

FACULTAD DE CIENCIAS ECONÓMICAS Y EMPRESARIALES DEPARTAMENTO DE GESTIÓN FINANCIERA

CDS: A RELEVANT RESEARCHERS TOOL AND GLOBAL RISK PROXY

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1. Introduction

"The financial crisis that erupted in August 2007 has highlighted the need for tools that can analyse risks and vulnerabilities in financial systems in a holistic way."

Castren and Kavonius (2009)

During the past decades, severe financial problems have unfortunately hit our world and the analysis of financial risks has become a relevant field of study and an area of particular interest to regulators, practitioners and policy makers.

The purpose of this thesis is to contribute to the analysis of these financial threats in a global context. Furthermore, it helps filling some gaps regarding current financial risks by using a meaningful instrument: the Credit Default Swap (hereafter CDS).

A look at the last financial crises evidences some degree of commonality, but it also hints at the evolution of the term "financial risk": In the 1970s the threat was the stagflation which led to the recession of the world's economy. The issue of the 1982' LatAm sovereign debt crisis was that these countries were unable to repay their foreign debt which had quadrupled in seven years. The failure of more than 700 associations in the US was the crunch of the savings and loans crisis in the 1980s. In 1987, it was the stock market that crashed and the Dow Jones index, among others, lost 23% of its value in one day and continued falling. The critical point of the significant recession that hit the US in the late 1980s was the junk bond crash in 1989. Interest rates played the main role in the 1994 Tequila crisis affecting Mexico but also Argentina and other markets across the developed world. The baht's, Thailand's currency, collapse and the fact that the country could not pay back the huge amount of debt to foreign entities carried out the Asia crisis from 1997 to 1998 which spread across the region

affecting South Korea, Indonesia, Laos, Hong Kong and Malaysia too. The bull rush of technology and internet-related stocks carried out the Dotcom bubble between 1999 and 2000 and ended in the default and liquidation of many of those companies. The collapse of several large financial institutions and the consequent global financial crisis in 2007-2008 (considered to be the worst crisis since the Great Depression) hit the entire world's financial markets. Finally, the 2009-2015 European sovereign debt crisis affected primarily Eurozone members but also some countries outside the area.

All this turbulent periods have evidenced, first, that identifying the threats that are being faced by companies, states and the economy in general is paramount when it comes to predict, measure and mitigate the effects of those hazards. Second, that the concern on risk-taking is not enough to understand financial crises, but that the unintended, or unanticipated accumulation of large risks by individuals, institutions or governments, plays a main role (Draghi, Giavazzi, and Merton, 2003). And third, that, nowadays, the understanding of systemic risk is crucial, and it becomes imperative to be aware of the main issue of its nature, contagion (De Bandt and Hartmann, 2000). Therefore, the identification of significant interactions that drive spillover between entities and countries turns into necessary.

In this context, this work aims to go further in the study of global financial risks under the framework of such contagion and systemic threat. In order to achieve this goal, we use an instrument that involves a valuable guide with which to understand the risks that have worried researchers, regulators and all the participants of the financial system as a whole from the beginning of the millennium: the CDS.

CDS were born to diversify and mitigate financial risks after the savings and loan crisis in the 90s. They were perceived as very valuable in risk management in times of volatility and evolved quickly. Its use was so extended that it quickly became a trillion US dollar market.

Moreover, since 2000, many researchers have used CDS spreads in their investigations and given the extensive literature existing about it or regarding the usefulness of its data, we have found it a helpful conductor to deepen in the evolution of financial risks.

But CDS not only appear to be a relevant tool for understanding the evolution of financial risks, it also helps to deepen in current threats, and more specifically in nowadays global risk.

For this reason, this thesis is impulsed by the purpose of, first, achieving a better understanding of what the term "financial risk" implies nowadays; second, filling the gap that exists when it comes to corporate risk in a global context; and third, offering appropriate tools to face and manage those current risks.

To meet these goals, this study first addresses the importance of CDS markets. It is convenient, in the current environment of deregulation discussions, and going beyond controversies about its use, to distinguish the nature, power and value of this derivative contract.

Secondly, this work uses CDS for researching about risks implied in a global and complex context where companies, countries and markets are connected to the rest of the world's economy. This is crucial to become aware of the implications of a globalized world and to be able to suggest convenient instruments to face those hazards.

1.1. Objectives and methodology

This thesis is motivated by the fact that the extant literature regarding financial risks is scarce when it comes to analyse global risks in other sectors than the financial industry. Since the 2007-2009 financial crisis, a large body of research investigates the connectedness and

risk spillover among financial institutions and therefore, systemic risk is broadly studied. However, while globalization has turned the corporate sector out considerably entangled, we find that few efforts have been made regarding the subsequent global risk.

The main goal of this investigation is to shed light to the financial risks and their contagion along a global and complex economy. For this purpose, we aim to explore the existence of a latent risk of failure driven by global factors. By doing so we look for complementing the broadly analyzed systemic financial risk.

Bearing in mind this major target, firstly we look for a better understanding of financial risks in the 21st century. While tracing this awareness, we address the importance and evolution of CDS. By using them as a guideline, we look for organizing, structuring and disentangle the complex financial risks' issues that concerned researchers prior, during, and after the subprime and sovereign crises.

We use an unbiased bibliometric approach to select the main inputs within a financial risks restricted field and to improve the understanding of CDS. By doing so, we aim to identify the contributions that have become a milestone and determined the course of financial research between 2000 and 2015. Additionally we develop a conceptual map gathering the various purposes and meanings given to the CDS.

Due to the large CDS literary productivity found, we also detect as relevant a deeper exploration of the interactions between CDS aggregate trading volumes and the number of CDS research articles, in order to discern the value or reliability of the CDS market. By exploiting the results of a search on textual analysis and by means of a cointegration and informational leadership analysis, we look for the links between both variables. Because there is no potential structural model, we follow a reduced form approach in this analysis. Reduced

form models are useful precisely when there are questions over the specification of a structural framework. In our exploratory analysis we measure the contribution of each of the two variables to the revelation of the common fundamental by means of a vector error correction model (VECM) analysis.

After accepting the importance and usefulness of the CDS market, and in order to achieve our main goal, we propose a simple method for analyzing global credit risk by using multinational corporate CDS spreads. In this framework, we analyse the world's largest public companies searching for a diversified portfolio of firms with a heterogeneous geographical source of incomes.

We use principal components analysis to evidence common factors driving the risk changes in a global context. We also test for Granger-causality to find out the statistically significant relations among these multinational corporates and in an inter-sectoral framework. Additionally, and to make the research complete, we also attend to assess the relevance of global sectors in predictive causality terms and the relationship between global credit risk and market risk. Finally, we use the portfolio of global companies to better understand investment diversification when facing global credit risk.

Everything considered, CDS markets and global credit risks are deeply studied, being the findings relevant to regulators, academics and investors. This work contributes to the revelation of the CDS market as a variable of scientific interest and sheds light to the ongoing debate regarding trading position limits. It also provides evidence of a non-financial global corporate credit risk and highlights the relevance of analysing the risk spillover between non-financial industries. Finally, it analyses the interrelations between the global credit risk and the global market risk and contributes to market risk diversification theory.

1.2. Outline and contents of the document

In order to address the previous objectives, and besides this introductory section, this thesis is structured in three parts. The first part is a State of art section. In Chapter 2 Credit Default Swaps are introduced as well as their evolution. A 15-year bibliometric analysis of the various types of financial risks studied in the context of the CDS is performed. Based on this exhaustive literature search, a conceptual map is proposed in order to chronologically analyze the various permutations of the CDS. By accounting all of the relevant acceptations displayed in the literature, we detail the major items that have resulted in milestones in how we understand financial risks.

The second part is driven by the empirical analysis. After figuring out the usefulness of CDS spreads, and in the threshold of a new deregulation era, in Chapter 3 we address the relevance of the CDS market for the academic publishing activity. By analyzing the trading, publishing and regulation processes regarding these instruments, the cointegration between the trading and the literary activity, and their common fundamental through a VECM analysis, we shed light to the ongoing debate regarding trading position limits.

In Chapter 4 global credit risk is analyzed by using multinational corporate CDS spreads. We first search for a sample of large companies with high degree of geographical revenues diversification and CDS liquidity requirements. After presenting the descriptive statistics we look for correlations. By means of a Principal Component Analysis we extract the common factors underlying variations in CDS spreads to evidence if the risk of failure is driven by sector and/or country specific factors, or by global ones. We also conduct a sectoral analysis by performing a PCA to find out the degree of connectedness between the firms in each industry, and Granger-causality networks to model the dynamics between the sectors.

Finally, in the last part of this chapter, the dynamics between global credit risk and market risk are analyzed, and we purpose a new methodology of investment diversification while facing global credit risk.

The third part of this thesis presents Chapter 5 with the major conclusions, contributions and lines for future research, followed by references and appendices.

2. Credit Default Swaps

"In spite of misgivings about the role of CDS in potentially destabilizing markets, their role as indicators

of credit quality has, in fact, expanded."

Subrahmanyan, Tang and Wang (2014)

2.1. Concept

After the savings and loan crisis in the 1990s, an almost-new financial instrument gained

popularity to diversify and mitigate financial risks, and specifically, credit risks: the credit

default swap. CDS protect against the risk of a credit event by a particular company or

country in a manner similar to that of an insurance contract, although speculators can also use

CDS to take long/short positions on credit risk.

The buyer of protection makes periodic payments to the seller (typically a recurring

quarterly fee) until either the occurrence of a credit event or the maturity date of the contract,

whichever comes first. The annualized fee is called the CDS price, CDS premium or CDS

spread. This premium will be higher for CDS on reference entities with poor credit quality

(Blanco, Brennan and Marsh, 2005). If a credit event occurs, the buyer is compensated for the

loss incurred as a result of the credit event, which is equal to the difference between the par

value of the bond or loan and its market value after default, and the buyer must pay the

accrued fee. If there is no default event before maturity, the protection seller pays/receives

nothing.

The economic effect of a CDS is similar to that of an insurance contract. The legal

distinction between the two arises due to the fact that it is not necessary to hold an insured

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asset (e.g., the underlying bond or loan) to claim "compensation" under a CDS. Speculators can take long (short) positions on credit risk by selling (buying) protection without the need to trade the cash instrument. CDS also allow a bank to exchange its current borrowers' credit risk for the credit risk of a different set of borrowers: the risk-return profile of the bank may thus be improved without negatively affecting its relationship with customers (Draghi et al., 2003).

Such contracts were very valuable in the risk-management industry in times of volatility and evolved quickly. They are the most liquid of the diverse credit derivatives traded, and provide a very feasible method of trading credit risk (Blanco et al., 2005).

2.2. Evolution

Consistent with Weithers (2007), credit derivatives were first publicly introduced by ISDA (International Swaps and Derivatives Association)¹ in 1992; however, they were not broadly traded until after the 1999 standardization of CDS documentation. A volatile economic situation enhanced the incentive to use derivatives to achieve better risk distribution in the economy.

ISDA began to survey CDS use at mid-year 2001. In an act of foresight, the chairman of the ISDA's board noted that "...the credit derivative numbers show impressive growth during a difficult period (...) being this a testimony to the value that these products bring to market participants in managing risk in times of volatility and uncertainty".²

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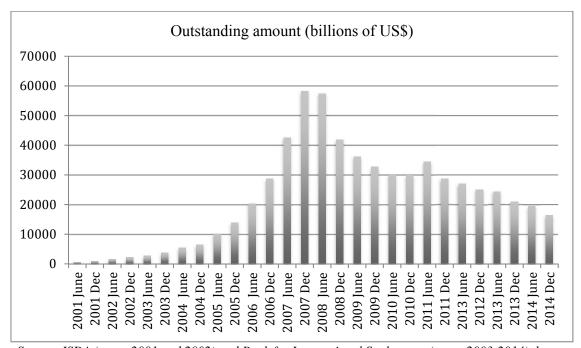
¹ ISDA (International Swaps and Derivatives Association) has worked since 1985 to make the global derivatives markets safer and more efficient. Their research helps to increase the market transparency.

² International Swap and Derivatives Association Market Survey 2001 (year-end).

Trading activity increased significantly becoming a trillion dollar market and reaching its peak in 2007. Outstanding values grew from \$631 billion in June 2001 to \$58.244 billion by the end of 2007. As stated in the 2008 1Q Report on Bank Derivatives Activities of the OCC US department of the Treasury, the demand for credit derivatives boomed as dealers increasingly used them for better risk distribution and to structure securities to meet demand for higher yields. From 2003 to 2007, they grew at a 100% compounded annual growth rate.

