Systematic Risk from a Corporate Structural Model Approach: From Merton 1974 to Merton 2013

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Abstract

We apply the Corporate Structural Model and its extension, the Contingent Claims Approach, to understand the sectors of an economy as interconnected portfolios, and, making use of a global sample of financial assets, find a common risk factor. The paper analyzes the main features of this systematic risk factor, study its consistency, and its geographical structure, since it affects the diversification potential of global portfolios. The factor is related to the VIX index and its properties lead us to propose it as a background financial risk factor, which also serves as measure of integration in the international markets.

Keywords: Systematic Risk, Corporate Structural Model, Contingent Claim Analysis, Principal Component Analysis, Credit Default Swaps.

JEL codes: G15; G30

1. Introduction

The search for a common factor to explain risk 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.

Pukthuanthong and Roll (2009) defined a global integration measure across markets based on the explanatory power of a multi-factor model applied to different countries. In the same spirit, we use a novel approach to estimate a common underlying risk factor. Using a worldwide sample, we take information embedded in the prices of three different financial instruments: Sovereign Credit Default Swaps (SCDS hereafter), Corporate Credit Default Swaps (CCDS) and equities to create a global measure of systematic risk. This differs from previous studies of risk in two main ways. First, our analysis addresses the global financial system instead of specific regions. In addition to this, rather than focusing on one or at most two financial instruments, we consider three SCDS, CCDS and Equity, which are strongly related but could bring specific information to the model. We do find a common risk factor for the global sample of financial assets. The implications of this finding are extremely relevant for investors, as they limit the diversification potential of global portfolios.

To understand the relationship among CCDS, SCDS and Equity, we follow the structural model introduced by Merton (1974). We provide conclusive evidence on how macro-financial information is embedded into companies' liabilities and bring together our results and the predictions of the structural model.

Next, we make use of the Contingent Claims 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, specifically understanding equity as a contingent claim on the assets of a company once debtors have been satisfied. This provides a link between equity and credit risk (Gray et al. 2007). 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).

We quantify this interdependence among markets and regions using Principal Components Analysis (PCA). PCA provides a broad view of these connections and allows us to estimate a factor underlying the movements of these financial instruments and to gauge the value of this underlying financial risk. PCA was used by Cotter et al.

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

(2017) and Pukthuanthong and Roll (2009) to measure the diversification potential and to assess its reciprocal, the markets' integration condition.

Using PCA, we uncover an underlying financial risk factor that should be understood as a systematic factor related to common economic forces that have an influence across markets and countries and therefore cannot be diversified. Its meaning also matches the common systematic component reported by Collin-Dufresne et al. (2001) and Longstaff et al. (2011) among others.[2]

Within this framework we study a worldwide sample of 135 institutions: 121 companies, financials (54) and non-financials (67) across 14 different countries, through the three financial instruments (SCDS, CCDS and equities) during 9 years (2007-2015). The sample range has been selected following a liquidity criterion and considering global representativeness. However, due to liquidity restrictions in CDS prices we do not include emerging markets in our sample. We find a very similar behavior pattern in all these companies. Moreover, this pattern is consistent with the predictions of the structural model. Granger causality and a lead-lag study prove that macroeconomic risks (for which SCDS movements serve as a proxy) are incorporated efficiently into the two corporate financial instruments considered (CDS and stocks), although not always simultaneously and often with some feedback loops. SCDS also move with, and sometimes after, the stock market. The same lead-lag relationships are found globally.

Some important contributions emerge from this analysis:

We study the links among Equity, CCDS and SCDS using Vector Autoregressive models (VAR) and PCA to estimate the importance of the common factors driving the returns of these institutions and countries. To estimate quantitatively the existing feedback effects, we perform Granger causality tests. Our findings support the predictions of the structural model.

Second, we identify a single risk factor underlying 86% of our sample financial assets, which explains 36% of the total variance and presents a 57% average correlation with all the considered financial variables. Both CCDS and equities, as well as SCDS, contribute to this factor revelation, providing aligned information. These results support a strong source of commonality. Recent research by Cotter et al. (2016) point to market credit risk as one of the causes of the international diversification decline, and our results considering CDS inputs support this outcome.

In addition, this risk factor is common not only to the financial assets studied but also in the regions considered: seven countries inside the Eurozone and 7 others outside of it. It

[2]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.).

should be noted that, although a vast amount of research has been conducted in Europe since the sovereign crisis (2010-2012), the rest of the world has been less explored.

We report factor dynamics during the period under consideration, showing a stable condition consistent with a background financial risk proxy (FBR hereafter). We consider the "background" as the set of conditions against which an occurrence is perceived, in this case, the underlying common economic conditions. We also report the geographical distribution of corporates and countries contributing to this factor. Alternatively, this factor can be interpreted as a market integration measure, and it is interesting to note that Japan is the most isolated country in this respect, preceded by China and Canada. Again, this result is aligned with adjacent literature (e.g., Mullen and Berrill 2017, Cotter et al. 2016). The behavior of Eurozone countries and companies, compared to the rest of the world, is remarkably different. We find the highest contribution to this underlying global FBR from some Eurozone countries and companies. Consistently with that, the highest commonality appears inside Eurozone countries as well. North America, however, is found to lead FBR movements. These different relationships with FBR have direct implications in investment themes around the globe.

Finally, we validate the use of this FBR as a stochastic discount factor by studying its relationship to the VIX index. We find a strong co-movement and non-negligible feedback loops.

The rest of the paper is structured as follows. Next, we present a visual inspection of the data, focusing on some relevant examples, to motivate the analysis intuitively. Then, in section 3, we explain the theoretical framework, the corporate structural model and the Contingent Claims Approach. Section 4 describes the data sample. Sections 5 and 6 are devoted to the empirical analysis, first using a VAR model and granger causality relations, and then extracting a common systematic factor by means of PCA. Conclusions can be found at the end of the paper.

2. A preliminary look at the data

Financial theory indicates that innovations in macroeconomic variables are risks that are rewarded in the stock market (Chen, Roll and Ross 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)[3], 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.

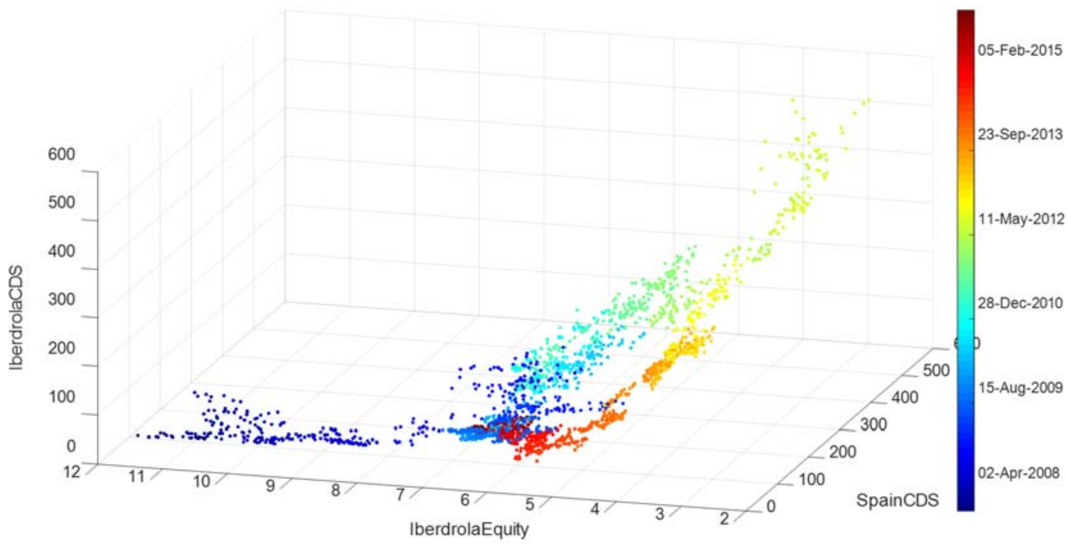
We find a long array of research works connecting CCDS and SCDS, since there is an intimate relationship between sovereign and corporate credit risk (e.g., Ejsing and Lemke 2011, Arce et al. 2013, Acharya et al. 2014, Bedendo and Colla 2015), and connecting

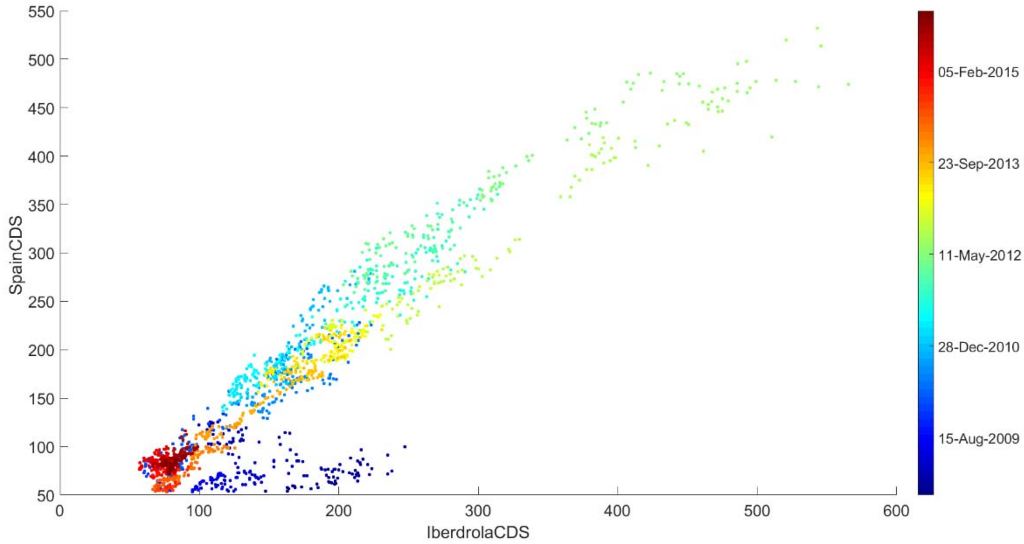
[3] For a review on the wide CDS literature, see Augustin et al. (2016).

equity and sovereign risk (e.g., Norden and Weber 2009, Corzo 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 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.

