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 understanding 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 CCDS 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 financial instruments (SCDS, CCDS

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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 diversifying 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. 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.

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 market’s 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)\(^5\), 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 networks 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., Ejiting and Lemle, 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 Santamaria 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 linearity 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 CDS 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 CDS 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 interconnectness in financial markets while managing the potentially harmful side effects (Yellen, 2013).

\(^{5}\) A recent attempt to disentangle the interconnectedness 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 Depository 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).
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 Bühl 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
empirical analysis with a visual exploration of the relationship between the three variables under consideration, since the linearity 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 (S CDS, 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 Deutsche 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 (continued)

| Country | Issuing Country/Company | Rating Moody’s 2015 | CDS | Stock Price |
|---------|-------------------------|---------------------|-----|-------------|
| U.K.    | Sovereign               |                     |     |             |
|         | A1                      | 1,868 16.74 93.35 146.49 |     |             |
|         | Baa1                    | 2,349 18.72 164.79 30.25 |     |             |
|         | Aaa1                    | 2,342 44.22 2,349 11.56 148.67 |     |             |
|         | Baa2                    | 2,340 45.55 2,342 12.46 149.56 |     |             |
|         | Moody’s 2015 CDS Stock Price |                     |     |             |
| USA     | Sovereign               |                     |     |             |
|         | A1                      | 1,568 16.72 93.35 43.61 |     |             |
|         | Baa1                    | 2,349 18.72 164.79 30.25 |     |             |
|         | Ba2                     | 2,340 45.55 2,342 12.46 149.56 |     |             |
|         | Moody’s 2015 CDS Stock Price |                     |     |             |
|                         | Obs Min Max Mean Stdev Stdev/ Mean Obs Min Max Mean Stdev Stdev/ Mean |
|                         | 1,868 16.74 93.35 146.49 |     |             |
|                         | 2,349 18.72 164.79 30.25 |     |             |
|                         | 2,340 45.55 2,342 12.46 149.56 |     |             |

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 583.28 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. Therefore, we test normality using the Kolmogorov-Smirnov test. Table 4 shows very low evidence of normality.

11 Skewness and Kurtosis are not presented in Tables 2 and 3, but they are available upon request.
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.
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%    |

Figure 2. Daily evolution of Deutsche Sovereign CDS, Deutsche 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 Deutsche Sovereign CDS, Deutsche Bank CDS and Deutsche Bank Equity. b) Evolution of Spanish Sovereign CDS, Banco Santander CDS and Banco Santander Equit.
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. 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.
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 loads 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 can identify which assets are connected more intensely to each factor.

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 | Issuing Country/Company | Full Sample | 01/07/2007–12/31/2009 | 01/07/2010–06/30/2011 | 07/01/2011–12/31/2015 |
|---------|-------------------------|-------------|------------------------|------------------------|------------------------|
| **Japan** | **FIN** | | | | |
| Australia | | | | | |
| ANZ | | | | | |
| C.B.A. | | | | | |
| N.A.B. | | | | | |
| Westpac | | | | | |
| NO FIN | GPT RE | | | | |
| BHP BILLION | | | | | |
| Rio Tinto | | | | | |
| Telstra | | | | | |
| Qantas | | | | | |
| Woodside Petroleum | | | | | |
| | | | | | |
| Canada | FIN | | | | |
| Fairfax F.H. | | | | | |
| NO FIN | Barrick Gold | | | | |
| Bombardier | | | | | |
| Encana | | | | | |
| C.N.R. | | | | | |
| Agrium | | | | | |
| | | | | | |
| China | FIN | | | | |
| Bank of China | | | | | |
| Oversea-Chinese Banking | | | | | |
| NO FIN | Hutchison Whampoa | | | | |
| Cencos | | | | | |
| Noble | | | | | |
| Pccw-Hkt Telephone | | | | | |
| Swire Pacific | | | | | |
| | | | | | |
| Japan | FIN | | | | |
| Mizuho Bank | | | | | |
| Bank of Tokyo-Mitsubishi | | | | | |
| Sumitomo Mitsui Bank | | | | | |
| ACOM CO. | | | | | |
| Orix | | | | | |
| NO FIN | Nippon Steel | | | | |
| Ricoh | | | | | |
| Sony | | | | | |
| | | | | | |
| Sweden | FIN | | | | |
| Nordea Bank | | | | | |
| Svenska Handelsbanken | | | | | |
| Skandinaviska Enskilda | | | | | |
| Swedbank | | | | | |
| NO FIN | A. Volvo | | | | |
| A. Electrolux | | | | | |
| Svenska Cellulosa | | | | | |
| U.K. | FIN | | | | |
| Barclays Bank | | | | | |
| Lloyds TSB Bank | | | | | |
| Royal Bank of Scotland | | | | | |
| Aviva | | | | | |
| HSBC | | | | | |
| Experian Finance | | | | | |
| NO FIN | Anglo American | | | | |
| Glencore | | | | | |
| Bae Systems | | | | | |
| BP | | | | | |
| British Airways | | | | | |
| British American Tobacco | | | | | |
| British Telecom | | | | | |
| Centrica | | | | | |
| Dixons Retail | | | | | |
| GKN Holdings | | | | | |

(continued on next page)
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 world. 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.](image-url)