CDS were introduced in the mid-1990s but total notional amounts outstanding are not available until 2001. Since then, first ISDA and then Bank for International Settlements (BIS)³ have surveyed CDS semi-annual outstanding amounts. Figure 1 depicts the evolution of CDS trading activity recorded by ISDA (International Swaps and Derivatives Association).

Figure 1: Total notional amount outstanding for CDS.



Source: ISDA (years 2001 and 2002) and Bank for International Settlements (years 2003-2014) data.

As shown in Figure 1, the CDS market grew rapidly and CDS acquired great importance as an indicator of credit quality. The increasingly use of this product led to the creation of

-

³ Established on 17 May 1930, the Bank for International Settlements (BIS) serves central banks by carrying out research and policy analysis on issues of relevance for monetary and financial stability, among others.

CDS premiums data for a large number of firms and sovereigns. Many researchers found that CDS data were less likely to be influenced by the liquidity problem that affected many bond spreads, thus transforming the price of this contract into a more reliable default risk proxy. Other researchers focused on the flexibility and diversification advantages achieved through this derivative instrument. For a third group, the real innovation of this tool was not only that credit risk could be traded separately from the underlying debt but also that the CDS entailed a leverage effect (e.g. Das and Hanouna, 2006). In sum, CDS spreads were seen as important indicators of credit quality and began to be used in many studies. Thus, since 2000, many researchers became interested in understanding the CDS and the information that it provides for its use as an instrument to measure various types of risks.

However, after the US subprime crisis (2007-2008), outstanding amounts decreased rapidly, as CDS became controversial. Credit risk transfer activities were perceived as increasing the fragility of the financial system, rather than contributing to better risk diversification. Researchers realized that CDS were complex instruments with an unexpected downside effect in scenarios of financial distress. Others went further, stating that CDS played a prominent role in the bankruptcy of Lehman Brothers, the collapse of American International Group (AIG), and Greece's sovereign debt crisis (Subrahmanyan, Tang and Wang, 2014).

Nonetheless, and due to the 2009-2011 European sovereign debt crisis, outstanding volumes briefly recovered to support the need for hedging the exposure of banks to Greece's default risk. Trading activity continued then its downward trend in the aftermath of the European credit risk crises as a result of the CDS market emerging opacity, non-uniformly distributed liquidity and the absence of a compensation system (Oldani, 2011).

2.3. Bibliometric analysis and literature review

In order to understand financial risks in the 21st century we propose the use of CDS literature as a guideline for organizing, structuring and disentangle the complexity of financial risks.

As both, the literature on CDS and the literature that uses CDS data are extremely wide, it has been necessary to perform a 15-year bibliometric analysis to track the relevant studies and main contributions within a financial risks restricted field. Based on this exhaustive literature search, we will then detail the major items that have resulted crucial in how we understand financial risks.

Through this search, we identify the most relevant journals and papers on financial risks that use CDS. In order to be replicable by interested readers, we next provide data tables and details of how the research was been conducted.

We first conduct two parallel searches and then combine the results to identify the most relevant journals. On the one hand, we search for the most important finance/business journals through WoS, Scopus, the Academic Journal Guide of the Chartered Association of Business Schools and Google Scholar, disregarding journals on accounting, auditing, real estate, mathematics, and futures markets. The journals found are organized by considering their influence as expressed through the JCR, SJR and SNI impact factors and their AJG and H5 indexes.⁴ The use of these tools has allowed us to identify both the relevant publications in the area and their influence at a citation level.

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⁴ Appendix A details the different Impact Indices

On the other hand, we look for the papers that have examined financial risks using CDS data. This systematic literature search has been conducted using the terms "risk" and "CDS" or "credit default swap" and their derivations (risks, risky, credit default swaps, etc.). We have restricted the search to the title, abstract, and keywords fields, because we believe that if the desired concepts were not included in these fields, the publication would not be sufficiently specialized in the theme of the research. Both simple and advanced searches have been carried out to achieve the smallest possible number of false positives and false negatives.

Table 1 and Figures 2 and 3 show a summary of the results obtained through WoS between January 2000 and December 2015. The specific results of the search of the keywords through the mentioned databases (WoS, Scopus, Ebsco, Dialnet) to identify the most relevant papers can be found in Appendix B.

Table 1: Papers found while searching through WoS.

Title	(risk*) AND (credit default swap*)
Published between	2000 and 2015
Results found	38
Times cited	498
Times cited without self-citations	480
Citing articles	400

-

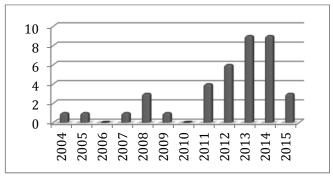
⁵ Because of the dynamic nature of the terms, and given that CDS were created in the mid-1990s, we have traced the first 15 years of the 21st century.

⁵ When searching references, it has been necessary to filter the searches thoroughly to avoid missing any chance of finding relevant information. Therefore, we have used the Boolean operators to make each search more precise. Parentheses and quotation marks have also been used to avoid ambiguity, as in the cases in which it was necessary to use two words together and in a particular order ("credit default swap") and in the cases involving the use of elements such as (*) for all possible endings ("credit default swap" or " credit default swaps").

Citing articles without self-citations	387
Average citations per Item	13.11
h-index	7

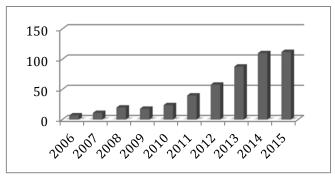
Data as for December 2015

Figure 2: Published works with (risk*) and (credit default swap*) in the title.



Source: WoS. Updated to December 31st, 2015

Figure 3: Citations of papers with (risk*) and (credit default swap*) in the title.



Source: WoS. Updated to December 31st, 2015

The search reveals that the highest literary productivity has been performed between 2011 and 2015. Similarly, the number of citations increases every year during that period. In sum, we note that after the fall of Lehman Brothers and the subprime crisis, researchers' interest in risks and the use of the CDS significantly increases. This is especially true during the sovereign debt crisis, when studies about financial risks associated with CDS are triggered.

The third step is to combine the previous results to obtain the top journals publishing about financial risks using CDS. By considering business/finance journals, their influence through the JCR, SJR and SNIP impact factors and their AJG and H5 index, along with the papers about financial risks using CDS published in those journals, the top 20 journals were selected and are shown in Table 2.

Table 2: Selected main business/finance journals (avoiding journals on accounting, auditing, real estate, mathematics, and futures markets) publishing about financial risks using CDS.

		JCR		SNIP	AJG	H5-index GS
	JOURNAL	2014	SJR 2014	2014	2015	2015
1	JOURNAL OF FINANCE	5.424	17.138	5.609	4*	108
2	JOURNAL OF FINANCIAL ECONOMICS	4.047	10.116	4.200	4*	113
3	REVIEW OF FINANCIAL STUDIES	3.174	10.726	3.299	4*	101
4	JOURNAL OF INTERNATIONAL MONEY AND FINANCE	2.117	1.114	1.418	3	45
5	JOURNAL OF FINANCIAL MARKETS	2.111	3.732	2.238	3	
6	REVIEW OF FINANCE	2.012	3.796	1.620	4	40
7	JOURNAL OF MONETARY ECONOMICS	1.726	4.779	1.952	4	
8	INTERNATIONAL REVIEW OF ECONOMICS AND FINANCE	1.704	0.754	1.589	2	
9	JOURNAL OF FINANCIAL INTERMEDIATION	1.661	1.700	1.760	4	34
10	JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS	1.566	3.355	1.948	4	51
11	FINANCIAL ANALYSTS JOURNAL	1.548	2.116	1.429	3	
12	IMF ECONOMIC REVIEW	1.525	3.764	2.095	3	
13	JOURNAL OF FINANCIAL STABILITY	1.506	1.370	1.852	3	32
14	WORLD BANK ECONOMIC REVIEW	1.488	0.970	1.309	3	
15	FINANCE AND STOCHASTICS	1.441	2.585	2.265	3	
16	JOURNAL OF FINANCIAL ECONOMETRICS	1.302	1.607	1.219	3	
17	JOURNAL OF BANKING and FINANCE	1.299	1.059	1.587	3	73
	JOURNAL OF INTERNATIONAL FINANCIAL MARKETS, INSTITUTIONS	1.237	0.712	1021	3	
18	AND MONEY					
19	JOURNAL OF FINANCIAL SERVICES RESEARCH	1.200	0.874	1.153	3	
20	JOURNAL OF CORPORATE FINANCE	1.193	1.516	1.528	4	46

Explanations of the various impact indexes can be in Appendix A.

Finally, after disregarding papers published in very specific areas (both because of their lack of representativeness and because they do not really use CDS to research financial risks) and combining the results obtained through the search of the main journals with those obtained through the search of the most-cited papers and the latest working papers, the main authors and articles were identified. We find that the most appropriate papers are those that

provide basic and updated sources of knowledge and are published in a recognized journal, along with conference proceedings and working papers series that help track, almost in real time, topics of current interest. This methodology leads to the selection of 81 papers as leading research pieces (for a complete list, see Appendix C), from which 40 were published in the top 20 journals. Of the remaining articles, 6 studies appeared in the Working Papers Series (ECB, IMF, NBER, NCCRFVRM and CAMP) and the remainder were published in 34 journals, revealing that the CDS is both a topic of interest for many editors and a cross-curricular subject because it affects multiple financial concepts. 56 of the 81 papers were published between 2011 and December 31, 2015, whereas only 25 were published during the previous 11 years.

Once completed the bibliometric analysis, we are now able to conduct a deep financial risks literature review, which evidences that CDS data have served researchers in many domains.

2.4. Conceptual map

Through the exhaustive literature search, we find that first studies on credit risk were focused on pricing issues. Little empirical work was carried out. These studies were related to the bond market and concerned the determinants and dynamics of the yield spread between a risky bond and a government bond (considered secure).

However, some authors such as Blanco et al. (2005) and Longstaff, Mithal and Neis (2005) began suggesting that CDS prices are useful indicators of credit risk and can be used as measures of default risk. Empirical studies using CDS started then to analyze the influence of various factors on CDS rates and therefore on credit risk, addressing the complexity of

pricing this type of hazard. Authors such as Hricko, Aunon-Nerin and Huang (2003) suggested that CDS prices are better proxies for credit risk than the difference between the yield on a bond of a risky counterparty and a government bond. In this comparative context, other researchers have investigated whether CDS spreads and bond spreads are in line with each other and which one responds faster to changes in credit conditions, i.e., which one leads what it is referred to as the price-discovery process.⁶

However, academicians have not only searched for factors affecting CDS and bond spreads but also for correlations between different types of risks using CDS data, such as market and credit risk correlation or correlation between the default risk of the protection seller and that of the underlying entity.

Furthermore, during the turmoil of 2007-2009, authors such as Jorion and Zhang (2007, 2009) also examined the information-transfer effect of credit events across the industry and the effect of bankruptcy announcements on creditors, attempting to explain the excess clustering observed in defaults.

The crisis also led to different studies about sovereign risk contagion, risk transmission from peripheral to central EU economies, the "flight-to-quality" phenomenon, and risk spillovers between banks and sovereigns, among others, resulting in the need to analyze private-to-public and public-to-private risk contagion.

Along this contagion line, the systemic feature of the recent financial crisis captured the interest of researchers who denoted the CDS paradox: these contracts help transfer risk but concentrate systemic risk because of increased interconnections in the financial system. In concert with this paradox, the benefit of clearinghouses has been also questioned.

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⁶ The price discovery process is explained in section 2.4.2, "Role of CDS in the Price Discovery Process."

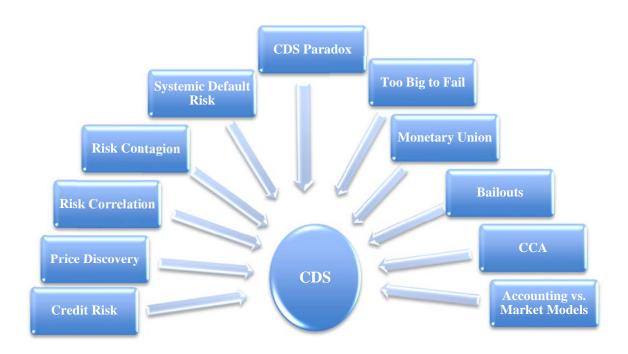
Following the path of this interconnection issue, some authors have concentrated in what are known as systemically large banks, suggesting some of them that they are "too large to fail" or "too interconnected to fail" institutions, while others conclude that they are "too big to save". On the other hand, it has also attracted the interest of researchers to determine whether a country's membership in an economic and monetary union is significant given such unions' sensitivities to the health of the financial system, as well as the effect of government rescue packages on risk spreads and sensitivities.