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 (additional graphs can be found in Appendix Figure 1)

Figure 1a: 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; second, we plot them by twos. In dark blue are year 2007 observations; colors lighten up as we approach more recent dates. In bright red are year 2015 observations.





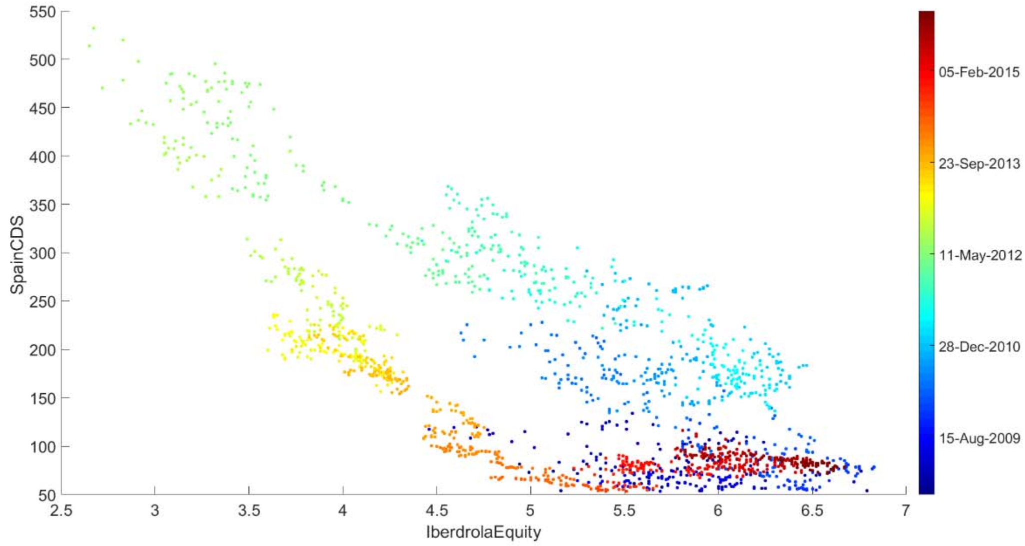
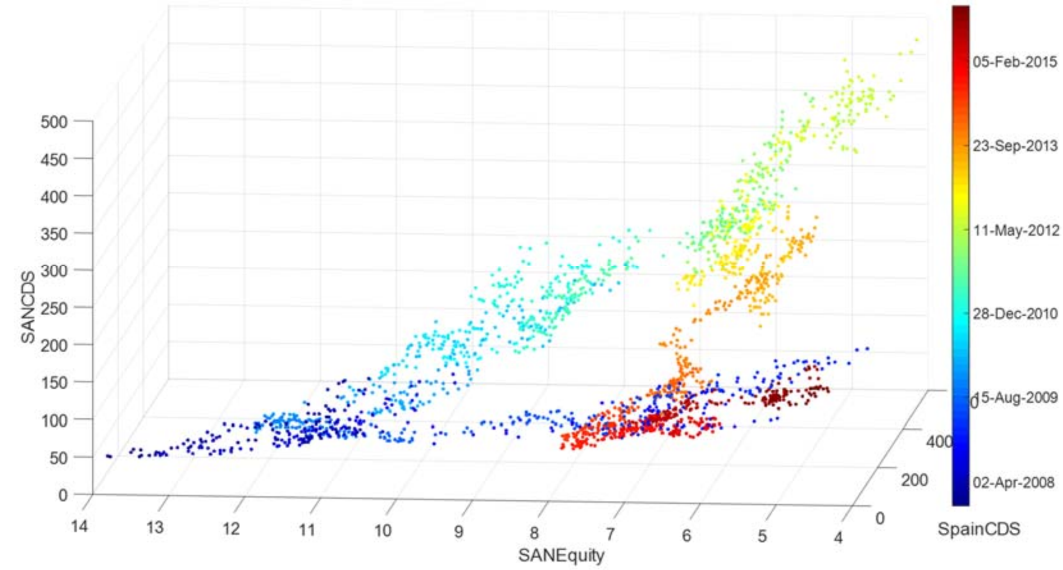
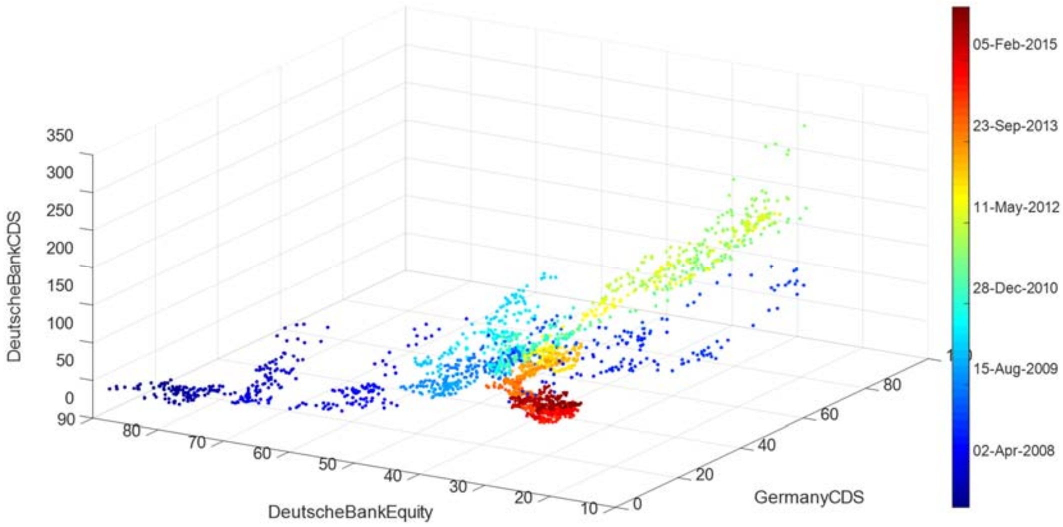


Figure 1b: Daily evolution of Deustche Sovereign CDS, Deustche Bank CDS and equity; Spanish Sovereign CDS, Banco Santander CDS and equity, during the period 2007-2015.

In dark blue are year 2008 observations; colors lighten up as we approach more recent dates. In bright red are year 2015 observations.





In Figure 1, we plot the values of the three financial variables we consider (SCDS, CDS and equity) for some pairs of companies-countries. We observe how the evolution of the three variables develops in an inclined plane. At the beginning of our sample period, the stock prices are high, and the level of risk evidenced by the CDS premium is low. However, as the subprime crisis develops, CDS start to move up and equity prices, down. 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 CDS, both sovereign and corporate, return slowly to lower levels, reflecting a more controlled credit risk environment. We can observe a linear relationship between the SCDS and the CCDS, both representing the credit risk market (see Figure 1a for Iberdrola stock).

However, equity prices do not return to pre-crisis levels and remain at lower levels, lagging the CDS prices (Figure 1a for Iberdrola data, and 1.b 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 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. Next, we present our inductive reasoning to link them together.

3. Theoretical background and model' implications

The interaction between market risk and credit risk has been a fruitful area in the financial literature during the early 21st century. Several papers have investigated how market risk and credit risk are related 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 2016), common fundamentals (e.g., Byström 2008, 2016b, Forte and Lovreta 2015) or causality links (e.g., Fung et al. 2008, Forte and Peña 2009, Shahzad et al. 2017). As Mateev and Marinova (2016) note, these two markets (credit and equity) are very different, and the analysis of the relationship becomes challenging.

With all the previous research supporting the rational long run interdependencies between the credit and stock markets, we follow the structural model introduced by Merton (1974) to link a company' assets and liabilities. As a first step, we explore how macrofinancial information is incorporated into companies' liabilities and connect our results with the predictions of the structural model. According to it, bondholders own put options sold by shareholders; equity can be understood as a residual claim on the assets of a company.

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. He showed that stock can be viewed as a call option on the firm with a strike price equal to the face value of a single-payment debt issue. The basic Merton model has been extended in many ways, yielding models that have considerable explanatory power (e.g., Ingersoll 1977, Delianedis and Geske 2003, Carr and Zhu 2017 among many others).

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.

The key consideration lies in the sensitivity to the value of the underlying assets. Since we can understand that bondholders have bought put options to the holders of the firm's equity, equity can be understood as a residual claim on a company. From this point of view, equity can be considered as junior debt that is actually the most sensitive to credit risk. Let us explain this point following Merton et al. (2013): equity holders have sold puts on the company assets, and puts are by nature convex, this means that, after a decrease in asset value, and due to convexity, a second shock of the same magnitude will have a greater effect than the first one. As financial scenarios worsen, this nonlinear relationship should be more intense in equity compared to debt.

Along the same reasoning line, options have sensitivity to the volatility of the underlying assets. An increase in volatility, even if asset values remain unchanged, will raise the value of the put sold, damaging the position of stockholders.[4]

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 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 corporate theory, we explore the empirical connection among SCDS, CDS and equity and postulate that the transmission of financial risks needs to be incorporated timely into the different liabilities. According to previous research, the main expected result is that equities lead other markets in times of crisis while they move together in more tranquil periods.

However, companies are not isolated entities, and risks propagate among them. At the national level, the sectors of an economy can be viewed as interconnected portfolios of assets, liabilities and guarantees. Structures that look similar to 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 guarantee the banks, formally with deposit insurance and then implicitly even when they are not required to do so. These governments are writing a guarantee on the bank assets, and bank assets are effectively short put options, so these governments are guaranteeing a put: are

[4] Relationship between stocks' volatilities and credit risk is a profuse area of study that we do not examine here; see Byström 2016a.

writing a put on a short put. These government guarantees are being driven by assets in the corporate sector or the residential housing sector.

Credit risk propagates among the different sectors, once the shock occurs in any sector. 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 at the same time, generating professional and business opportunities and threats, and facing complexities that become risk sources (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.[5] 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.[6]

To view the global economy as a set of inter-related balance sheets allows for extracting a measure of the intensity of these connections (or a markets' integration measure) and to observe whether there is a uniform underlying measure.[7] To study this, we follow a non-structured approach and pool analyze jointly our worldwide sample.

4. Data

We have chosen CCDS and SCDS instead of bond prices due to their higher homogeneity and liquidity during the sample period; the aforementioned 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.