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 |
|---------|-------------------------|-------------|------------------------|------------------------|------------------------|
| USA FIN | MBIA Inc. | 0.136** | -0.048 | 0.280 | 0.041 | 0.143** | -0.06 | 0.128** | -0.047 |
| General Electric | 0.994** | -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 | 0.122** | -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 |
| PulseGroup | 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.

| | 536 |
|---|---|
| N | 536 |
| Variables | 239 |
| 5 principal component | 36% |
| Factor number with Eigenvalue >1 | 52% |
| Common Risk Factor (1st principal component) | 36% |
| Kaiser-Meyer-Olkin (Bartlett's Test of Sphericity) | 0.968 (0.000) |
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's 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's performance goes from 25% (in 2013/14) to near 45% in 2011 and 2011/12. 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.

| 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       |

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

| 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% |
| TOTAL SAMPLE AVERAGE: 57% | | |

| By asset type | Financial Assets (SCDS, CCDS, stocks) | Loading Average |
|---------------|--------------------------------------|-----------------|
| SCDS          | 14 | 55.3% |
| CDS           | 105| 57.2%|
| Equity        | 120| 56.6%|
| TOTAL SAMPLE AVERAGE: 57% | | |

| By Rating | Financial Assets (SCDS, CCDS, stocks) | Loading Average |
|-----------|--------------------------------------|-----------------|
| Rat A     | 94 | 59.5% |
| Rat Non A | 145| 55.0% |
| TOTAL SAMPLE AVERAGE: 57% | | |

| By Sector | Financial Assets (SCDS, CCDS, stocks) | Loading Average |
|-----------|--------------------------------------|-----------------|
| Fin       | 96 | 59.4% |
| Non Fin   | 129| 55.0% |
| SCDS      | 14 | 55.3% |
| TOTAL SAMPLE AVERAGE: 57% | | |

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.

T. Corzo et al. Heliyon 6 (2020) e03980
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.
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 11. Evolution of common risk factor and VIX Correlation.

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

### Table 12. Different groups’ PCA main features.

|                | Obs. | Vbles | 1st PC | 1st and 2nd 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.
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 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 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.

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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 asset 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 its 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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References

Acharya, V., Drechsler, L., Schnabl, P., 2014. A pyrrhic victory? Bank bailouts and sovereign credit risk. J. Finance 69 (6), 2689–2739.

Ang, A., Bekaert, G., 2002. International asset allocation with regime shifts. Rev. Financ. Stud. 15 (4), 1137–1187.

Ang, A., Longstaff, F.A., 2013. Systemic sovereign credit risk: lessons from the US and Europe. J. Monetary Econ. 60 (5), 493–510.

Amihud, Y., Mendelson, H., Pедерсен, L.H., 2006. Liquidity and asset prices. Found. Trends® Finance 1 (4), 269–364.

Arce, O., Mayordomo, S., Peña, J.I., 2013. Credit-risk valuation in the sovereign CDS and bonds markets: evidence from the euro area crisis. J. Int. Money Finance 33, 124–145.

Augustin, P., Subrahmanyam, M.G., Tang, D.Y., Wang, S.Q., 2016. Credit default swaps: past, present, and future. Ann. Rev. Financ. Econom. 8, 175–196.

Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2009. Credit ratings and the cross-section of stock returns. J. Financ. Mark. 12 (3), 469–499.

Badaoui, S., Cathcart, L., El–Jahel, L., 2013. Do sovereign credit default swaps represent a clean measure of sovereign default risk? A factor model approach. J. Bank. Finance 37 (7), 2392–2407.

Baele, L., Bekaert, G., Englebrecht, K., 2010. The determinants of stock and bond return comovements. Rev. Financ. Stud. 23 (6), 2374–2428.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61 (4), 1645–1680.

Bedendo, M., Colla, P., 2015. Sovereign and corporate credit risk: evidence from the Eurozone. J. Corp. Finance 33, 34–52.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. J. Polit. Econom. 81 (3), 637–654.

Billo, M., Getmansky, M., Lo, A.W., Pelizzon, L., 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. J. Financ. Econom. 104 (3), 535–559.

Braslavski, I., Laopedis, N.T., Kouretas, G.P., 2015. Systemic Risk and Financial Market Contagion: Banks and Sovereign Credit Markets in Eurozone. Available at SSRN: http://www2.ebueb.gr/conferences/Crete2015/Papers/Kouretas_1.pdf.

Bühler, W., Trapp, M., 2009. Time-varying Credit Risk and Liquidity Premia in Bond and CDS Markets (No. 09-13). CIR working paper. Available at: https://www.econstor.eu/bitst ream/10419/41349/1/616612656.pdf.

Byström, H., 2008. Credit default swaps and equity prices: the iTraxx CDS index market. In: Wagner, N. (Ed.), Credit Risk - Models, Derivatives, and Management. Chapman & Hall, pp. 69–83.

Byström, H., 2018. Stock return expectations in the credit market. Int. Rev. Financ. Anal. 55, 85–92.

Carr, P., Linetsky, V., 2006. A jump to default extended CEEV model: an application of Bessel processes. Finance Stochast. 10 (3), 303–330.

Carr, P., Wu, L., 2010. Stock options and credit default swaps: a joint framework for valuation and estimation. J. Financ. Econom. 8 (4), 409–449.

Chen, N.F., Roll, R., Ross, S.A., 1986. Economic forces and the stock market. J. Bus. 59, 383–403.