Finally, other risks studies have focused on diverse issues such as: new approaches to measure default risk, the contingent claim analysis, the benefits of accounting and market models for explaining credit risk, the liquidity factors in the valuation of CDS, the impact of sovereign wealth fund investments on the credit risk of target companies, etc.

Based on this holistic approach to CDS, we now propose a conceptual map in order to chronologically analyze the various permutations of the CDS. By accounting all of the relevant acceptations displayed in the literature, we detail the major items that have resulted enlightening in how we understand financial risks.

As a result of the researching, we next conceive a CDS conceptual map shown in Figure 4 and delve into the details of the various permutations of the concept.

Figure 4: Map of the various CDS purposes, ordered according to chronological emergence



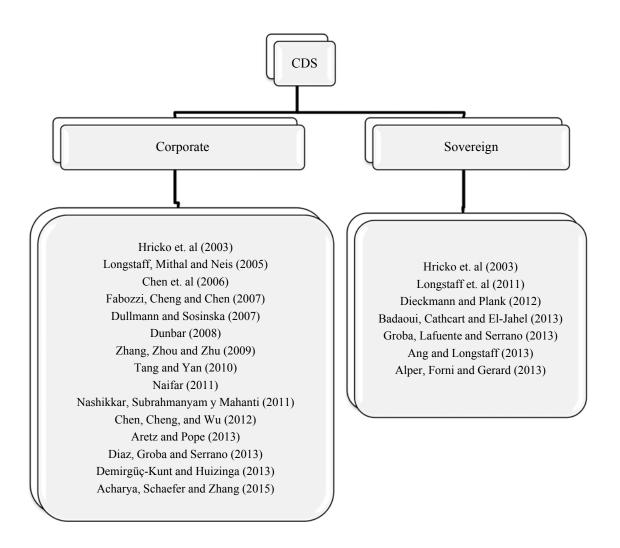
Next section details the major items that have resulted in decisive points in how we understand CDS and thus, their financial risks. For this purpose, we take into account all of the relevant acceptations displayed in the literature.

2.4.1. CDS as a source of information on credit risk: What determines the price?

Many studies have analyzed the CDS spread determinants to understand the pricing of corporate/sovereign credit risk, seeking for the sources of this type of hazard. In fact, this is the area regarding financial risks using CDS where the highest amount of research has been

found and, as shown in Figure 5, we have categorized these papers depending on whether they address corporate or sovereign credit risk.

Figure 5: Literature on the determinants of the credit risk price classified according to focus on corporations/sovereigns.



Research regarding the determinants of the CDS spread and their relevance is revealed as an area of clarifications and specifications due to the dynamic nature of these instruments. While some authors find that default is linked to the performance of the local economy (e.g. Hricko et al., 2003), others reveal that changes in firms' default risk depend more strongly on global than on country effects (Aretz and Pope, 2013). This is also supported from the

sovereign credit risk point of view (e.g. Longstaff, Pan, Pedersen and Singleton, 2011). The discrepancy is clarified when it is specified that, since the beginning of the crisis, the state of the world's financial system together with the state of a country's domestic financial system has strong explanatory power for the behavior of CDS spreads (Dieckmann and Plank, 2012). Furthermore, peripheral risk plays also a key role in explaining CDS increments for the other EU members until the approval of the European Financial Stabilization Mechanism (EFSM) in May 2010 (Groba, Lafuente and Serrano, 2013).

Regarding the underlying's rating relevance, Hricko et al. (2003) note that it is the most important single source of information on credit risk overall, although the sensitivity of these rates to ratings is different for high/low rated debt and for sovereigns versus corporations. However, Zhang, Zhou and Zhu (2009) conclude that equity volatility and jumps are the most significant factors -even more significant than the rating- when it comes to explain corporate CDS premia. Furthermore, firm-level cash flow volatility increases credit spreads (Tang and Yan, 2010) and US systemic sovereign credit risk is significantly negatively related to changes in the VIX index (Ang and Longstaff, 2013).

Nevertheless, during the last financial crisis, CDS indices became more sensitive to both stock market conditions and macroeconomic variables (Naifar, 2011). However, systemic sovereign credit risk is found to be more closely related to financial market variables such as stock returns (Ang and Longstaff, 2013) rather than to macroeconomic fundamentals, and same conclusions are drawn by Diaz, Groba and Serrano (2013) regarding corporate CDS spreads. In this sense, albeit fiscal issues are found to be related to CDS premia (e.g. Demirgüç-Kunt and Huizinga, 2013, consider that bank CDS spreads are positively related to the fiscal cost relative to GDP of resolving any previous banking crisis) the explanation power

of variables related to fiscal sustainability is evidenced to be limited and lower than the one of financial or purely global variables (Alper, Forni and Gerard, 2013).

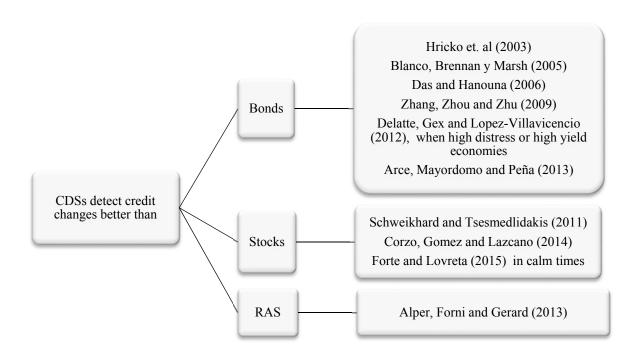
Interest rates are also found to affect CDS spreads (Fabozzi, Cheng and Chen, 2007), and to be, together with default probability and recovery, the major source of credit risk (Chen, Fabozzi, Pan, and Sverdlove, 2006). It is evidenced to be a negative relationship between spreads and risk-free interest rates (Das and Hanouna, 2006, and Chen, Cheng, and Wu, 2013) and the deterioration of the credit condition (widening of credit spreads) tends to lead to future easing in monetary policy (lowering of the current forward interest-rate curve). Furthermore, US interest rates are found to influence all CDS spreads, although outside the US the local slope of the yield curve is more significant than the US slope (Hricko et al., 2003).

Finally, it was first observed that a large proportion of corporate bond spreads were determined by liquidity factors that did not necessarily reflect the default risk of the underlying asset (Longstaff et al., 2005). But then, researchers such as Dunbar (2008) became aware of the fact that liquidity was also relevant in the CDS valuation process as it indirectly affects credit risks through credit quality. Indeed, CDS spreads may imply high liquidity risk instead of high default risk (Fabozzi et al., 2007), and when these liquidity risk premiums increase, the value of CDS spreads as market indicators is limited (Düllmann and Sosinska, 2007). In this sense, fluctuations in prices in credit markets are sometimes unrelated to changes in equity markets (Acharya, Schaefer and Zhang, 2015), and therefore do not fully account for the effect of credit risk on bond prices (Nashikkar, Subrahmanyam and Mahanti, 2011). In such circumstances, sovereign bond spreads would represent a better proxy for sovereign default (Badaoui, Cathcart and El-Jahel, 2013).

In summary, we can infer that credit risk is not homogenous amongst corporations/sovereigns and that ratings, interest rates, equity volatility, fiscal items and liquidity factors do affect the CDS spread. Nevertheless, it seems that it is still unclear whether CDS spreads are mostly explained by global/local factors (or both) or by macroeconomic/financial variables (or both). We will research further in this issue in the forthcoming empirical section.

2.4.2. Role of CDS in the Price Discovery Process

Figure 6: Literature regarding the price discovery process classified according to the established comparison.



The initial empirical research on the CDS market focused on comparisons between the CDS spread and the spread of the corresponding cash market bond. The price discovery was

then assessed, in the sense of the efficient and timely incorporation of the information implicit in investor trading into market prices (Lehmann, 2002).

In a first stage, authors confirmed the parity between CDS and bond markets in the long run (Blanco et al., 2005) while stating that the CDS market leads the discovery process because it does not suffer from the limitations of bond spreads (Hricko et al, 2003) regarding liquidity and taxes effects (Das and Hanouna, 2006) and due to the absence of funding and short-sale restrictions in the derivatives market in the short run (Blanco et al., 2005). Thus, authors such as Zhang et al. (2009) find that CDS spreads provide relatively pure pricing of the underlying entity's default risk.

But researchers became then aware of the fact that liquidity also affected CDS spreads (as explained in the previous section), that persistent deviations in the theoretical parity relation between the sovereign CDS and bond markets existed (Arce, Mayordomo and Peña, 2013) and that the price discovery process depended on the market distress level (Arce et al., 2013; Delatte, Gex and Lopez-Villavicencio, 2012). Delatte et al. (2012) distinguished then that the bond market plays a dominant role in the price discovery process in the less-risky countries during calm periods, but that the higher the distress, the more the CDS market dominates the information transmission. Furthermore, the CDS market dominates all regimes in the high-yield economies.

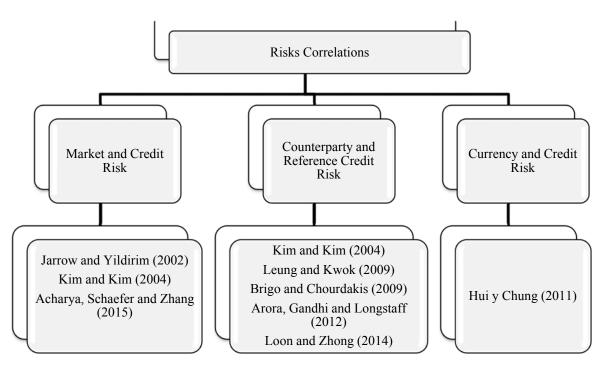
This has also been the conclusion when studying the price discovery process between CDS and stock markets: CDS are found to play a stronger role than equity markets in economies with higher perceived credit risk (Corzo, Gomez and Lazcano, 2014). In contrast, other studies suggest that the CDS's contribution to price discovery is equal to or greater than that of the stock market during tranquil times too (Forte and Lovreta, 2015). Anyhow, it is stated that equity prices and CDS premia should be considered together to fully exploit their

information content and to mitigate their respective drawbacks (Düllmann and Sosinska, 2007), although in most cases, CDS lead the timely incorporation of credit-sensitive information (Schweikhard and Tsesmedlidakis, 2011).

Finally, Alper et al. (2013) find that CDS spreads also anticipate changes in Relative Asset Swap (RAS) spreads⁷ and lead the process of pricing sovereign credit risk.

2.4.3. CDS and financial risk correlations

Figure 7: Literature on risk correlations using CDS data



⁷ According to Alper et al. (2013) a RAS spread measures the difference between a benchmark government bond wield and the fived rate arm of an interest rate given in the demostic currency with the same maturity. BAS

yield and the fixed rate arm of an interest rate swap in the domestic currency with the same maturity. RAS spreads allow for meaningful comparisons across countries or economic regions using different currencies, and they can be deemed a more restrictive indicator of the sovereign default risk than bond spreads.

First studies about risks correlation using CDS refer to market and credit risk. Jarrow and Yildirim (2002) provide a simple analytic formula for valuing default swaps when market and credit risk are correlated, whereas Kim and Kim (2004) also consider counterparty default risk for valuing these instruments.

Acharya et al. (2015) suggested that price fluctuations in credit markets are unrelated to changes in equity markets, at least some of the time, due to institutional frictions and liquidity effects. However, Kim and Kim (2004) stated that, when ignoring the correlation between market and credit risk, along with between-counterparty and reference credit risk, pricing error in CDS can be substantial. They also suggest that the sensitivity to market risk increases with the number of reference entities, and therefore, the valuation error can be more substantial in pricing basket credit default swaps.

Counterparty/reference entity correlation and credit spread volatility are thereupon found to be significant in valuing counterparty risk (conversely, Brigo and Chourdakis, 2009). In this sense, the impact of the correlation between the protection seller and the underlying reference entity becomes substantial on CDS rates when jumps in the default intensities of various parties occur as a consequence of several external shocks (Leung and Kwok, 2009). Furthermore, Arora, Gandhi and Longstaff (2012) have deepened in this issue while examining the extent to which the credit risk of a dealer offering to sell credit protection is reflected in the prices at which the dealer can sell it. They find strong evidence of the fact that counterparty credit risk is priced in the market, and that the higher the dealer's credit risk, the lower the price at which the dealer can sell credit protection. Nevertheless, they find that the magnitude of the effect is fairly small, and that this relation between CDS spreads and dealer

credit risk weakens when central clearing is implemented, lowering in such wise the systemic risk (Loon and Zhong, 2014).