Our sample has been selected considering market liquidity and to fulfill this condition: to include 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®. For representativeness reasons, the sample was designed considering the 10

[5] 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).
[6] 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.
[7] This rationale for understanding the worldwide financial relations reminds us of fractals. Self-similarity is a defining property of fractals, a structure found across the natural world: the pattern seems to repeat itself, with the pattern replicating that of the overall structure; it implies a level of persistence. According to Mandelbrot (2005), fractals are bound to remain central to finance. Fractals are everywhere in nature and culture.

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 USA and for the UK, since the number of CCDS traded for these countries were much higher than for the others.

Due to illiquidity in some CCDSs during some parts of our sample period, the final sample resulted in 14 countries that cope with the requisites, 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 USA, 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 appendix section (Tables A.1 and A.2).

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

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). 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 on the basis of Granger causality. We identify periods when the p-value for the Granger causality test is larger than 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.

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.[8]

During these periods, we study how the relationships between the three financial assets (SCDS, CCDS and stocks) have evolved over time: before, during and after the financial crisis.

Tables A.1 and A.2 show that there is a 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 (bp) for the Japanese Ricoh CCDS and an average of 983.28 bp for the American Radian Group CCDS. Nevertheless, we find lower dispersion when observations of the same company are analyzed. The ratio Standard Deviation to Mean is below 1 for almost all the companies and Sovereigns analyzed.

To enable the joint study of equities and CDS and track the commonalities in their dynamics, we transform our variables into log-changes and analyze daily log-changes.

At the sovereign level, Table A.3 in Appendix shows the Spearman correlations of log-changes in SCDS.[9] We find that, considering the total sample period, all correlations are positive and statistically significant at the 1% level. The overall average correlation amounts to +0.35, being the USA, Canada and Japan, the countries exhibiting the lowest average correlations with the other countries' sovereigns. The higher movements' correlations are found during the European Sovereign crisis period (2010-June 2011) among the European countries, with eight countries having correlations above +0.5. We find that the final period July 2011 to December 2015 is the one with the lowest total average correlation: +0.31, indicating that during this timeframe, the movement in sovereigns became less coordinated, even in Europe. All through the paper, we validate

[8] Detailed rolling VAR results are available upon request.

[9] 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%.

the tendency of correlations to increase during periods of financial crisis (this is already a known stylized fact, see, i.e., Ang and Bekaert 2002).

In Tables A.4 and A.5 in the Appendix, we report Spearman correlations between SCDS and CCDS spread log-changes, and SCDS and equities log-changes for each country. As expected, we find positive correlations between SCDS and CCDS movements, while negative correlation between SCDS and companies' stock. In each country, the correlations are higher for CCDS than for stocks. However, the results vary widely across countries. For the Eurozone, CCDS movements correlate an average of +0.4 with their sovereign, and the companies' equity correlate an average of -0.3. Outside the Eurozone, the averages are +0.25 and -0.18. On average, correlations are larger for Eurozone countries than for countries outside the Eurozone. 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 USA 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 2010-2011 period. After that period, correlations drop.

For the variables under study, we find 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.

Table 2: 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%

5. VAR and the Structural Corporate Model

In this section, we investigate connectedness between SCDS, CCDS and Equities. To quantitatively estimate feedback effects between these three variables, we perform Granger causality tests. To assess the general connectedness and its direction, we use the VAR framework. VAR models have been widely used, Norden and Weber (2009) and Forte and Peña (2009) find the stock market tends to lead the bond and CDS markets, and Norden and Weber (2009), Blanco et al. (2005) and Forte and Peña (2009) stress the CDS market tends to lead the bond market. One recent study by Forte and Lovreta (2015) analyses the dynamic relationship between the stock and CDS markets during the period 2002-2008. They find a stock market leadership during financial crisis; however, during tranquil times, the CDS market´s contribution to price discovery is equal or higher than that of the stock market.[10] Nevertheless, there is little research linking the three financial instruments and comparing Eurozone companies with RoW companies.

Within each country (*j*) and for each company (*i*), we estimate the following three-dimensional model:

$$R_t = \alpha_1 + \sum_{p=1}^{n} \beta_{1p} R_{t-p} + \sum_{p=1}^{n} \gamma_{1p} RSCDS_{t-p} + \sum_{p=1}^{n} \varphi_{1p} RCDS_{t-p} + \varepsilon_{1t}$$

$$RSCDS_t = \alpha_2 + \sum_{p=1}^{n} \beta_{2p} R_{t-p} + \sum_{p=1}^{n} \gamma_{2p} RSCDS_{t-p} + \sum_{p=1}^{n} \varphi_{2p} RCDS_{t-p} + \varepsilon_{2t} \quad [1]$$

$$RCDS_t = \alpha_3 + \sum_{p=1}^{n} \beta_{3p} R_{t-p} + \sum_{p=1}^{n} \gamma_{3p} RSCDS_{t-p} + \sum_{p=1}^{n} \varphi_{3p} RCDS_{t-p} + \varepsilon_{3t}$$

where R_t is the equity log-return in period *t* for company *i*, $RSCDS_t$ is the sovereign CDS spread log change in period *t*, and $RCDS_t$ is the *i*-company CDS spread log change in period *t*. The lag order of the VAR is *p*, and ε_{qt} is the innovation in market *q* in period *t*.

We estimate this model for each company (*i*) in our sample. The following table shows three companies´ results (Telefonica in Spain; Daimler in Germany; and MBIA in the USA) during the three periods analyzed. These companies are a good illustration for the general results. In most companies and during the first period (2007, 2008 and 2009), there is a bidirectional relationship among the three variables; only in some Spanish and German companies' stock markets did they take a leading role with respect to SCDS and CCDS. This equity-leading role during the sub-prime crisis corroborates the conclusions in previous empirical tests based on data from the dot-com-crisis (Norden and Weber 2009; Forte and Peña 2009; Forte and Lovreta 2015) and are in line with the predictions of the structural model.

As the year 2010 progressed, the leading role of the stock market disappeared. During this year, sovereign debt attracted all the attention and relegated the stock market to a secondary role. This process was deeper in some countries such as Spain, Germany, France and Italy and more intense in financial companies than non-financial companies. Although the stock market was relegated to a secondary role, it still continued, leading ahead of the third variable (the CCDS). However, we do not see this pattern in the

[10] Other seminal studies using the VAR framework are Longstaff 2010, Longstaff et al. 2011, Merton et al. 2013, and Gray et al. 2013.

companies that do not belong to the Eurozone, where the SCDS does not take a leading role.

Finally, in the last period (July 2011 to December 2015) and for our global sample, the stock market did obtain the leading position incorporating information once more. This is an important insight indeed because stock data is more universal, available and liquid than CDS spreads.

Table 3: Company lead-lag analysis with the VAR model. This table shows the coefficients and p-values. The latter indicate if the explanatory variable is significant for each country and for each period. The p-value test (GC) is only highlighted in those cases in which p is significant at the 5% level, e.g., in the first column for Telefonica, it can be seen that ΔSCDSt is Granger caused by both CCDS changes and stock price changes.

Spain.Telefónica			01/01/2007-12/31/2009						01/01/2010-06/30/2011						07/01/2011-12/31/2015			
Dep.Var	ΔSCDSt		$\Delta CCDS_t$		R_t		ΔSCDSt		$\Delta CCDS_t$		R_t		ΔSCDSt		$\Delta CCDS_t$		R_t	
	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.
$\Delta SCDS_{t-1}$	-0.253	0.000	0.012	0.556	-0.007	0.405	0.279	0.000	0.321	**0.000**	-0.073	**0.000**	0.027	0.476	0.097	**0.002**	-0.002	0.868
$\Delta SCDS_{t-2}$	-0.085	0.019	-0.034	0.094	-0.007	0.400	-0.073	0.302	-0.052	0.308	0.018	0.290	-0.002	0.941	-0.011	0.723	-0.007	0.644
$\Delta CCDS_{t-1}$	0.219	**0.001**	0.113	0.004	0.010	0.536	-0.128	0.203	-0.041	0.573	0.025	0.305	0.022	0.638	0.103	0.007	0.021	0.284
$\Delta CCDS_{t-2}$	0.101	0.135	0.052	0.173	0.006	0.712	-0.064	0.504	-0.003	0.963	0.054	**0.025**	-0.055	0.212	-0.007	0.842	-0.003	0.857
R_{t-1}	-0.321	**0.047**	-0.186	**0.043**	-0.032	0.406	0.168	0.509	0.400	**0.030**	-0.146	0.021	-0.231	**0.007**	-0.301	**0.000**	0.062	0.082
R_{t-2}	-0.110	0.494	0.007	0.933	-0.067	0.083	0.019	0.938	-0.190	0.303	0.081	0.201	0.109	0.204	0.047	0.502	-0.023	0.514
Obs.	764		764		764		388		388		388		1137		1137		1137	
R^2	0.0719		0.0339		0.0076		0.0574		0.1248		0.0830		0.0207		0.0891		0.0036	
GC test ΔSCDSt			---		---					0.000		0.000				0.007		---
GC test $\Delta CCDS_t$	0.001				---			---				0.042		---				---
GC test R_t	---		---					---		0.048				0.011		0.000		

