly distributed across assets and countries, with the noticeable exception of Japan, which follows a divergent risk pattern. This is also true, to a lesser extent, for the US, Canada and China. We also find a higher commonality within the Eurozone financial assets than in other markets. In addition, we confirm that the common risk factor becomes more important in times of crisis.

We perform robustness checks to understand the behavior and properties of the common risk factor. We find its high relationship with the VIX index, used in financial literature as a proxy for risk, validating is representativeness. We also find that the explanatory power of the model is aligned with the most relevant precedents in the literature.

Our results confirm the dominant role of global investors and the importance of their perception of risk, which permeates the whole economic system. These findings are especially valuable for global market participants who gain insights into the complexities of worldwide investing and can improve their investment strategies and mitigate this underlying risk by anticipating how portfolios might perform in the future.

Some future research lines follow this exploratory study: First the construction and tracking of some international portfolios to check the practical investment performance' implications of the common risk factor and its diversification potential. Second, with different debt instruments, further study the implications for investors of the relationship between debt and equity in the common risk factor. Third, do a back-testing exercise to check for the temporal stability of the common risk factor.

One of the main limitations of this study is the lack of liquidity of corporate swaps, which doesn't allow us to work with a wider sample. Also, it is important not to place too much emphasis on absolute performance or to make gross generalizations based on these findings, since we only have one history of financial data and can not recreate a new time series.

Declarations

Author contribution statement

Teresa Corzo: Conceived and designed the analysis; Wrote the paper.

Laura Lazcano: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

Javier Márquez: Conceived and designed the analysis; Analyzed and interpreted the data; Contributed analysis tools or data; Wrote the paper.

Laura Gismera: Contributed analysis tools or data; Wrote the paper.

Sara Lumbreras: Contributed analysis tools or data.

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Competing interest statement

The authors declare no conflict of interest.

Additional Information

No additional information is available for this paper.

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