Other authors such as Hui and Chung (2011) complete the correlation issue while analysing the relationship between currency and credit risk. They evaluate the crash risk of the Euro in the sovereign debt crisis of 2009-2010 and evidence an information flow from the sovereign CDS market to the currency option market. They suggest that a country's economic-political instability, which is closely tied to its credit risk, often leads to depreciation and heightened volatility in its currency.

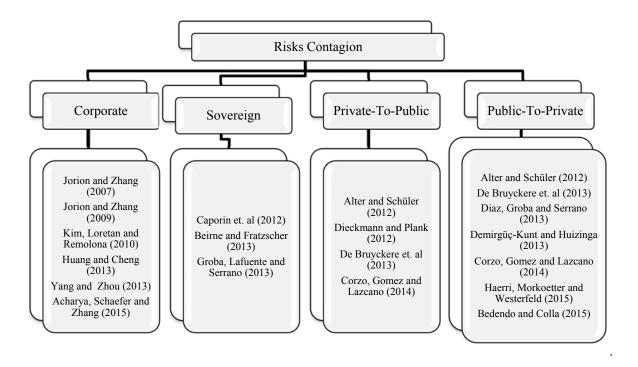
2.4.4. CDS and Financial risks contagion

Various definitions have been given to the term contagion over the years, and as noted by Caporin, Pelizzon, Ravazzolo, and Rigobon (2013), Europe's sovereign debt crisis, which began in late 2009, has reignited the literature on this issue.

We adopt the literature's usual contagion definition: the change in how countries' own fundamentals or other factors are priced during a crisis period, i.e., a change in the reaction of financial markets in response to either observable or unobservable factors (e.g., Beirne and Fratzscher, 2013). It entails an excess correlation over and above what is explained by common factors (e.g., De Bruyckere, Gerhardt, Schepens, Vander Vennet, 2013).

Although the first publications about contagion using CDS were focused on corporate contagion, the European sovereign crisis marked the beginning of sovereign contagion studies, opening the door to the analysis of risk transfers between the private and the public sectors.

Figure 8: Literature regarding risks contagion classified according to corporate/sovereign scope and the flow between the private and public sectors.



In the corporate sphere, Jorion and Zhang (2007) examine the information transfer effect of credit events across the industry as captured in the CDS and stock markets over the period 2001-2004 to empirically measure the credit contagion created by counterparty risk. They find strong evidence of a dominant contagion effect for Chapter 11 bankruptcies (i.e. reorganization of the entity) in spite of a competition effect for Chapter 7 bankruptcies (i.e. liquidation of the firm). They also suggest that the strongest evidence of credit contagion across the industry is led by purely unanticipated events.

In 2009, the same authors, Jorion and Zhang, went further by studying the effect of bankruptcy announcements on creditors. They found negative stock price responses and increases in CDS spreads and suggested that the distress effects are stronger for industrials

than those for financials, concluding that the excess clustering observed in defaults can be potentially explained by counterparty risk.

For their part, Huang and Cheng (2013) investigated about a possible relationship between information risk (as dispersion of analyst forecasts) and the credit contagion effect suggesting that firms with higher information risk suffer a greater contagion effect in advance of credit default events.

But contagion has been probably most analysed in the financial sector. Specifically after the last financial crisis and some financial firms' bailouts, systemic risk and risk spillover have been issues of major interest. A good example is the work of Yang and Zhou (2013) who find that those who are prime senders or exchange centres of credit-risk information might be systemically important financial institutions (SIFIs). They show evidence of leverage ratios and certain aspects of corporate governance such as CEO duality being significant determinants of the roll of financial institutions in credit risk transfer, in contrast to other factors such as size, liquidity and write-downs. Further research on systemic default risk literature will be presented in next section.

Moreover, authors such as Kim, Loretan and Remolona (2010) wondered about the case of Asia in the turmoil of 2007-2009. Although direct exposure to problem mortgages had been minimal, credit spreads for major borrowers widened even more than they did in Europe and the United States. They reached the conclusion that there is an important global component to risk aversion and a rise in such risk aversion is a source of contagion.

The research on default risk contagion between sovereigns became also important following the start of the Greek crisis in 2009. In this context, Caporin et al. (2013) analysed how much potential contagion exists within the European sovereign debt market, finding no

change in the intensity of the transmission of shocks among these countries during the onset of the fiscal crisis. In fact, Beirne and Fratzscher (2013) find that a deterioration in countries' fundamentals and fundamentals contagion⁸ were the main explanations for the global increase in sovereign yield spreads and CDS spreads during the European sovereign debt crisis. In contrast, Groba et al. (2013) find a significant risk transmission from peripheral to central EU economies as a reaction to some common global shocks during the period from 2008-2010. As we already reported, they find that peripheral risk plays a key role in explaining CDS increments for the other EU members until the approval of the European Financial Stabilization Mechanism (EFSM) in May 2010.

But researchers went further. They aimed to understand the risk-transmission channels between sovereigns and corporates too and so many articles provide insights from the perspective of the credit derivative market. Demirgüç-Kunt and Huizinga (2013) for instance, conclude that government finance variables do not materially affect bank CDS spreads over the 2001-2008 sample period, but that the increase in bank CDS spreads between 2007 and 2008 is significantly related to the deterioration of the public deficit. However, De Bruyckere et al. (2013) do identify significant interactions that drive contagion between banks and countries in the 2006-2011 period. They confirm a home bias, i.e. a stronger contagion between banks and their home countries, and specify different risk spillover intensity: the lower the bank's proportion of short-term funding in total debt, the lower the intensity of risk spillovers, and the higher the debt-to-GDP ratios, the higher the degree of bank/sovereign contagion, which is more notable in the presence of higher sovereign CDS spreads.

⁸ "Fundamentals contagion" or "wake-up call" contagion is explained by the authors as a sharp increase in the sensitivity of financial markets to fundamentals, unlike "regional contagion," which results from an intensification of spillovers of sovereign risk across countries, and "herding contagion," which results from a temporary overreaction of financial markets that is clustered across countries.

Interestingly, Diaz et al. (2013) find a public-to-private risk transfer between the sovereign CDS spreads and corporate risk premia in Europe during the 2006-2010 period, while Dieckmann and Plank (2012) suggest a private-to-public risk transfer in Europe during the financial crisis. In this two-way spillover, Alter and Schüler (2012) distinguish between the period preceding government interventions from the following period. During the first one, they find evidence of contagion from domestic bank credit spreads into the Eurozone sovereign CDS market (which, according to them, evidences the systemic feature of the recent financial crisis), whereas after government intervention, sovereign CDS spreads become an important determinant of banks' CDS premia. They suggest that this interdependence of government and bank credit risk is heterogeneous across countries, but homogeneous within the same country. In this sense, Corzo et al. (2014) also find a private-to-public risk transfer during the subprime crisis, as equity markets led the process of incorporating new risk information, although a reversal to a public-to-private path during the sovereign debt crisis as the leading role was assumed by sovereign CDS markets.

More recent works such as Haerri, Morkoetter and Westerfeld (2015) evidence that sovereign risk overlaps the pricing of corporate debt instruments in the 2009-2011 European market, not only for banks but also for companies in other sectors. They add that this impact is the highest in the peripheral Eurozone countries, increasing for the entire sample with the intensification of the sovereign debt crisis in 2010/11. They suggest a home bias in favour of the local market too, but find no significant empirical evidence that the link between sovereign risk and corporate credit risk is driven by access to local bank financing. Similarly, Bedendo and Colla (2015) note that the translation of the increase in sovereign risk in the 2008-2011 Eurozone into a significant increase in corporate credit risk is higher for firms that enjoy government guarantees, place most of their output on the domestic market, or rely heavily on bank financing.

2.4.5. Systemic and systematic default risks

There is no doubt about the relevance of systemic risk for researchers and policymakers as it is manifested by the formidable amount of literature regarding this issue. However, it is hard to define and there is no commonly accepted definition of the concept (ECB Financial Stability Review, December 2009), although we think we know it when we see it (Billio, Getmansky, Lo and Pelizzon, 2012).

De Bandt and Hartmann's (2000) review suggests that "a systemic crisis can be defined as a systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning of the financial system." Billio et al. (2010 and 2012) agree with this statement when suggesting that systemic risk involves the financial system by definition, as well as Gauthier and Souissi (2012) who note that systemic risk is given at the level of the entire financial system. Generally, systemic risk is understood as the potential for multiple, simultaneous defaults of major financial institutions (Chen, Cummins, Viswanathan, and Weiss, 2014) over a short time span.

Following this interpretation, there is an extensive literature about systemic risk regarding bank entities but also about the high interrelation between banks, brokers, insurance companies and hedge funds (e.g. Billio et al., 2012). These studies are not limited to the traditional view of the vulnerability of individual banks depositors panic (De Bandt and Hartmann, 2000). For these authors, at the heart of the concept of systemic risk is the notion of contagion, while Brunnermeier, Crockett, Goodhart, Persaud and Shin (2009) go beyond this contagion idea and state that systemic risk has much to do with reducing market liquidity and decreased funding liquidity. In sum, the efforts of researchers since the financial and economic crisis affecting the world economy in the last years led to the evidence of the need

of analysing the risks and vulnerabilities of financial systems in a holistic manner (Castrén and Kavonius, 2009).

The relevance of this issue in the empirical literature is evidenced by the classification structured by Billio et al. (2010). They stablish a first group that focuses on the banking contagion and is based on bank earnings and funds withdrawals, as well as on the exposures between banks where the fail of one could make other banks insolvent. A second group that focuses on banking crises, the aggregate fluctuations and in the lending booms. And a third one which focuses on the spillover, side effects, and collective failures in the financial markets.

The importance of this topic is also manifested by the intense search for a systemic risk indicator (e.g. Rodríguez-Moreno and Peña, 2013). Indeed, the requirements to measure systemic risk have been established: the method must identify the risk in the system where the institutions are so large and so interconnected that can cause negative effects on others (Brunnermeier et al., 2009). This need of mapping the relationships between financial institutions is not new and a consequence of the last financial crisis but rather Allen (2001) had already laid the ground of this before.

Anyhow, Rodríguez-Moreno and Peña (2013) find that regulators searching for reliable systemic risk indicators should stick to simple, robust indicators based on credit derivatives and market data interest rates. Along this line, Chen et al. (2014) use CDS spreads and stock prices to create a systemic risk measure for the insurance sector. They find evidence of significant bidirectional causality between the banking and insurance industries during the financial crisis, being the impact of banks on insurers stronger and of longer duration. They point out that although the core activities of insurers are not a significant source of systemic risk, banking functions such as derivatives trading are.

However, for deepening in the concept and its relevance, it must be underscored that systemic banking crises are harmful events not only for the financial system, but for the economy as a whole (Laeven and Valencia, 2012). According to the ECB Financial Stability Review of December 2009, "systemic risk refers to the risk that financial instability becomes so widespread that impairs the functioning of a financial system to the point where economic growth and welfare suffer materially". Moreover, the review distinguishes between a horizontal perspective of systemic risk, which concentrates the attention on the financial system, and a vertical perspective in which the two-sided interaction between the financial system and the economy at large is taken into account. In this sense, it notes the effect that systemic events have on consumption, investment and growth or economic welfare. The other way interaction is also suggested by Gray, Merton and Bodie (2006) who refer to "macrofinancial risk" while noting that the problems that appeared isolated in the corporate sector can have far-reaching consequences, causing severe financial crises. In sum, it seems necessary to control the links between the financial system and the rest of the economy (Billio et al., 2010).

At this point, the fact that crises in the entire financial system affect the whole economy may lead to assume that all systemic crises become systematic, in the sense of wide shock. In this context, the work of De Bandt and Hartmann (2000) is very lightening while distinguishing systemic from systematic risk: a systematic (large) shock may involve a systemic event in the broad sense, i.e. a first shock to several institutions or markets. However, a systemic event need not necessarily be the source of a systematic shock, as in the case of the transmission of an idiosyncratic shock to an institution that involves the falling of another.