Germany.Daimler	01/01/2007-12/31/2009						01/01/2010-06/30/2011						07/01/2011-12/31/2015					
Dep.Var	$\Delta SCDSt$		$\Delta CCDS_t$		R_t		$\Delta SCDSt$		$\Delta CCDS_t$		R_t		$\Delta SCDSt$		$\Delta CCDS_t$		R_t	
	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.
$\Delta SCDS_{t-1}$	-0.281	0.000	0.017	0.423	-0.005	0.669	0.331	0.000	0.256	**0.000**	-0.029	0.297	0.006	0.854	0.011	0.680	0.000	0.954
$\Delta SCDS_{t-2}$	0.017	0.707	-0.000	0.989	-0.016	0.277	0.034	0.546	-0.020	0.653	0.010	0.724	-0.000	0.997	-0.020	0.445	0.003	0.821
$\Delta CCDS_{t-1}$	-0.091	0.294	0.220	0.000	0.025	0.389	-0.137	**0.047**	-0.033	0.555	0.016	0.647	-0.004	0.914	0.039	0.249	0.019	0.337
$\Delta CCDS_{t-2}$	0.023	0.781	-0.005	0.905	-0.004	0.879	-0.105	0.120	-0.022	0.685	0.018	0.594	-0.001	0.963	0.065	0.052	0.008	0.656
R_{t-1}	-0.281	**0.000**	-0.191	**0.005**	0.060	0.169	-0.088	0.412	-0.044	0.618	0.047	0.388	-0.117	0.074	-0.253	**0.000**	0.093	0.006
R_{t-2}	0.017	0.707	0.078	0.252	-0.031	0.471	0.084	0.433	0.116	0.189	-0.048	0.382	-0.019	0.773	-0.044	0.442	0.021	0.529
Obs.		626		626		626		388		388		388		1160		1160		1160
R^2		0.0852		0.0851		0.0059		0.1096		0.0952		0.0106		0.0380		0.0380		0.0074
GC test $\Delta SCDSt$				---		---				0.000		---				---		---
GC test $\Delta CCDS_t$		---				---		0.042				---		---				---
GC test R_t		0.008		0.011				---		---				---		0.000		

USA. MBIA Inc.	01/01/2007-12/31/2009						01/01/2010-06/30/2011						07/01/2011-12/31/2015					
Dep.Var	$\Delta SCDSt$		$\Delta CCDS_t$		R_t		$\Delta SCDSt$		$\Delta CCDS_t$		R_t		$\Delta SCDSt$		$\Delta CCDS_t$		R_t	
	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.
$\Delta SCDS_{t-1}$	0.036	0.823	-0.186	0.141	0.120	0.721	0.149	0.004	0.077	0.065	-0.075	0.262	-0.245	0.000	-0.029	0.353	0.021	0.513
$\Delta SCDS_{t-2}$	-0.171	0.297	-0.027	0.397	0.244	0.478	0.087	0.090	0.040	0.334	0.005	0.930	-0.023	0.470	0.030	0.333	0.008	0.787
$\Delta CCDS_{t-1}$	0.145	0.504	-0.186	0.000	-0.019	0.965	-0.096	0.174	0.394	0.000	-0.037	0.681	-0.000	0.996	0.186	0.000	0.039	0.306
$\Delta CCDS_{t-2}$	-0.108	0.611	0.0109	0.873	-0.436	0.330	0.036	0.587	0.086	0.106	-0.024	0.774	0.056	0.109	-0.030	0.380	-0.051	0.141
R_{t-1}	-0.084	0.309	0.051	0.435	-0.166	0.338	0.008	0.841	-0.098	**0.006**	-0.025	0.658	-0.060	0.115	-0.362	**0.000**	0.101	0.007
R_{t-2}	-0.033	0.688	0.096	0.138	0.099	0.565	-0.059	0.170	-0.011	0.745	0.010	0.849	0.045	0.250	-0.019	0.617	0.039	0.316
Obs.	36		36		36		378		378		378		908		908		908	
R^2	0.1043		0.4338		0.0993		0.0393		0.2944		0.0056		0.0636		0.02032		0.0130	
GC test $\Delta SCDSt$				---		---				---		---				---		---
GC test $\Delta CCDS_t$		---				---		---				---		---				---
GC test R_t		---		---				---		0.021				---		0.000		

To provide a complete insight into the relationships among the three markets, we perform two complementary analyses. First, for each country and period, we estimate two different pooled VAR models[11] - one with the financial sector companies and the other one with non-financial companies.

Given that our panels are "large-T", we use traditional time series methodologies to estimate the panels. In particular, we perform a GLS estimation of the panel allowing for the error terms to be autocorrelated across time with panel-specific autocorrelation.

Panel data results confirm and qualify our previous findings. For the companies located in countries that belong to the Eurozone and more intensively for financial companies, the main result that emerges from the panel analysis is the strong role of SCDS with respect to CCDS and stocks during the sovereign crisis. Before 2010, we observe a bidirectional relationship among the three variables with a stock leadership in some countries (Spain, Germany, France, USA and Canada). This occurs again in the last period in which we do not detect any clear relationship except the stock lead in Germany, the USA, the United Kingdom, Sweden and Canada. We report a summary in Table 4, and two countries results´ as an example of our findings in A.6.

[11]We have not included Portugal and Belgium in the pooled VARs due to the limited number of companies with enough liquidity available.

Table 4: Aggregate lead-lag country analysis with fixed-effect large- T panel regressions. For each country, we estimate large-T (GLS with autocorrelated errors) panel regressions to study the aggregate lead lag relationship across variables. We report in bold the variable which lead the information process. When the SCDS takes the lead, we report in bold significant p-values at the 5% level.

Country		January 2007-December 2009		January 2010-June 2011		July 2011-December2015	
		Financial companies	No Financial companies	Financial companies	No Financial companies	Financial companies	No Financial companies
EURO	SCDS-CCDS	COMOVEMENT	COMOVEMENT	SCDS lead **0.000** 0.646	COMOVEMENT	COMOVEMENT	COMOVEMENT
	SCDS-Equity			**0.000** **0.001**			
France	SCDS-CCDS	COMOVEMENT	**Equity lead**	SCDS lead **0.000** **0.028**	COMOVEMENT	COMOVEMENT	COMOVEMENT
	SCDS-Equity			**0.000** 0.274			
Germany	SCDS-CCDS	**Equity lead**	**Equity lead**	SCDS lead **0.000** 0.693	SCDS lead **0.000** 0.906	**Equity lead**	**Equity lead**
	SCDS-Equity			**0.000** 0.214	**0.006** 0.942		
Italy	SCDS-CCDS	COMOVEMENT	COMOVEMENT	SCDS lead **0.000** 0.483	Equity lag	COMOVEMENT	CCDS lag
	SCDS-Equity			**0.000** **0.002**			
Netherlands	SCDS-CCDS	COMOVEMENT	COMOVEMENT	SCDS lead **0.000** **0.009**	Equity lag	COMOVEMENT	COMOVEMENT
	SCDS-Equity			0.319 **0.031**			
Spain	SCDS-CCDS	**Equity lead**	CDS lead	SCDS lead **0.000** 0.097	COMOVEMENT	COMOVEMENT	COMOVEMENT
	SCDS-Equity			**0.000** **0.000**			
ROW	SCDS-CCDS	COMOVEMENT	COMOVEMENT	COMOVEMENT	COMOVEMENT	COMOVEMENT	CCDS lag
	SCDS-Equity						
Australia	SCDS-CCDS	COMOVEMENT	COMOVEMENT	COMOVEMENT	COMOVEMENT	COMOVEMENT	COMOVEMENT
	SCDS-Equity						
Canada	SCDS-CCDS	**Equity lead** CCDS	**Equity lead** CCDS	CCDS lag	SCDS lag	**Equity lead** CCDS	**Equity lead** CCDS
	SCDS-Equity						
China	SCDS-CCDS	CCDS lag	COMOVEMENT	SCDS lead 0.089 **0.000**	SCDS lead 0.000 **0.001**	CCDS lag	COMOVEMENT
	SCDS-Equity			0.275 0.521	**0.004** **0.051**		
Japan	SCDS-CCDS	Equity lag	COMOVEMENT	COMOVEMENT	COMOVEMENT	COMOVEMENT	COMOVEMENT
	SCDS-Equity						
Sweden	SCDS-CCDS	COMOVEMENT	**Equity lead**	COMOVEMENT	COMOVEMENT	COMOVEMENT	**Equity lead**
	SCDS-Equity						
United Kingdom	SCDS-CCDS	COMOVEMENT	COMOVEMENT	SCDS lead **0.000** **0.000**	SCDS lag	SCDS lag	**Equity lead**
	SCDS-Equity			0.540 0.089			
USA	SCDS-CCDS	COMOVEMENT	**Equity lead**	CCDS lag	CCDS lag	COMOVEMENT	**Equity lead**
	SCDS-Equity						

Second, we estimate a two-pooled VAR models for the Eurozone, one with all the financial companies, and another with the non-financial companies, and two pooled VAR models for the non-Euro countries, as before, one pooling the financial companies, and the other one pooling the non-financial ones.

The results for the panels in Table 5 confirm the previous findings. There is no clear leadership between the three variables at the beginning and at the end of the sample, but we identify SCDS leadership during the sovereign-debt crisis. We find several feedback loops between the three variables confirming their complementary roles building in information.

In summary, an aggregate level analysis emphasizes a bidirectional lead-lag relationship among SCDS, CCDS, and equity before and after the sovereign crises. However, as previously noted, the analysis of some companies and countries reveals the predominant leading role of the equity market. This evidence is aligned with implications of the structural model: when the firm's financial situation is healthy, the put option embedded in risky debt is far out of the money, and the links between equity valuation and credit valuation are weak. However, if macroeconomic shocks cause earnings and cash-flows to fall, uncertainty increases, and the equity cushion is reduced: the equity put option gets closer to the money, and the relationship between credit and equity intensifies (Carr and Linetsky 2006).

Table 5: Aggregate lead-lag country analysis with fixed-effect large- T panel regressions. For Eurozone and RoW large-T (GLS with autocorrelated errors) panel regressions are run to study the aggregate lead-lag relationship across variables (ΔSCDS, ΔCCDS y ΔStock Price). We report coefficients and p-values. We show three tables: for each period analyzed, we report the results for Eurozone and Rest of the World distinguishing between financial and non-financial companies. In bold are shown significant p-values al the 5% level.