In this context, many authors analyse CDS spreads by splitting total default risk premia into an idiosyncratic and a systematic component: Pu and Zhao (2012) suggest the existence of a systematic component while understanding that there is an economically significant comovement in CDS spreads caused by unobservable risk factor(s) that remain unexplained. Furthermore, Feldhütter and Nielsen (2012) note that the systematic default risk is explosive but has low volatility whereas idiosyncratic risk is more volatile and less explosive. Berndt and Obreja (2007) find that during the 2003-2006 time period, most European liquid firms show a systematic risk component which captures 21% of the time variation in the returns of defaultable assets, while a common credit market factor explains 63% of the time variation. Chan-Lau (2006) proposes the use of single tranche collateralized debt obligations prices as measure of default risk as the systematic component can be separated from the idiosyncratic component in the corporate sector (unlike the spread of a credit derivatives index which also reacts to idiosyncratic default risk changes).

Going back to systemic risk contributions, in what refers to the extent to which a default by a particular institution influences systemic risk, it has been evidenced that it is more likely to increase during the crisis period than during the pre-crisis period (Suh, Jang and Ahn, 2013), and when systemic risk increases, all banks in the Euro zone, tend to increase the home bias of their portfolios, further segmenting the Euro-zone sovereign market (Battistini, Pagano and Simonelli, 2014).

Elsewhere, many authors warn about systemic risk increase caused by the use of CDS: Nijskens and Wagner (2011) note that after using CDS and collateralized loan obligations (CLOs), the share price beta of banks increases significantly due to an increase in their

⁹ CLOs are securities backed by a portfolio of debt, often low-rated corporate loans. Investors receive scheduled debt payments from the underlying but in return they assume most of the risks in case of borrowers default.

correlations, concluding that although they may have shed their individual credit risks by using these instruments, they have also created a greater systemic risk.

In this context, many researchers have analysed the role played by the CDS market in the last financial crisis and how its excessive use has helped to generate or increase systemic risk. Kress (2011) highlights that CDS increases interconnections in the financial system, creating systemic risks. Similarly, Markose, Giansante and Shaghaghi (2012) investigate the systemic risk caused by the concentration in CDS exposures between a few, highly connected US banks, suggesting that the size of CDS markets far exceeds their capacity to internalize the potential losses that follow from the failure of highly connected financial intermediaries.

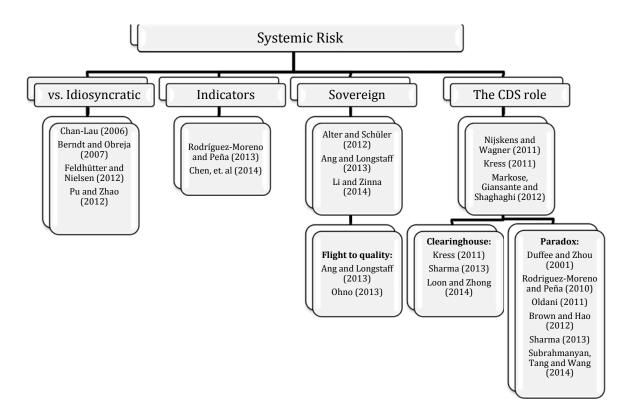
Given the increased awareness of this new reality (what we will call, as do many authors, the paradox of CDS), researchers consider the role of a clearing house. It helps to bring greater transparency and standardisation to the CDS and other derivatives markets (Sharma, 2013), and systemic risk decreases due to the weakening of the relation between CDS spreads and dealer credit risk (Loon and Zhong, 2014). However, clearinghouses must have access to central bank liquidity to alleviate the concentrated risks they achieve by the attempt of reducing the interconnections in the financial system (Kress, 2011).

On the other hand, the contagion from bank credit spreads into the sovereign CDS market is evidenced, confirming the systemic feature of the recent financial crisis (Alter and Schüler, 2012). Along this line related to systemic sovereign risk, Ang and Longstaff (2013) find that the US's systemic sovereign credit risk is highly correlated with Europe's systemic credit risk, given that they are rooted in financial markets rather than in macroeconomic fundamentals. Li and Zinna (2014) find that in the 2008-2013 time period, Eurozone sovereign systemic credit risk reaches its peak in late 2011 and that European banks are exposed to both systemic and country-specific sovereign risk. They also evidence that Spanish banks displayed the highest

exposures to systemic sovereign risk, although, together with the Italian banks, showing lower exposures to systemic risk than their sovereigns, highlighting the sovereign nature of the crisis. They also note the French and German banks' significant vulnerability to systemic sovereign risk due to their large international exposures, concluding that the fraction of banks' credit risk caused by exposure to systemic/country-specific sovereign credit risk co-moves with their holdings in Eurozone/domestic sovereign debt.

Finally, it is suggested that observing shifts in banks' equity volatility and stress in the CDS market can be helpful in detecting the degree to which the financial system is suffering a systemic event (Calice, Ioannidis and Williams, 2012). US systemic credit risk is found to be significantly negatively related to changes in the VIX index, suggesting that the US's financial position improves as flights to quality occur in turbulent periods (Ang and Longstaff, 2013). Likewise, the knock-on effects of sovereign risk on the CDS of German financial institutions during 2007-2011 were evidenced to be light due to this "flight-to-quality" phenomenon, which had the effect of lowering the German sovereign's CDS premiums (Ohno, 2013).

Figure 9: CDS literature ranging from systemic risk to the paradox of credit derivatives, including indicators and sovereign systemic risk.



2.4.6. The CDS Paradox

After the last financial crisis and coinciding with the arguments of those who warn about systemic risk expansion, researchers start suggesting that the use of these instruments increases the fragility of the financial system, rather than contributing to better risk diversification. Empirical evidence on this point is unambiguous and CDS have been found guilty.

In 2001, Duffee and Zhou had already warned about the fact that theory alone cannot determine whether a market for credit derivatives will help banks better manage their loan credit risks because it could cause other markets for loan risk-sharing to break down. More recently, Rodriguez-Moreno and Peña (2010) suggested that in an environment of mild economic conditions, although financial institutions have taken advantage of many financial

innovations such as CDS, these products show unexpected downside effects in scenarios of financial distress.

Oldani (2011) goes further by suggesting that although the relevant exposure of European banks in the bond market to Greece's default risk supports the need for hedging tools such as CDS, and even though they have smoothed the cost of debt and/or hedge, CDS on sovereign bonds represent a small, but dangerous threat to financial stability because of mispricing, opacity, non-uniformly distributed liquidity and the absence of a compensation system.

Furthermore, CDS use is found to enable individual money managers to safely increase leverage while causing a system-wide build-up of leverage and financial fragility (Brown and Hao, 2012). It increases the risks of insurance companies, leading to lower firm value caused by the higher cost of capital (Fung, Wen and Zhang, 2012). Moreover, authors such as Subrahmanyan et al. (2014) find that "CDS played a prominent role in the bankruptcy of Lehman Brothers, the collapse of AIG, and the sovereign debt crisis of Greece." While analysing the CDS trading of North American corporate issuers between 1997 and 2009, they notice that the number of creditors increases after CDS trading begins, exacerbating creditor coordination's failure to resolve financial distress, and more than doubling the likelihood of bankruptcy. This bankruptcy risk is found to decrease when CDS contracts expire.

All in all, it becomes apparent that efforts to improve CDS' regulation and supervision should be made (Sharma, 2013).

2.4.7. CDS and "Too Big to Fail" institutions

Systemic risk is often triggered by financial institutions that are either "too big to fail" or "too interconnected to fail" (Chen et al., 2014). Schweikhard and Tsesmedlidakis's (2011)

provide positive evidence of this "too big to fail" hypothesis when analysing the impact of government guarantees on the pricing of default risk. A marginal increase in bank risk rises the implicit subsidy from the financial safety net relatively more for systemically large banks, and therefore, these are found to be too large to fail (Demirgüç-Kunt and Huizinga, 2013).

Following the issue of the paradox discussed in the previous section, Markose, Giansante and Shaghaghi (2012) warn about the size of CDS markets that far exceed their capacity to internalize the potential losses caused by the failure of highly connected financial intermediaries. Macro-prudential regulation to identify systemically important financial institutions (SIFIs) and their connectedness with other financial institutions is therefore needed (Yang and Zhou, 2013).

Nonetheless, after the recent failure of several large, complex financial institutions, Calice et al. (2012) illustrate that the "too big to fail" paradigm predominant in the analysis of financial stability of large mainstream commercial and investment banks is no longer valid. Greater market discipline of systemically large banks suggests that these banks are too big to save, offsetting the effect of too-big-to-fail subsidies (Demirgüç-Kunt and Huizinga, 2013).

2.4.8. Does it matter if a country is member of a monetary union?

According to Dieckmann and Plank (2012), it does matter whether a country is a member of the Economic and Monetary Union of the European Union (EMU): member countries' sensitivities to the health of the financial system are higher than those of non-EMU members. Along the same lines, Ghosh, Ostry and Qureshi (2013) find that in quiet times, both CDS and bond rates were lower for Eurozone members than would be expected given their fiscal space (a bonus of currency union membership) but these rates rose more sharply for Eurozone

members than would be predicted when the crisis erupted (i.e. sharper penalties for sovereigns that belong to a currency union).

Groba et al. (2013) find a significant risk transmission from peripheral to central EU economies as a reaction to some common global shocks during the period from 2008-2010, concluding that peripheral risk plays a key role in explaining CDS increments for other EU members. Nevertheless, Ang and Longstaff (2013) note that systemic credit risk represents a much smaller fraction of total credit risk for US states than for members of the EMU, thus concluding that systemic risk is not primarily an artefact of common macroeconomic fundamentals and thus leaving the question open. Nonetheless, Janus, Jinjarak and Uruyos (2013) partially solve the question by evidencing that economies with similar fundamentals can experience different prices for default risk due to heterogeneous investor beliefs and overconfidence.

2.4.9. CDS, bailouts and rescue packages. European Financial Stabilization Mechanism and Quantitative Easing

The 2007-2009 financial distress led public authorities of major economies to intervene in markets through capital injections, debt guarantees, and purchases/guarantees of toxic assets.

On the one hand, the US Fed conducted the first round of liquidity known as QE1 (Quantitative Easing 1) from November 2008 until March 2010 injecting 600 billion dollars. From November 2010 until June 2011, QE2 was developed, injecting another 600 billion dollars. In September 2012, the Fed launched the third round of liquidity, QE3, with 85 billion dollars per month.

On the other hand, the European Financial Stability Facility (EFSF) was created as a temporary crisis-resolution mechanism by the Eurozone Member States in June 2010. The EFSF was authorised to borrow up to €440 billion through bonds and other debt instruments on capital markets.

Researchers such as Schweikhard and Tsesmedlidakis (2011), analysed the impact of those government guarantees on the pricing of default risk. They note that the interventions were successful in preventing a further escalation of the distrust at the peak of the crisis and provide evidence of the asymmetric treatment of debt and equity in rescue measures to favour creditors.

Furthermore, some researchers questioned the impact of the interventions. Ejsing and Lemke (2011) suggest that the rescue packages announced by governments in the fall of 2008 induced a decrease in risk spreads for banks at the expense of a marked increase in governments risk spreads. This increased the sensitivity of sovereign risk spreads to any

further aggravation of the crisis, whereas the sensitivity of bank credit risk premia declined and became more sovereign-like.

In sum, the bailout programs changed the composition of both banks' and sovereigns' balance sheets and affected the link between the default risk of governments and those of their local banks (Alter and Schüler, 2012). Bailouts triggered increased sovereign credit risk in 2008 and post-bailout changes in sovereign CDS explain changes in bank CDS (Acharya, Drechsler and Schnabl, 2014). The higher the expected level of government support in the Eurozone in the 2008-2013 time, the higher the probability that the banks default as a country-specific sovereign shock arrives (Li and Zinna, 2014). This translation of the increase in sovereign risk into a significant increase in corporate credit risk is significantly higher for firms that enjoy government guarantees, place most of their output on the domestic market, or rely heavily on bank financing (Bedendo and Colla, 2015).

On the one hand, Ghosh et al. (2013) suggest that sovereign bailouts did not occur with the hoped-for alacrity in Euro-crisis countries, generating more serious penalties for sovereigns that belong to a currency union. Furthermore, after the approval of the EFSM in 2010, the impact of peripheral risk on central EU economies vanishes (Groba et al., 2013), although the knock-on effects of crisis among the Eurozone's core countries heighten due to the concerns about the instability of the financial system (Ohno, 2013).

On the other hand, Calice et al. (2012) find that US government re-capitalization programs underestimated the necessary capital injections for the large complex financial institutions (LCFIs), and Hammoudeh, Bhar and Liu (2013) point out that QE1 reduced the banks and insurance companies risk premia, but increased inflationary expectations.