Eurozone
01/01/2007-12/31/2009

	Financial companies						No financial companies					
Dep.Var	ΔSCDSt		$\Delta CCDS_t$		R_t		ΔSCDSt		$\Delta CCDS_t$		R_t	
	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.
$\Delta SCDS_{t-1}$	-0.290	0.000	0.031	**0.000**	-0.010	**0.002**	-0.303	0.000	0.015	**0.000**	-0.008	**0.001**
$\Delta SCDS_{t-2}$	-0.081	0.000	0.005	0.375	-0.011	**0.001**	-0.096	0.000	0.000	0.808	-0.008	**0.001**
$\Delta CCDS_{t-1}$	0.117	**0.000**	0.135	0.000	-0.021	**0.000**	0.160	**0.000**	0.142	0.000	-0.004	0.424
$\Delta CCDS_{t-2}$	-0.003	0.827	0.017	0.065	0.028	**0.000**	0.100	**0.000**	0.027	**0.001**	0.004	0.435
R_{t-1}	-0.166	**0.000**	-0.168	**0.000**	0.032	0.001	-0.221	**0.000**	-0.149	**0.000**	-0.004	0.645
R_{t-2}	0.005	**0.000**	0.077	**0.000**	-0.018	0.049	-0.122	**0.000**	0.020	0.168	-0.046	0.000
Obs.		12614		12684		12726		14359		14478		14485

Rest of the world
01/01/2007-12/31/2009

	Financial companies						No financial companies					
Dep.Var	ΔSCDSt		$\Delta CCDS_t$		R_t		ΔSCDSt		$\Delta CCDS_t$		R_t	
	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.
$\Delta SCDS_{t-1}$	-0.137	0.000	0.075	**0.000**	-0.009	0.174	-0.103	0.000	0.084	**0.000**	-0.002	0.652
$\Delta SCDS_{t-2}$	0.040	0.000	0.039	**0.001**	-0.031	**0.000**	0.012	0.170	0.039	**0.000**	-0.017	**0.001**
$\Delta CCDS_{t-1}$	0.078	**0.000**	-0.125	0.000	-0.002	0.699	0.096	**0.000**	-0.022	0.011	-0.022	**0.001**
$\Delta CCDS_{t-2}$	0.028	**0.003**	-0.007	0.467	0.028	**0.000**	0.063	**0.000**	0.037	0.000	-0.010	**0.050**
R_{t-1}	-0.122	**0.000**	-0.143	**0.000**	0.029	0.004	-0.109	**0.000**	-0.157	**0.000**	0.038	0.000
R_{t-2}	-0.066	**0.000**	-0.013	0.436	-0.040	0.000	-0.077	**0.000**	-0.056	**0.000**	-0.067	0.000
Obs.		9387		9490		9697		13198		13287		13551

Eurozone
01/01/2010-06/30/2011

	Financial companies						No financial companies					
Dep.Var	ΔSCDSt		$\Delta CCDS_t$		R_t		ΔSCDSt		$\Delta CCDS_t$		R_t	
	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.
$\Delta SCDS_{t-1}$	0.234	0.000	0.255	**0.000**	-0.081	**0.000**	0.241	0.000	0.213	**0.000**	-0.043	**0.000**
$\Delta SCDS_{t-2}$	-0.065	0.000	0.005	0.646	0.023	**0.001**	-0.009	0.451	0.013	0.180	0.010	0.032
$\Delta CCDS_{t-1}$	-0.008	0.631	-0.007	0.615	0.003	0.703	-0.102	**0.000**	-0.025	0.058	0.019	**0.003**
$\Delta CCDS_{t-2}$	-0.047	**0.003**	-0.006	0.632	0.009	0.254	-0.131	**0.000**	-0.027	0.038	0.022	**0.000**
R_{t-1}	0.032	0.251	-0.054	**0.024**	-0.003	0.801	-0.025	0.443	-0.055	0.030	0.010	0.397
R_{t-2}	0.000	0.996	-0.026	0.270	-0.047	0.000	0.033	0.327	-0.066	**0.009**	-0.019	0.114
Obs.		7596		7562		7596		8570		8567		8570

Rest of the world
07/01/2011-12/31/2015

	Financial companies						No financial companies					
Dep.Var	ΔSCDSt		$\Delta CCDS_t$		R_t		ΔSCDSt		$\Delta CCDS_t$		R_t	
	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.
$\Delta SCDS_{t-1}$	0.007	0.335	0.079	**0.000**	-0.032	**0.000**	0.018	0.011	0.082	**0.000**	-0.004	0.264
$\Delta SCDS_{t-2}$	0.002	0.803	0.032	**0.000**	-0.017	**0.003**	-0.002	0.716	0.008	0.179	-0.007	0.069
$\Delta CCDS_{t-1}$	0.059	**0.000**	0.036	0.000	0.001	0.829	0.045	**0.000**	0.002	0.784	0.007	0.111
$\Delta CCDS_{t-2}$	-0.032	**0.000**	-0.047	0.000	0.023	0.000	-0.027	**0.002**	-0.003	0.607	0.008	0.082
R_{t-1}	-0.117	**0.000**	-0.198	**0.000**	0.023	0.004	-0.123	**0.000**	-0.254	**0.000**	0.051	0.000
R_{t-2}	0.031	**0.006**	-0.006	0.537	-0.020	0.012	0.026	0.064	-0.033	**0.003**	-0.006	0.371
Obs.		20471		20483		20549		24676		24754		24780

Eurozone
07/01/2011-12/31/2015

	Financial companies						No financial companies					
Dep.Var	ΔSCDSt		$\Delta CCDS_t$		R_t		ΔSCDSt		$\Delta CCDS_t$		R_t	
	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.
$\Delta SCDS_{t-1}$	0.053	0.000	0.089	**0.000**	-0.021	**0.001**	0.017	0.043	0.078	**0.000**	-0.024	**0.000**
$\Delta SCDS_{t-2}$	0.056	0.000	0.064	**0.000**	-0.002	0.707	0.047	0.000	0.031	**0.000**	-0.002	0.587
$\Delta CCDS_{t-1}$	-0.021	**0.021**	-0.066	0.000	-0.012	0.051	-0.007	0.052	-0.008	0.013	0.000	0.740
$\Delta CCDS_{t-2}$	-0.003	0.690	-0.008	0.393	0.012	**0.046**	-0.002	0.334	-0.004	0.023	-0.000	0.968
R_{t-1}	-0.094	**0.000**	-0.234	**0.000**	0.033	0.000	-0.126	**0.000**	-0.220	**0.000**	0.014	0.091
R_{t-2}	0.048	**0.001**	-0.043	**0.003**	-0.026	0.006	0.072	**0.000**	-0.055	**0.000**	-0.034	0.000
Obs.		11837		11896		11958		13971		14053		14108

Rest of the world
07/01/2011-12/31/2015

	Financial companies						No financial companies					
Dep.Var	ΔSCDSt		$\Delta CCDS_t$		R_t		ΔSCDSt		$\Delta CCDS_t$		R_t	
	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.	Coeff.	p-val.
$\Delta SCDS_{t-1}$	-0.131	0.000	0.051	**0.000**	-0.020	**0.000**	-0.128	0.000	0.039	**0.000**	-0.023	**0.000**
$\Delta SCDS_{t-2}$	0.006	0.335	0.019	**0.001**	0.001	0.663	0.002	0.686	0.011	**0.015**	-0.010	**0.002**
$\Delta CCDS_{t-1}$	0.032	**0.000**	-0.014	0.026	-0.025	**0.000**	0.003	0.091	0.007	0.000	-0.001	0.239
$\Delta CCDS_{t-2}$	-0.000	0.969	0.030	0.000	0.009	0.051	-0.000	0.647	0.004	0.000	-0.000	0.812
R_{t-1}	-0.104	**0.000**	-0.244	**0.000**	0.004	0.506	-0.118	**0.000**	-0.235	**0.000**	0.014	0.011
R_{t-2}	0.007	0.491	-0.042	**0.000**	0.038	0.000	-0.012	0.183	-0.088	**0.000**	0.031	0.000
Obs.		26354		26431		26601		31331		31378		31642

The previous worldwide results shed light on the relationship between different markets and support the understanding of these financial assets as complementary. The three instruments are efficient in terms of the timely incorporation of information (with different temporary leaderships), although depending on the economic condition, their relationship, in terms of feedback loops, is softened or tightened.

6. Principal Component Analysis and the Financial Background Risk

Considering that the economy is widely connected, we use cross-country and cross-market information to estimate a global underlying financial risk factor. Given its global nature, this risk cannot be adequately captured by any country-specific macroeconomic variable. However, we validate its presence relating it to the VIX index. Alternatively, this factor can be interpreted as a measure of global market integration as it reflects a common factor across markets and regions (Pukthuanthong and Roll 2009).

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.

6.1. Worldwide Factors. Context and components of the Financial Background Risk Factor.

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

Thus, according to the recent financial literature, we can affirm that there is a general factor affecting sovereign credit risk, and debt and equity markets, in most of the companies and countries, no matter when and where the evolution of assets is studied. We approach this risk factor and propose to name it Financial Background Risk (FBR) in honor of Penzias and Wilson Cosmic Microwave Background Radiation found in 1964.[12]

We use PCA applied to the three previously described financial variables, 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

[12] CMWB is a relic radiation left over from a very early period in the history of the universe. While the CMWB propagated throughout space in an extremely uniform way, only becoming dimmer as time goes by, our Background Financial Risk factor varies with time reflecting relatively tranquil or turbulent periods. Moreover, it does not spread evenly but rather appears more strongly in some assets than in others. However, it does tie together the movements of all assets and markets, acting like a descriptor of the financial situation as a whole. A clear description of how this radiation was discovered can be found in Penzias (1979). This is not the first simile between astrophysics and finance. For instance, the global contracts and convention changes in North American CDS contracts, which came into effect on April 8, 2009, have been called Big Bang (Gündüz at al. 2016).

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. In other words, the higher are the proportion of asset returns explained by common factors, the less is the diversification potential offered, and the higher is the market integration. This relates to the underlying risk factor regarded here.

Additionally, 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.

This paper applies PCA first for the full sample, then, as a robustness check, to different groups of criteria.