Finally, Bertoni and Lugo (2014) also show (a quite different) evidence of the effect of guarantees on the corporate CDS spread: their study analyses a sample of 371 Sovereign Wealth Fund (SWF)¹⁰ investments between 2003 and 2010 and concludes that their impact is to reduce credit risk by implicitly guaranteeing financial support in the event of short-term distress.

2.4.10. A new approach to sovereign default risk: Contingent Claim Analysis and Real Government Guarantees out of balance.

As we have noted, recent studies show evidence of the mispricing of the CDS market for sovereign bonds after the recent crisis, (i.e. Oldani, 2011). It has become obvious to some researchers that under normal market conditions, CDS spreads are a very useful source of information about country risk; however, they might lead to some under/overpricing of fundamentals in the event of excessively low or excessively high risk aversion (i.e. Revoltella, Mucci and Mihaljek, 2010).

In this context, alternative measures of country risk have been developed in recent years. Remolona, Scatigna and Wu (2008), for instance, construct a measure of ratings-implied expected loss from sovereign defaults using sovereign credit ratings and historical default rates provided by credit rating agencies. They compare that information with stand-alone credit ratings and examine its relationship with CDS spreads, showing that their measure is more informative about price sovereign risk. Conversely, Revoltella et al. (2010) also develop

and some of the features of pension funds (Bertoni and Lugo, 2014).

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¹⁰ A commonly accepted definition of SWF was set out by the IWG (2008): SWFs are special-purpose investment funds or arrangements created by the general government for macroeconomic purposes and those hold, manage, or administer assets to achieve financial objectives, employing a set of investment strategies that includes investing in foreign financial assets. Essentially, SWFs combine some of the features of hedge funds

a measure of country risk premium based on a long-term relationship between CDS spreads and external ratings, showing that adverse market sentiment was a key driver of the sharp increase in the sovereign CDS spreads of Central and Eastern European countries during the most serious phase of the crisis.

Gapen, Xiao, Gray, and Lim (2008) work out a comprehensive new framework to measure and analyze sovereign risk by applying contingent claims analysis (CCA) to the balance sheet of the combined government and monetary authorities and testing their model with spreads on sovereign CDS, among other financial instruments. Their results evidence that their risk indicators can be examined in individual country cases to evaluate whether market expectations of sovereign vulnerabilities are increasing or decreasing not only over time but also across countries to rank relative risk.

It is useful to note that this CCA approach has its origins in the 70s when it was used to measure the risk and to price derivative securities. According to Gray and Malone (2008), CCA risk-adjusted balance sheets has also been used to quantify the risk sensitivity of a country or sector's assets and liabilities to external "shocks." At the national level, the corporate, financial and governmental sectors of an economy are viewed as interconnected portfolios of assets, liabilities, and guarantees – some explicit and others implicit. Traditional sovereign-risk models have difficulty in analysing how risk exposures can be rather benign at a point in time and then without any apparent change in asset or liability holdings, those exposures increase rapidly and erupt into a full-blown crisis. The CCA approach is well-suited to capturing the impact of such non-linearity and quantifying the risk effects of asset-liability mismatches within and across institutions.

In recent years, the CCA has also become an interesting tool to measure risk at the sovereign level. In this context, Merton et al. (2013) use the CDS prices to determine

sovereigns' expected loss ratio. They suggest that the degrees of connectedness across various types of entities (household, corporate, financial and government sector) change over time and financial models that capture this dynamic are needed to monitor the connectedness of the system. Meanwhile, in the sphere of the financial sector, Calice et al. (2012) use a CCA to track the evolution of default risk for a sample of 16 large complex financial institutions (LCFIs). They find that systemically important financial institutions are exposed simultaneously to systematic credit derivatives shocks. They also point out that the reason for the underestimation of the necessary capital injections for the LCFIs by the US government was that its model did not reflect any explicit or implicit government guarantees.

2.4.11. Accounting-based versus Market-based models

In recent years, the use of accounting variables in the modelling of default has been challenged by both the use of option pricing methods (structural models) and the use of models that explicitly define debt value as a function of default intensity, enabling the latter to be extracted from calibration using bond prices (reduced-form models). However, empirical evidence suggests that a conjunction of accounting-based and market-based models is a better path to measure default risk (Das, Hanouna and Sarin, 2009; Trujillo-Ponce, Samaniego-Medina and Cardone-Riportella, 2014). In this domain, CDS have prevailed as the best proxy for credit risk and consequently, as the benchmark to explain.

2.5. Concluding remarks

Through the literature on financial risks that uses CDS during the 2000-2015 period, we have followed the concerns of researchers, regulators and financial-market participants. By

doing so, CDS have emerged as a polyhedral financial tool, i.e. an instrument with several permutations (faces). In itself, each permutation constitutes a polygon with sides, angles and twists, relating permutations to one another and building an interconnected piece.

To help unwind these facets, we have drawn a conceptual map to evidence how the credit derivative contract has evolved, e.g. from being the perfect product to manage credit risks in times of volatility and uncertainty to playing a prominent role in increasing the fragility of the financial system (known as the CDS paradox).

This conceptual map helps to understand that credit risk is not homogenous amongst corporations/sovereigns and that it is still unclear whether CDS premia are mostly explained by global/local factors (or both) or by macroeconomic/financial variables (or both). It also validates the versatility of this instrument, confirming the relevance of CDS in many frameworks, e.g. to disentangle financial risks and their correlations and to analyse current dangers such as contagion (corporate, sovereign and public/private spillover) and systemic risk. It points out the relevance of CDS spreads when it comes to provide relatively pure pricing of default risk, to create a systemic risk measure or to analyse the impact of government guarantees on the pricing of default risk. It also helps understanding that CDS play an important role in the price discovery process, the relevance of a country being a member of an economic and monetary union, and the "too big to fail/save" hypothesis.

In sum, it is not easy to find a financial innovation as versatile, as diverse, and, above all, as meaningful as the CDS contract.

For this reason, we aim to deepen in the nature, power and value of this instrument. We find this a critical point in the current environment of deregulation discussions. Going beyond

controversies about its use, we next research about the importance of CDS markets using notional amounts and literary productivity.

Second part: Empirical Analysis

3. CDS: a variable of scientific interest

"While existing research primarily looks at the existence of CDS or CDS trading initation, future research ought to

focus also on the intensity of CDS trading... Our

understanding of CDS trading volumes is still pretty much

in its infancy."

Augustin, Subrahmanyam, Tang and Wang (2017)

3.1. Introduction

As explained in the first part of this thesis, the 21st century has witnessed an extraordinary

boom in the CDS market. Along with the increased popularity of CDS instruments as

investment and hedging vehicles, the CDS research literature has experienced a parallel

development. Many researchers have given a prominent role to CDS premia as reliable

default risk proxies and have taken advantage of its versatility and informational content in

several studies. This motivates us to explore further the relationship between the CDS

notional amounts and the level of research activity over the 2001 - 2015 time frame. By doing

so we aim to contribute to the revelation of the CDS market as a variable of scientific interest

by itself, leaving aside controversies such as the CDS paradox.

In a next step, and in the intend of clarifying whether CDS spreads are mostly explained

by global, local factors, or both, we will also explore if there are common factors driving the

risk changes in the current global context. We will look for significant relationships among

multinational corporates and global sectors. We will then go a step further by analysing the

closeness between the global credit risk and well-known market indices and finally, we will

also look for market risk diversification while facing global credit risk.

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3.2. The relevance of the CDS market

We find important to explore the interactions between CDS aggregate trading volumes and the number of CDS research articles by exploiting the results of a search on textual analysis. This is a word base classification scheme that captures the number of CDS published papers using a CDS tittle-abstract search methodology that converts qualitative information into quantitative measures. This method has been applied in the finance literature by, e.g., Loughran and McDonald (2011). In their paper they study the impact of text based information on stock returns. Their results demonstrate that their methodology represents an efficient alternative way for analysts to capture relevant sources of information (other example is Tetlock, Saar-Tsechansky and Macskassy, 2008). In this spirit, we present the use of textual analysis for a different purpose: the assessment of an underlying factor, i.e., the relevance of the CDS market. To our knowledge, this is the first study to relate these two variables and to use textual analysis beyond the framework of event studies.

3.2.1. The trading process

As already explained in previous sections and showed in Figure 1, the market of credit derivatives came into existence in 1992 and grew exponentially during the first years of the 21st century (at a 100% compounded annual growth rate between 2003 and 2007). Outstanding notionals reached \$58 trillion by the end of 2007. This amount was reduced in the post-crises period to \$29 trillion in 2011. According to OCC, ¹¹ credit derivative outstanding held by U.S. commercial banks declined by 12% in 2009. This collapse arises due to lower demand for structured products under industry efforts to eliminate offsetting trades.

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¹¹Office of the Comptroller of the Currency's Quarterly Report on Bank Trading and Derivatives Activities, Fourth Quarter 2009.

Total CDS outstanding amount fell by 49% from December 2007 (\$58.244 billion) to the end of 2010 (\$29.898 billion), according to BIS data.

Although volumes briefly recovered to support the need for hedging the exposure of banks to Greece's default risk during the 2009-2011 European sovereign debt crisis, they continued then their downward trend until nowadays (\$12 trillion by H1 2016).

3.2.2. The publishing process

Over the same period 2001-2015, academics responded to the significant growth seen in the CDS market by shifting their focus to these derivatives as reliable measures of credit conditions. The relevance of the CDS in the literature has been already evidenced through the holistic study of the first part of this thesis.

3.2.3. The regulation process

In what follows we describe how the regulation process influenced the trading process.

According to Augustin, Subrahmanyam, Tang and Wang. (2016) the July 2010 Dodd-Frank Act¹² as well as the October 2011 European MIFID II¹³ agreement impacted the negotiation in the CDS market. In this context, the Volcker Rule (Section 619 of the Dodd-Frank Wall Street Reform and Consumer Protection Act) represents the most significant constrain on banks activities since the Great Depression. It restricts banks from engaging in proprietary trading, including CDS trading, if it is not for market making or to facilitate client

¹² The Dodd-Frank Act is a compendium of federal regulations affecting financial institutions and their customers, in an attempt to prevent the recurrence of events that caused the 2008 financial crisis.

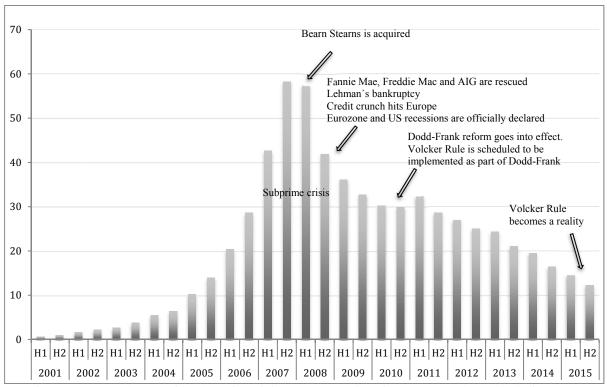
¹³ MIFID is the Markets in Financial Instruments Directive which has been applicable across the European Union since November 2007. MIFID II was approved on April 2014.

positions. It also regulates the central clearing of CDS indices which, according to Duffie, Scheicher and Vuillemey (2015), may increase collateral requirements making the market activity more difficult. While it was supposed to be implemented in July 2010, it was finally finished in December 2013 and repeatedly delayed until July 2015 as regulators had to ease the application of new restrictions. Consequently, several banks partially or totally closed their CDS business as reflected in the decrease of the notional outstanding amounts. Bank of America, Citigroup, Morgan Stanley and Goldman Sachs, among others, killed off their proprietary trading operations, pulled money from certain investment funds, and ceased other activities that would conflict with the rule's restrictions during these five years. The overall result was that while the rule finally arrived in July 2015, the consequences on trading activity were reflected in trading volumes from the date of the Dodd-Frank financial law (July 2010). These events are illustrated in Figure 10.

However, recent events could once again change the financial landscape under a new Trump era of looser regulation, higher interest rates and newly US capitalized banks. These conditions are likely to ease the re-engagement of big banks in previously banded trading activities.

Figure 10: The trading and the regulation processes.

In this figure, we graph the volume outstanding in the CDS market between 2001 and 2015, and main events regarding financial markets and financial regulation since the subprime crisis. It is depicted how volumes decreased partly in response to restrictions imposed by US regulators.



Based on ISDA (years 2001 and 2002) and Bank for International Settlements (years 2003-2014) data.

3.2.4. The data

In this analysis, we use a complete set of semi-annual data of outstanding CDS amounts surveyed by ISDA and BIS, as well as a measure of publishing activity quantified by the number of papers.

ISDA surveyed for the first time total notional outstanding volumes for single name credit default swaps, default swaps on baskets of up to ten credits, and portfolio transactions of ten credits and more in June 2001. 83 ISDA member firms supplied data on these products. The results for the first half of 2001 showed that global notional outstanding volume of credit

derivatives transactions was \$631.497 billion.¹⁴ Since then, the semi-annual ISDA survey publishes outstanding amounts as "Credit Default Swaps" or "Credit derivatives" indistinctly. Given that the notional value of CDS constitutes 95%-99% of the traded volume in credit derivatives,¹⁵ we take those surveyed by ISDA as CDS outstanding values until BIS initiated the publication of statistics on the market for CDS in the second half of 2004. From then on, data on notional amounts outstanding on CDS are taken from BIS.¹⁶

In order to construct a variable measuring publishing activity we have used a textual analysis in which we limit the search to articles that include "CDS" or "Credit Default Swap" in the title or topic (Web of Science, WoS) or in the title, abstract or keywords (Scopus). We consider that these two databases gather the vast majority of the qualified and relevant scientific research on the target topic. Because we do not consider any other publication sources we will assume that those CDS publications that are not captured by these databases evolve under a similar process. In WoS, we have restricted the category to Management or Business Finance or Economics or Multidisciplinary Sciences, and the research area to Business Economics, obtaining 558 papers (including 48 in 2016). While using Scopus, we have limited the subject area to Economics, Econometrics and Finance, Social Sciences and Business, Management and Accounting and reduced the type of papers to articles, conference papers, reviews, articles in press and conference reviews obtaining 958 pieces (including 81 in 2016). Figure 11 exhibits the trend of the publishing activity through the search in both databases.

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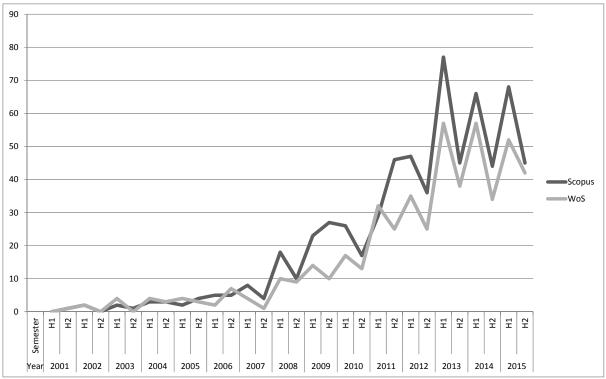
¹⁴ http://www.isda.org/statistics/recent.html#2004mid.

¹⁵ Expressly mentioned in OCC's Quarterly Reports on Bank Trading and Derivatives Activities since 2006 1Q.

¹⁶ http://www.bis.org/statistics/derstats.htm.

Figure 11: CDS publications in WoS and Scopus (in units).

This figure depicts the evolution of the academic productivity dealing with CDS between 2001 and 2015. We searched through WoS and Scopus for papers that include the terms "CDS" or "Credit Default Swap" in their title or abstract in an effort to measure academia's activity regarding this financial instrument.



Based on WoS and Scopus data.

After conducting the two parallel searches, we combined results from the textual analysis to identify the relevant papers published related to CDS, taking into account those which appeared in both data tools and excluding other which didn't have anything to do with Credit Default Swaps (e.g. those regarding Compact Discs). We look at the papers published between 2001 and 2015, resulting in an amount of 769 articles, detailed in Table 3.

Table 3: Total CDS papers

This table shows the number of papers dealing with CDS published between 2001 and 2015 found through the textual analysis using WoS and Scopus. The result of combining the publications found in both databases concludes in 769 relevant papers, 53% (405 papers) of which were published in the last 20% (3 years) of the time frame.

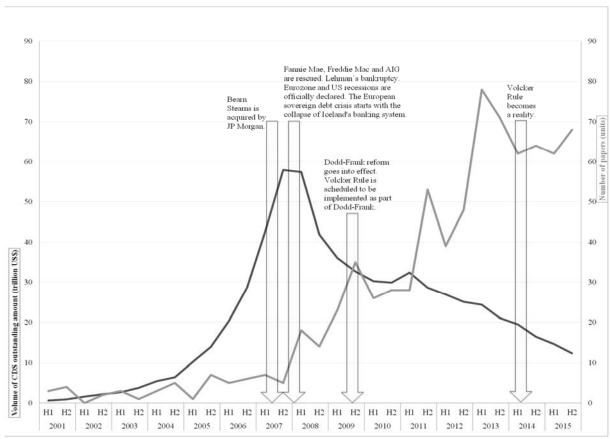
Year	20	001	20	002	20	003	20	04	20	05	20	006	20	07	20	800
Quarter	H1	Н2	H1	Н2	Н1	Н2	Н1	Н2	Н1	Н2	H1	Н2	Н1	H2	Н1	Н2
Papers (units)	3	4	0	2	3	1	3	5	1	7	5	6	7	5	18	14

Year	20	009	20	10	20	11	20	12	20	13	20	14	20	15
Quarter	Н1	Н2	Н1	Н2	Н1	Н2	H1	Н2	Н1	Н2	Н1	Н2	Н1	H2
Papers (units)	23	35	26	28	28	53	39	48	78	71	62	64	62	68

Additionally, Figure 12 depicts the evolution of the two analysed variables, volumes and publications, in the regulatory context, over the 2001-2015 period.

Figure 12: Total CDS publications vs CDS notional amount.

This chart shows the evolution of both CDS outstanding amounts (in trillion \$ and based on ISDA's and BIS' surveys) and number of publications dealing with CDS (in units and summarizing the results obtained through WoS and Scopus) in the financial and regulatory context. The change in the volumes traded trend in late 2007 and early 2008, as well as the maintenance of the publication activity bullish trend until nowadays is therefore highlighted.



Source: ISDA's and BIS' data.

CDS outstanding amounts decreased significantly since its peak in 2007. Figure 12 also shows a pronounced decline in traded volumes after 2011. However the number of papers published grew until 2013 H1. It rose from an average of 4 papers semi-annually over the 2001-2007 period to an average of 45 during the 2008-2015 time frame. Moreover, current research activity remains high, standing in 75 papers during 2016 H1.

The data illustrated in Figure 12 is consistent with the dual reality reported in Augustin et al. (2016). The authors underscore the role of CDS in the trading losses by the "London

Whale" at JP Morgan Chase in 2012¹⁷ and the anti-competitive practices in the CDS market by some banks willing to violate US antitrust laws. However they also point out that there is potential for future contribution of the CDS academic research, especially in the area of international finance.

It is important to note at this point, that the peer review process and time to publication in scholarly peer reviewed journals usually takes long time, commonly known as "turnaround time". There are a few stages underlying this process: several submissions, ¹⁸ rejections, rounds of major revisions and numerous drafts before the work is finally published in a journal. According to Björk and Solomon (2013), who studied the average publishing delays in 2700 papers published in 135 journals sampled from the Scopus citation index, in the business and economics discipline, it takes almost 11 months for a paper to be accepted from the moment it is received, and another 7 months until it is published. The process lengthens by the failed submission attempts that take place before initiating the mechanism in the last journal. As underlined by Azar (2004) a paper is likely to be submitted to three to six different journals before it is accepted for publication.

3.2.5. The empirical estimation

We start the empirical approach by estimating the lead-lag relationship between CDS volumes and CDS number of published articles (Volt and Pubt thereafter). From visual inspection it becomes apparent that the surge in volumes preceded the surge in papers up to a

¹⁷ In April and May 2012, a series of derivative transactions involving credit default swaps were entered, reportedly as part of the bank's "hedging" strategy accumulating outsized CDS positions in the market and a several billions dollar loss.

¹⁸According to Björk and Solomon (2013) when the author submits the manuscript to a particular journal, most journals require that it is not under consideration for publishing by another journal, causing publishing delays for authors whose work is rejected in the first and even second journal to which they submit.

date, and that these clean relationship changed somewhere after the subprime crisis. Thus, we perform an OLS regression relating semi-annual changes in papers published ΔPub_t to changes in volumes ΔVol_t .

Figure 12 evidences that volumes and papers evolved first in the same direction. It also shows the change in the volumes traded trend in late 2007 and early 2008, as well as the maintenance of the publication activity bullish trend until nowadays. In sum, the data suggests that there is a structural break in the relationship between volumes and papers in 2010 in response to the new bank regulation proposed by the Volcker Rule. To this effect, we test for the existence of a changing regime around the Dodd-Frank reform (2H 2010) and estimate the relationship between both variables introducing a dummy Dt variable taking value 0 before 2H2010, and 1 thereafter. We also account for the turnaround effect by including in the equation the fourth lag of the volumes' variable (the independent variable). Earlier lags of the volumes' variable are not significant so we exclude them from the analysis. The first lag of the dependent variable ΔPub_{t-1} is included to control for autoregressive effects. Estimated results are reported in Table 4.

Table 4: OLS estimation of model [1]

This table reports the Ordinary Least Squares estimation of the parameters in the linear regression model:

$$\Delta P u b_t = \alpha + \beta_1 \Delta P u b_{t-1} + \beta_2 \Delta V o l_{t-4} + \beta_3 D_t + \varepsilon_t.$$
 [1]

The data frequency is semiannual. The significance refers to autocorrelation and heteroskedasticity robust standard errors (Newey West 1987), indicating *, ** and *** significance at the 10%, 5% and 1% level, respectively. The fourth lag of the variable Volumes is statistically significant at a 1% level and the Dummy variable is also significant at a 10% level. We introduce the first lag of Publications to control for the residuals autocorrelation.

Dependent variable	ΔPub_t
Explanatory variables	
c	-0.970
	(-0.770)
$\Delta Pubt-1$	-0.361 **
	(-2.086)
$\Delta Volt-4$	0.855 ***
	(3.297)
Dummy	8.503 *
	(1.828)
# Observations	25
R^2	0.27

Estimated results confirm the impact of the volumes fourth lag on the number of publications, supporting the two years turnaround time already documented in the literature. It also suggests that there is a change in degree of co-movement between both variables around the introduction of the Dodd-Franck Act, as the dummy variable is reported to be significant at the 10% level with Newey West (1987) standard errors. This motivates the split of the analysis into two subsamples, a first sample covering the 2001-2010 period and a second sample covering the post Dodd Frank era ranging from 2011 to 2015.

Thus, we next start analysing the 2001-2010 time period, to determine the dynamics between the two measures by pursuing a cointegration test under the presumption that both of

them assess a common fundamental, the relevance and reliability of the CDS market. To address this goal we first perform a unit root test on the level series. Augmented Dickey Fuller test results are reported in Table 5. We can see that both series exhibit unit roots over the 2001-2010 sample period. Following the Engle and Granger (1987) two-step procedure we now test for unit roots in the OLS regression error. Because the volumes variable is expected to lead the price discovery process it is modelled as the independent variable. Dickey Fuller test results show that the error is stationary indicating that volumes and publishing processes are cointegrated over the 2001-2010 period.

Table 5: Dickey-Fuller test

This table shows Augmented Dickey Fuller test statistics for the null hypothesis of unit roots on the level series (Vol_t and Pub_t) and the residual

$$z_t = Vol_t - 3.459 - 0.298Pub_t [2]$$

for semi-annual data covering the 2001-2010 period. Mackinnon (1991) one-sided critical values are used. The SIC criteria is applied to calculate the optimal lag length. *** indicates significance at the 1% level.

ADF test	t-stat	p-value
Volt	-1.816	0.361
Pubt	-1.043	0.711
\mathbf{Z}_{t}	-4.829	0.002 ***

Given that there is cointegration, we model the dynamics between the two measures by performing a Vector autoregression (VAR) analysis extended by the cointegration error term (zt). In this way we follow the Granger Representation Theorem which establishes that if two variables are cointegrated the best representation is specified under a VECM.

Under the VECM framework the cointegrating error is expected to be useful in forecasting future movements in CDS publications and/or volumes. We therefore assume that the CDS volumes and papers variables have the following VECM representation:

$$\begin{pmatrix} \Delta P u b_t \\ \Delta V o l_t \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} [\widehat{z_{t-1}}] + k lags \begin{pmatrix} \Delta P u b_{t-1} \\ \Delta V o l_{t-1} \end{pmatrix} + \begin{pmatrix} u_t^{P u b} \\ u_t^{V o l} \end{pmatrix}$$

$$\widehat{z_t} = V o l_t - \beta_0 - \beta_1 P u b_t, \quad \text{ut is a vector white noise}$$
[3]

where the error correction coefficients α_1 and α_2 reflect the adjustment of volumes and publications each period based on deviations from the long term equilibrium relationship.