Table 6 and Figure 2 show the main PCA results run for the full sample, covering the world. The first five principal components capture more than 51% of the total variance explained, showing that FBR, the first principal component, 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 a PCA on our dataset.[13]

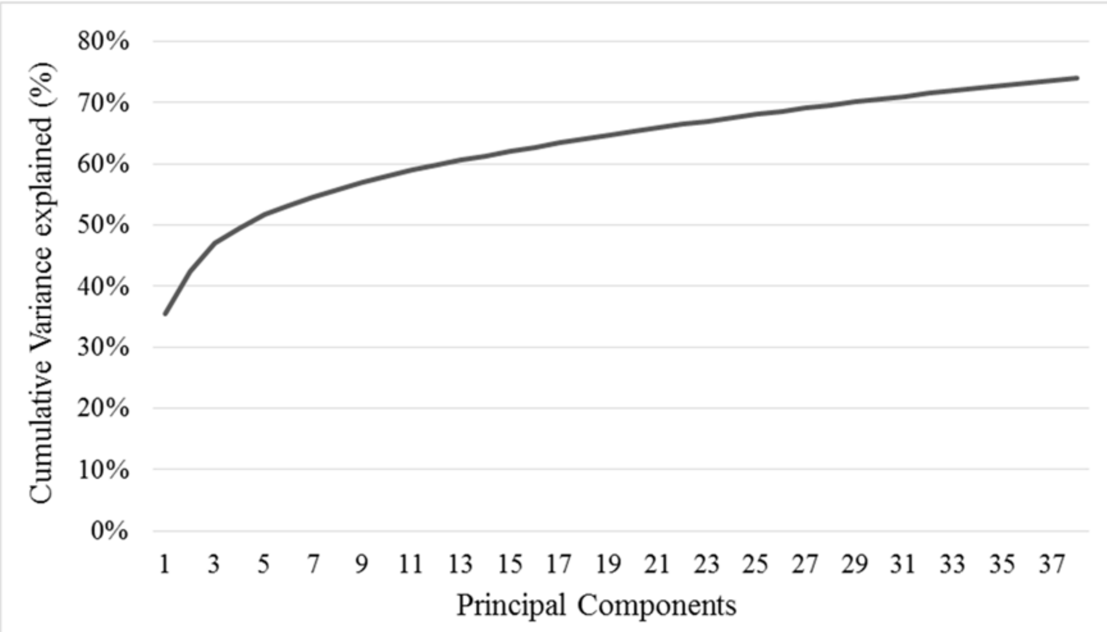
Table 6: PCA World main features.

N	536
Variables	239[14]
FBR (1st principal component)	36%
5 principal components	52%
Factor number with Eigenvalue >1	38
Average Commonality	74%
Kaiser-Meyer-Olkin (Bartlett's Test of Sphericity)	0.968 (0.000)

[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.

[14] Due to a large amount of missing data, 17 financial assets have been removed from the original database. Table A.6 in Appendix presents such assets.

Figure 2: 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.



We find positive loading of each equity onto the FBR factor and negative loading for each CDS (this different sign is in accordance with the negative correlation displayed by both assets' types). In average absolute value, we find a very high loading of 57% for all financial assets onto the FBR.

As indicated, we have also considered the variables by countries and groups. Table 7 and Figure 3 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.

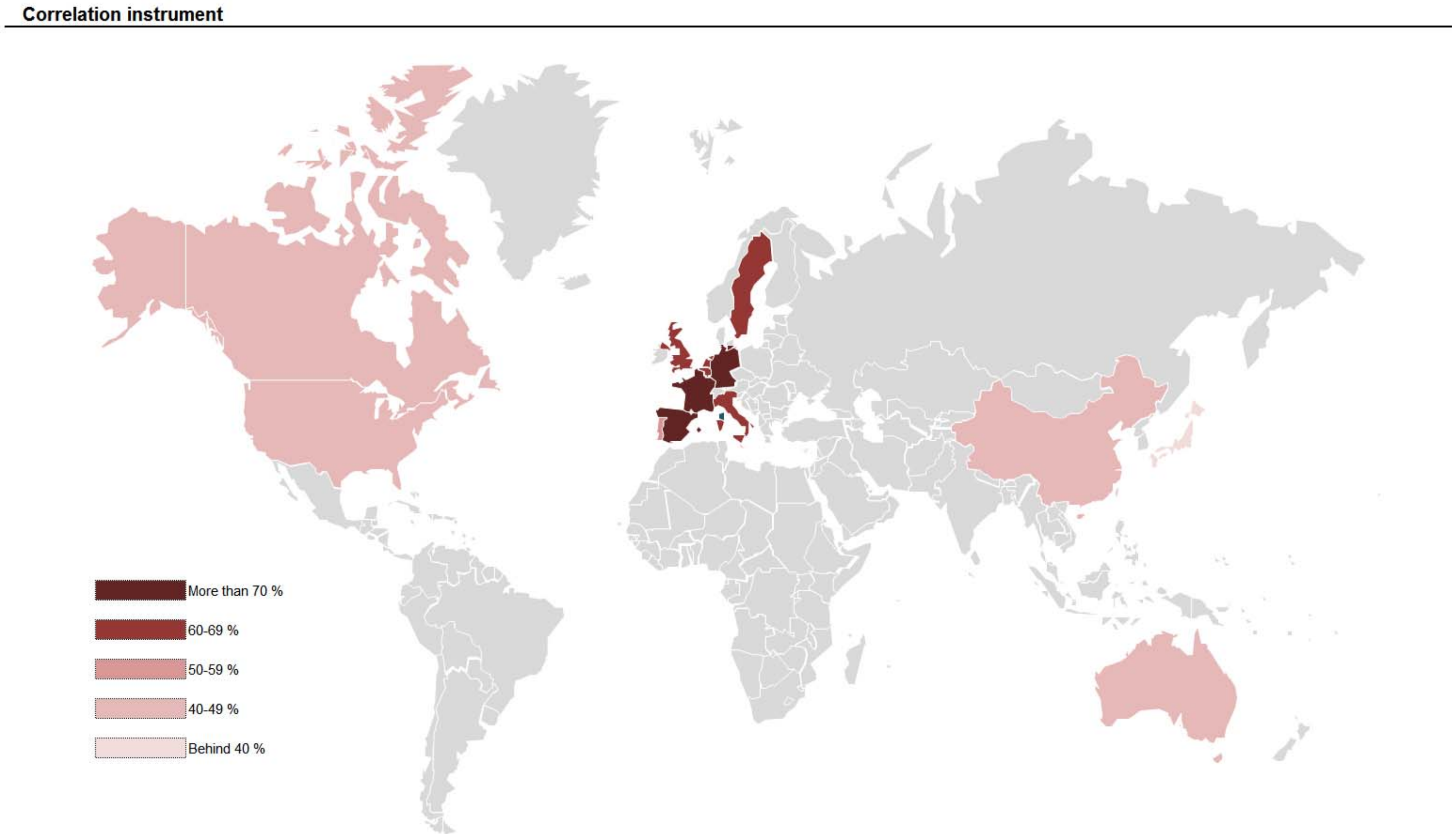
Table 7: Average loading of all variables onto the FBR, classified by countries and by groups. Loading average indicates the mean of the loadings or correlations among the FBR and the set of financial assets included in each country or group.

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%

Figure 3: Map of average countries' correlations with Financial Background Risk



Considering different assets' characteristics, we find that, by rating, A-rated companies present a higher loading onto the FBR than the rest: 59.5% against 55%. This is remarkable, bearing in mind that the sample contains less A than non-A companies (41% A and 54% non-A). By sector, financial companies' show a higher loading, 59.4%, vs. non-financial ones, 55%.

At the same time, we checked which variables can be easily tied in the FBR and which ones with any other factor. Every asset correlates with many factors. For instance, Santander stock returns correlate 76% with the FBR; 27.5% with the second factor, -24.2% with the third factor, 12% with the sixth factor, and so on. By looking at the factor loading of each variable, we can identify which assets are more connected with 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 FBR, and all of them (239) can be associated with 15 factors. In addition to the FBR, the remaining 14 factors include 33 financial assets, 14% of total sample. Figure 4 and Figure 5 present the number of assets placed in each factor, showing how the FBR relates primarily with most financial assets, while other factors relate primarily with a very few assets: the second factor link with 8 assets (the 3.3%), the third factor with 6 (the 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 FBR, we find that USA and Canada SCDS are out of the FBR. Only one asset of the Eurozone (the equity of KKPN, Netherlands) is out of the FBR, while the other 32 assets belong to the rest of the world, mainly to Japanese companies. Interestingly, only one Japanese financial variable contributes to the FBR: Japan SCDS. The remaining Japanese financial assets are distributed among 7 different factors. These results suggest a high dispersion for Japan and the very low commonality exhibited by Japanese companies with the rest of the word. Jitmaneeroj and Ogwang (2016), Muller and Berrill (2017) and Cotter et al. (2016) provide aligned evidence in relation to Japan.

Considering financial activity, we find more non-financial companies than financial out of the FBR (17 vs. 14), suggesting a tighter integration for financials. Finally, there are more CDS than stocks out of the FBR (18/15), pointing to a higher integration for stocks.

Other than the FBR, it is not easy to identify specific patterns in other factors. Nonetheless, we have tried to name them on the basis of the assets included. For instance, we can find that factor 3 includes Japanese 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 USA, 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 a pattern. Other factors include only one or two assets, except for factor 7, which includes CDS of 4 Japanese companies rating Non-A.

Figure 4: World factors and assets directly related with them. The figure shows the name of each factor given by its largest loading.

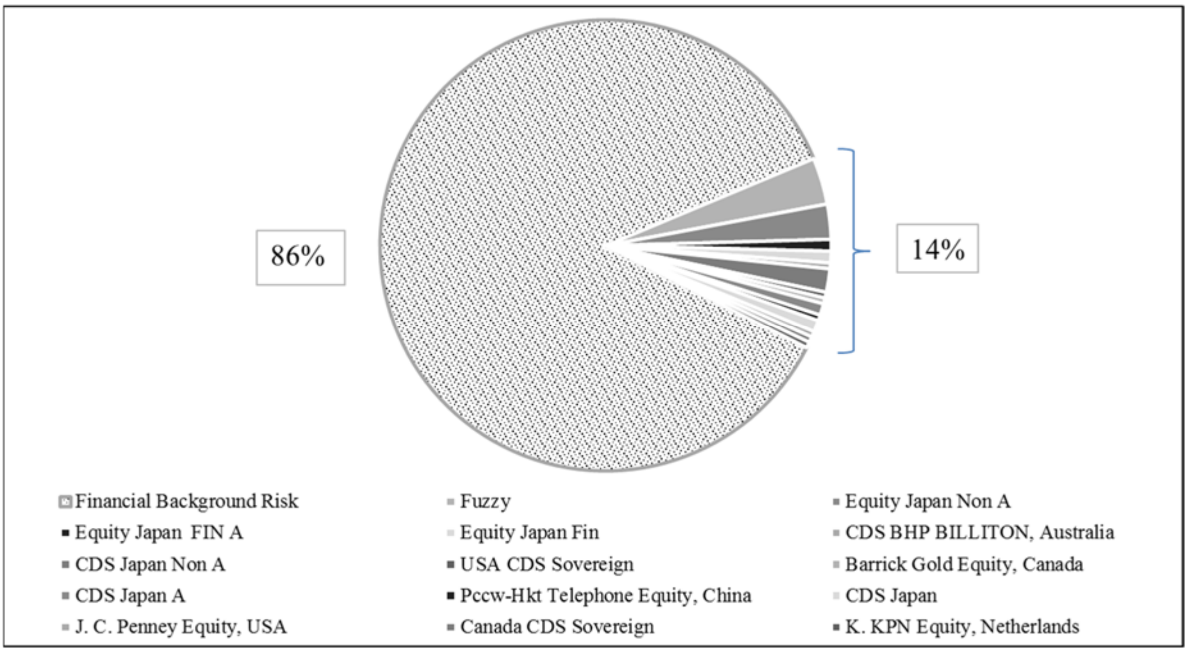
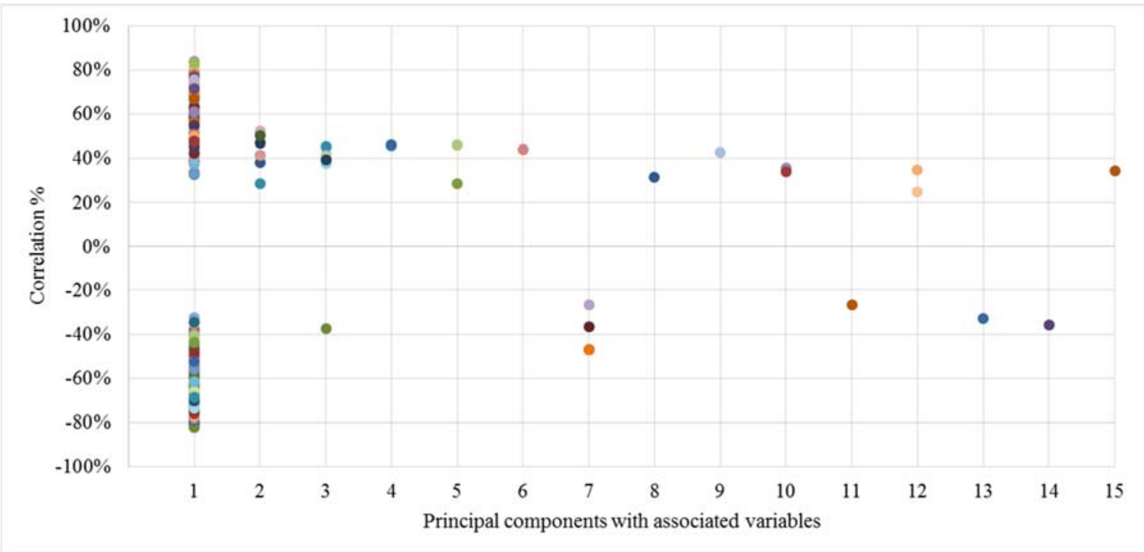


Figure 5: Number of financial variables with largest loading included in each World factor. We show for each factor, the number of variables directly related with it, and its pairwise correlation.



Finally, if considers only the 206 variables (86%) contributing to the FBR and recalculate the PCA, we find that the average loading of the assets onto the FBR increase 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; the FBR we define, explains approximately 57% of all the assets' movements. This FBR is a good measure of economy-wide variation due to its large influence in the markets worldwide, as noted by Hilscher and Willson (2016).

In addition, we find interesting insights from a global diversification perspective. Japanese companies as well as some Canadian and American companies display 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 FBR 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.

6.2. Robustness checks

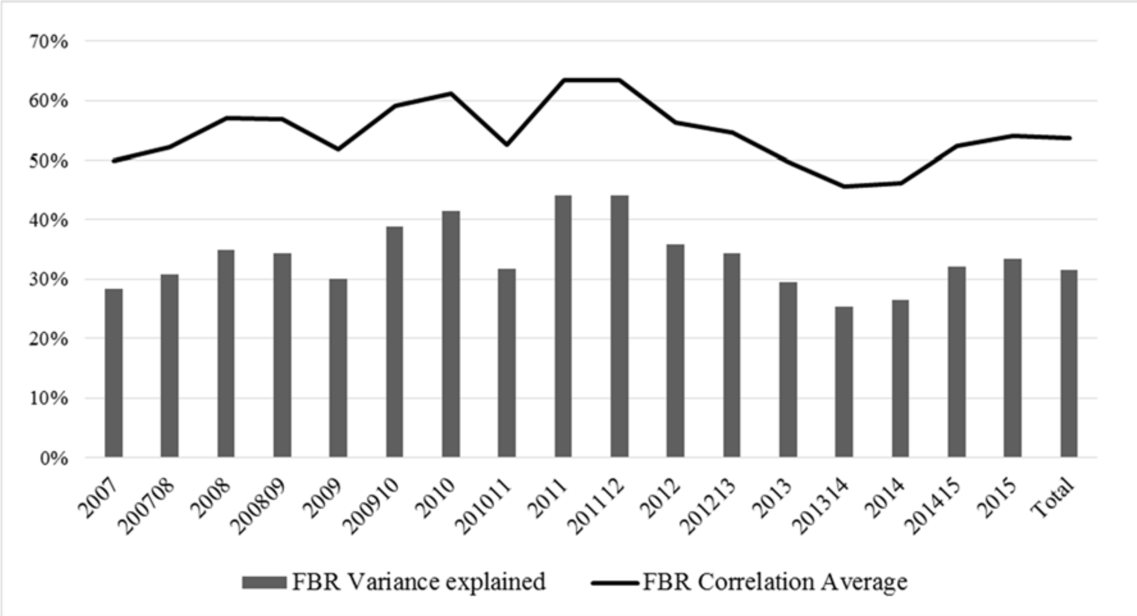
Time evolution of the FBR

We proceed to explore FBR dynamics, by means of an annual analysis using a semester rolling window, as in Billio et al. (2012). We observe that the FBR performance goes from 25% (in 2013/14) to near 45% in 2011 and 2011/12.[15] In addition, we also explore the evolution of the average correlation between all the financial assets and the FBR. 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%).

Figure 6: Evolution of FBR using a six month rolling window

The figure shows the evolution of FBR 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 FBR (absolute value) by a line. For example, in 2011, all the worldwide financial assets, correlated with the FBR in an average of 63.4%, and the FBR explained 44.2% of the variance. KMO is larger than 0.8 in every rolling year analyzed, indicating an exceptional adequacy for using PCA.

[15] 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.



According to the literature reviewed, 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 present worldwide 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 completely aligned with the previous findings.

FBR and VIX

For a common factor to be relevant for asset prices, it must be related to the stochastic discount factor: it must be noticeably higher during and immediately after recessions and financial crises, when economic theory suggests the stochastic discount factor is higher.

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

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.

The correlation sign found is negative given that FBR loading factors 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.

Table 8: Evolution of FBR and VIX Correlation

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

We also performed a lead-lag analysis between the FBR 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 FBR at a 3% significance level, while FBR Granger causes VIX movements at 9% significance level. These relations and feedback loops confirm the FBR soundness.

FBR and each country first component. Worldwide commonality versus inside country commonality

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

We find higher commonality in financial companies than non-financial ones (see Table 9); 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.

Table 9: Different groups' PCA main features

This table document the results of Principal Components Analysis taking into account 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.

	Obs.	Vbles	1st PC	1st and 2nd PC	PC Number	Average Loading	Standard Deviation
World	536	239	35.6%	42.4%	38	56.8%	0.18
EUR	1,301	96	48.4%	56.3%	8	68.7%	0.11
RoW	541	141	28.1%	37.2%	25	50.5%	0.16
FIN	576	110	39.5%	46.9%	16	59.4%	0.21
NO FIN	604	143	35.1%	41.9%	21	56.9%	0.17
RAT A	593	94	39.9%	48.0%	14	60.4%	0.19
RAT no A	949	145	32.1%	39.0%	24	53.8%	0.18
HVOLATILITY	585	123	35.6%	42.2%	19	56.8%	0.18
LVOLATILITY	592	129	36.3%	43.9%	19	57.4%	0.18
EUR FIN	1,452	46	53.1%	63.8%	5	72.3%	0.09
EUR NO FIN	1,484	57	43.6%	51.7%	6	65.1%	0.11
ROW FIN	577	64	30.3%	40.6%	12	51.9%	0.18
ROW NO FN	608	86	28.3%	36.9%	14	51.3%	0.14

Most likely due to the European Sovereign and Bank crisis, European movements have turned out to be more coordinated. We observe a higher degree of commonality within the Eurozone than the degree observed 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 USA, and they find that this risk is strongly related to financial market variables (note that we do use stock prices in this study), backing up our results. 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 FBR 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 7 almost perfectly parallels the ranking in Table 10; Japan is the country with the lowest loading factor in FBR and is also the country with the second to the lowest level of commonality inside. The results for Canada and the USA also indicate a very low level of commonality, pointing to a good diversification opportunity for global investors.

Table 10: Different countries' PCA main features

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; 1st PC, the variance explained by the first factor in each country, in %; 1st and 2nd 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.

	Obs.	Vbles	1st PC	1st and 2nd 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

Finally, we measure the lead–lag relationships between the FBR and countries' first factor. We find that contemporaneous correlations between France's, Germany's and the Netherlands' first factor and FBR are at a maximum, approximately 95%-97%. Most assuredly due to the differences in the markets' closing times, we find a Granger-cause relationship between North America (the USA and Canada) and the FBR: The USA and Canada lead FBR movements mainly with 1 lags (days), while the FBR leads other countries in the world such as China, Japan and Australia and three European countries (Belgium, Germany and the Netherlands). We find informational comovements between the UK, France and the FBR, and find four European countries that do not exhibit causal relations with the FBR.

Table 11: Granger causality tests and correlations between FBR and countries' first factor

	Country	GC test p-value	Lags	FBR and Countries' First Factor Correlation
Leaders	Canada	0.002	1	75.45%
	USA	0.000	2	80.70%
FBR lead	Belgium	0.004	1	85.54%
	Germany	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	FBR lead 0.001 France lead 0.004	1	96.90%
	United Kingdom	FBR lead 0.000 UK lead 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%

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

7. 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. It turns out to be a global systematic risk factor since it underlies 86% of our sample' assets movements. Moreover, the three different types of financial assets studied (SCDS, CCDS and stocks), which take into account corporates and countries risks, are highly represented in this risk factor, confirming the abovementioned cross-markets integration. We followed the approach in Merton et al. (2013) to understand the linkages among countries and companies worldwide, and propose the structural corporate model and its extension, the contingent claim analysis, as a model to provide a common ground to the three financial assets types.

The uncovered financial risk factor is robust across time periods, and it is evenly distributed across assets and countries, with the noticeable exception of Japan, which follows a divergent risk pattern, preceded by China and Canada. We also find a higher commonality within the Eurozone financial assets than in other markets.

The diversification potential should be high when assets returns are not well-integrated, and the results presented here reinforce previous studies that point to meaningful diversification opportunities while still investing in developed markets.

Our results confirm the dominant role of global investors. As found in Longstaff et al. (2011), the commonality found is consistent with risk pricing by a marginal investor with a global portfolio. The findings have a special value added for these global market participants who can improve their investment strategies and mitigate this background risk.

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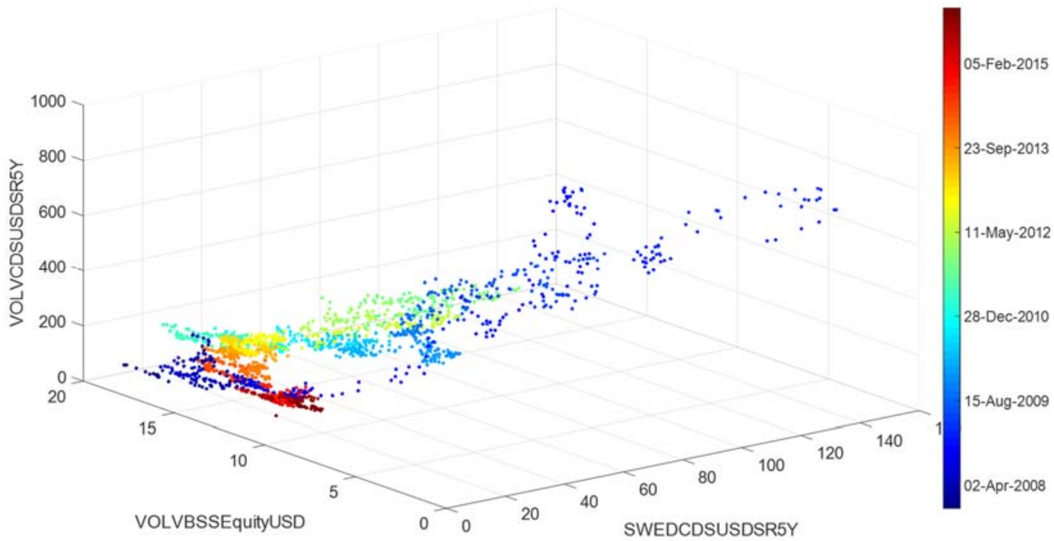
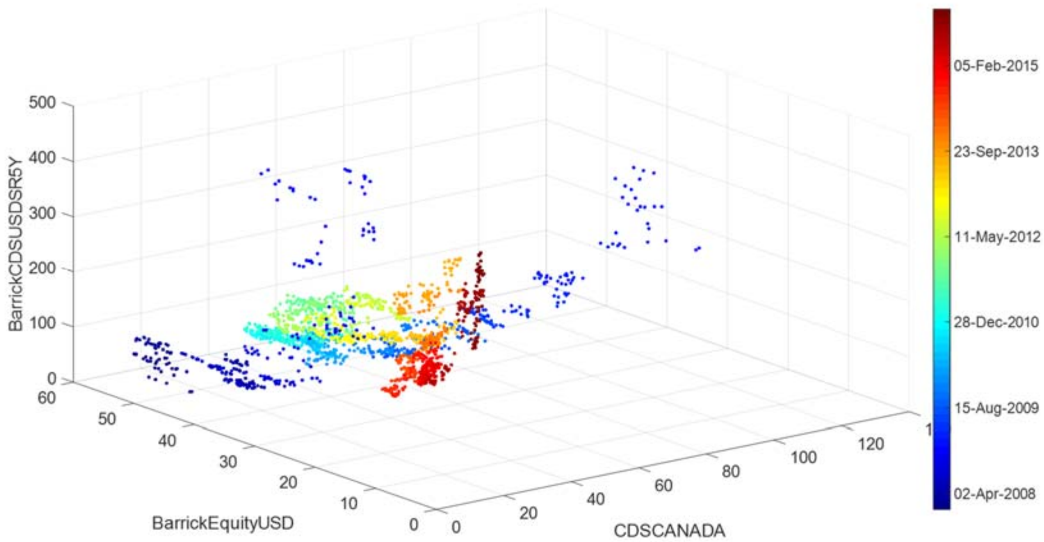
Appendices

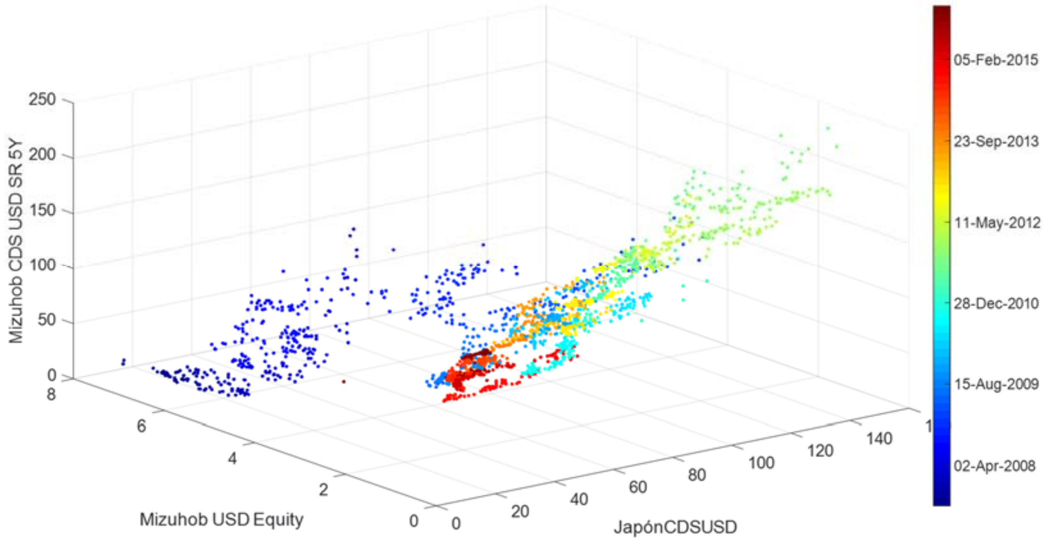
Figure A. 1:

Daily evolution of Swedish sovereign CDS, Volvo CDS and equity; Canadian Sovereign CDS, Barrick company CDS and equity; Japanese Sovereign CDS, Mizuho Bank CDS and equity; UK Sovereign CDS, Barclays CDS and equity, during the period 2007-2015.

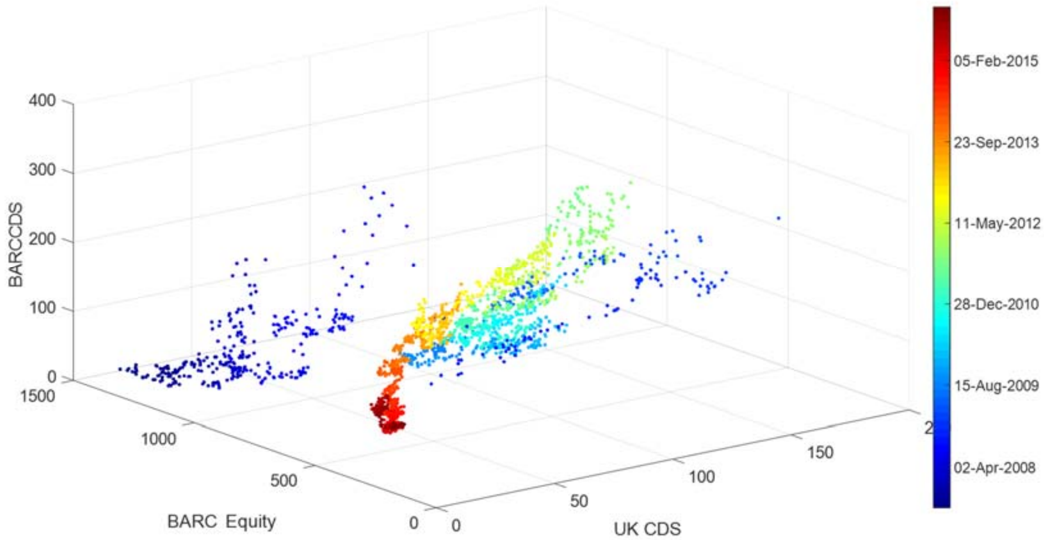
In dark blue are year 2008 observations, colors lighten as we approach more recent dates. In bright red are year 2015 observations.







Mizuhob CDS USD SR 5Y
Mizuhob USD Equity
JapónCDSUSD
05-Feb-2015
23-Sep-2013
11-May-2012
28-Dec-2010
15-Aug-2009
02-Apr-2008



BARCCDS
BARC Equity
UK CDS
05-Feb-2015
23-Sep-2013
11-May-2012
28-Dec-2010
15-Aug-2009
02-Apr-2008

Table A.1 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/M ean
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
	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
	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
	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	55.64	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