Table 6 reports results from estimating the two dimensional VECM model with ΔPub_t and ΔVol_t as dependent variables (t statistics are given in parenthesis). Note that the constant is included in the cointegrating vector. An optimal lag length of 2 is determined by the SIC criteria. The turnaround effect is in this framework captured by the long run relationship measured by the cointegrating error.

Table 6: Lead-lag analysis with two-dimensional VECM model. Semi-annual data 2001-2010

This table reports VECM estimates of the lead lag relationship between changes in Pub_t and changes in Vol_t for semi-annual data over the 2001-2010 period. Optimal lag length is chosen according to the SIC criteria and t statistics are given in parenthesis. No constant is included in the VECM as it is estimated within the cointegrating error. ** indicates significance at the 5% level.

$$\begin{pmatrix} \Delta Pub_{t} \\ \Delta Vol_{t} \end{pmatrix} = \begin{pmatrix} -0.841 \\ (-2.911) ** \\ -0.2385 \\ (-0.763) \end{pmatrix} [\widehat{z_{t-1}}] + klags \begin{pmatrix} \Delta Pub_{t-1} \\ \Delta Vol_{t-1} \end{pmatrix} + \begin{pmatrix} u_{t}^{Pub} \\ u_{t}^{Vol} \end{pmatrix}; \ R^{2} = \begin{pmatrix} 0.578 \\ 0.244 \end{pmatrix}$$
 With $\widehat{z_{t}} = Vol_{t} - 3.459 - 0.298Pub_{t}, \ k(SIC) = 2$

Results reported in table 6 show that α_1 is statistically significant while α_2 is not significantly different from zero. This implies that the publication variable does all the adjustment in terms of restoring the cointegrating equilibrium while the volumes variable does not react to shocks in the long term relationship. As demonstrated in Figuerola-Ferretti and Gonzalo (2010) this is consistent with the finding of informational leadership in the volumes variable. In this context both volumes and publications measure a common underlying factor, the relevance and reliability of the CDS market and volumes are the sole contributors to the revelation of the common fundamental. The improved forecasting ability of the cointegrating error in the publications equation is reflected in the R^2 (0.578) which is significantly higher than that reported in the volumes equation (0.244).

Although this study is limited by the small number of observations in the sample, we provide reliable results for exploratory empirical assessment of the interaction between trading and academic activity during more than 10 years. ¹⁹ As it is noted in the previous cointegration literature (see Otero and Smith, 2000) the power of cointegration tests is dependent to a greater extent on the data span than on data frequency.

Finally, we explore the lead lag relationship between both variables for the second period (2011-2015) representing the post Dodd Frank era. The results should be interpreted as preliminary and with caution due to the severe observations scarcity. As suggested in Figure 12, while both volumes and publications variables exhibit unit roots there is no evidence of cointegration. We therefore proceed to estimate an OLS regression to model the lead lag relationship. Table 7 reports estimated results.

Table 7: OLS estimation. Semi-annual data 2011-2015 [4].

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 $^{^{19}}$ As a robustness check we have tested the stationarity of the VECM equation residuals $(u_{1,t},u_{2t})$. We reject the null hypothesis of unit roots for the two errors implying that the assumptions underlying the VECM framework hold.

This table reports the Ordinary Least Squares estimation of the parameters in the linear regression model:

$$\Delta Pub_t = \alpha + \beta_1 \Delta Pub_{t-1} + \beta_2 \Delta Vol_{t-1} + \varepsilon_t.$$
 [4]

The data have a semi-annual frequency and consist of 11 observations between 2011 and 2015. The significance refers to autocorrelation and heteroskedasticity robust standard errors (Newey West 1987), indicating ** and *** significance at the 5% and 1% level, respectively. The first lag of the variable Volumes is statistically significant at a 1% level.

Dependent variable	ΔPub_t	
Explanatory variables		
c	11.777	***
	(4.290)	
ΔPub_{t-1}	-0.239	**
	(-2.868)	
$\Delta Volt-1$	4.480	***
	(7.401)	
# Observations	11	
R ²	0.40	_

Results reported in Table 7 show that while over the second sample period the strength of the relationship is lower, there remains some predictability in the publications variable as reflected by the value of the estimated R² (0.401). The volumes variable is significant in explaining variations in the publications variable at 1% significance level. As expected, the publications variable is not significant in explaining the changes in the volumes variable. We therefore present weak evidence of informational dominance in the volumes variable over the second sample period.

Having proved the relevance of the CDS market, we next use CDS for researching about current risks, i.e. threats implied in a global and complex context where companies, countries and markets are connected to the rest of the world's economy. This is crucial to become aware of the implications of a globalized world.

4. A global credit risk proxy

A global risk is an uncertain event or condition that, if it occurs, can cause significant negative impact for several countries or industries within the next 10 years.

The Global Risks Report 2016, World Economic Forum

In this section, we intend to explore if a global credit risk driven by global factors can be pointed out from CDS spreads. This entails a step further into the topic of the factors that explain CDS spreads and complements the broad analysis regarding systemic financial risk. The objective is to determine if there are also unobserved factors driving the changes in the CDS spreads of non-financial global companies which could provide evidence of an existing non-financial global corporate credit risk.

To do so, we first consider if a portfolio of global corporate CDS turns out to be a useful proxy of global credit risk. Second, we use this portfolio to explore the risk feedbacks between global sectors. Third, we also use it to analyse the interrelations between global credit risk and global market risk. Finally, it will also help us to propose a simple method of diversifying international portfolios while facing global credit risk.

Longstaff and Rajan (2008) already analysed the CDS spreads of non financial firms when they worked with the CDX index, which is based on a liquid basket of CDS contracts for 125 U.S. firms with investment grade corporate debt. We go further while including in the sample companies with domicile in 11 different countries (3 continents) and with investment and non-investment credit quality grade.

4.1. Global credit risk and systemic risk

Definitely, there has been an explosion of publications related to systemic risk linked to financial institutions and to contagion in the financial markets in recent years. The efforts of researchers have been concentrated in the financial sector and less in global risks of non-financial industries.

But due to the fact that systemic risk entails the instability of the financial system but also of the rest of the economy, the analysis of the complex interactions between non-financial, national and international, institutions is essential to complement the studies regarding systemic risk. This is an important issue as the economy is becoming increasingly global: big multinational corporates are more exposed to shocks from the international environment and the analysis of this corporate sector credit quality is crucial for the financial stability (Castren, Dees and Zaher, 2008). Corporates are interconnected within and between countries, making the risk transmission much simpler and faster, and what at first seemed an exclusive problem of the financial sector (systemic risk and contagion) turns out to be a much more important issue affecting various sectors and other economic activities.

Nevertheless, some studies about systemic risk have already dealt with its relation with the economy as a whole (eg, Laeven and Valencia, 2012, Merton et al., 2013, Gray et al., 2006, Financial Stability Report of the ECB 2009).

This understanding of global threats in a multinational context is a main point for macroprudential policy which requires a deep knowledge of the vertical perspective of systemic risk. Deepening in this analysis will help to predict in advance the effects of those relationships and to anticipate future crises. Additionally, it is also an important issue for investors looking for risk diversification. Following this path, we aim to go further in the analysis of the exposures in a global framework in order to achieve a better understanding of the risk transmissions between the various components of globally connected markets. Therefore, we analyse the corporate sector, its interdependence network and its relevance in the risk transmission to better understand if there is a common economic risk, which as complementary to a financial risk, does not involve the financial system but is found to be a global risk.

We start with theoretical predictions about the meaningfulness of multinational corporates CDS spreads. Because, as already mentioned in previous sections, corporate CDS spreads are found to be linked to the performance of the local economy (Hricko et al., 2003) but even more strongly on global effects (Aretz and Pope, 2013), we predict that the CDS spread of non-financial firms which are high geographically diversified has to evidence a global credit risk nature.

To investigate this prediction empirically, we start by searching for the largest companies, with incomes proceeding from as many different geographical sources as possible, and use their CDS spreads. ²⁰

Due to the fact that we are not dealing with equity prices, we cannot talk about a systematic risk in the sense of the Beta of the asset, although market and credit risk are intrinsically related to each other and not separable. Indeed, the Merton (1974) model is a well-known stock market based credit risk model. Furthermore, if the market value of the firm's assets unexpectedly changes, generating market risk, this affects the probability of default, generating credit risk, and viceversa (see Jarrow and Turnbull, 2000). Anyhow, we

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²⁰ As already noted in the first section of this thesis, CDS premia are found to be useful indicators of credit risk (Blanco et al., 2005; Longstaff et al., 2005).

use default option premia (which according to Pedrosa and Roll, 1998, are driven by systematic state variables) of global entities to analyse what hereinafter we refer to as "global credit risk", as opposed to an idiosyncratic or industrywide default risk.

The approach is, therefore, different from other works that have been carried out. First, because we focus on the impact of credit risk, secondly, because we consider globalization in a novel way: through corporations that carry out their activity internationally.

4.2. Data and descriptive statistics

The analysis of global risk is based on a highly-diversified portfolio of the world's largest public companies which are also the underlying of the most traded CDS contracts and whose revenues come from at least 3 continents, which singly do not represent more than 50% of the firm's incomes. The sample spans from January 3, 2007 to November 16, 2016, encompassing times of economic crisis (subprime and European sovereign crisis) and times of calm.

CDS contracts are only available if some debt level exists and are therefore only issued on companies with some credit risks. This implies that we do not account with some big multinational corporates, which might have been interesting, e.g. Inditex. Furthermore, for companies where the default risk is low, (which might be the case of companies like Apple, Google or Microsoft) there are no CDS contracts issued neither or their liquidity level is not high enough to enter this sample.

From the Forbes 2000 world's largest public companies list for 2016 (based on a composite score from equally-weighted measures of revenue, profits, assets and market

value),²¹ we select those which according to the December 2015 DTCC® survey are the underlying assets of the 1.000 most liquid CDS contracts, obtaining a sample of 572 firms which are the largest ones with the highest CDS liquidity. As we are looking for those with a global nature, from a business strategy perspective, i.e. with a global revenue profile, not home-country oriented but world-oriented companies, we select those whose incomes proceed from at least 3 continents and no one represents more than 50% of the company's income. 129 companies of the initial sample fulfil these criteria. When searching for the weekly closing premium of these corporate CDS, we use high quality restrictions and select only those where the percentage of missing observations²² does not exceed a 19% level, in a similar way as Diaz et al. (2013) do. This criterion results in 75 firms with an average of 508 weekly observations, summarized in Table 8.

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 $^{^{21}}$ Visit https://www.forbes.com/sites/steveschaefer/2016/05/25/the-worlds-largest-companies2016/46bf9f2fc45a6 for more information.

²² We enforce high quality requirements to our sample by requiring very "clean" data series and therefore we account as missing observations not only the dates in which there is no official spread published but also those spreads which show no change regarding the previous weekly closing price, as we understand that this means no trading activity during the last week and therefore no new relevant information embedded in the CDS premium.

Table 8: Firms in the study sample.

This table shows the distribution of firms across sectors, ratings and countries with their geographic revenues exposure. Ratings refer to the S&P local currency long-term category as for January 24th, 2017. The sector classification is based on information in Moody's website. Data for the geographic revenues exposure are taken form Factset (in case of doubts or missing data, the company has been contacted). They are 2015 year-end figures in almost all cases. (*) stands for 2016 data.

Company	S&P Rating	Industry	Domicile	Geographical Revenues Exposure
Aktiebolaget Electrolux	A-	Consumer products	Sweden	Africa and Middle East 4.2%, Americas 49.3%, Asia/Pacific 19.4%, Europe 27.1%
Aktiebolaget Volvo	BB	Manufacturing	Sweden	Africa and Middle East 6.7%, Americas 38.3%, Asia/Pacific 16.5%, Europe 38.4%
Akzo Nobel n.v.	A-	Chemicals	Netherlands	Africa and Middle East 5.2%, Americas 27%, Asia/Pacific 25%, Europe 42.8%
Apache Corporation	BBB	Energy	USA	Africa and Middle East 30.8%, Americas 49.1%, Europe 20.1%
Arcelormittal	BB	Other	Luxembourg	Africa and Middle East 10.5%, Americas 39.1%, Asia/Pacific 5%, Europe 45.4% (*)
Arrow Electronics, inc.	BBB-	Technology	USA	Africa and Middle East 6.7%, Americas 48%, Asia/Pacific 23.1%, Europe 22.2% (*)
Astrazeneca plc	A-	Pharmaceuticals	UK	Africa and Middle East 0.7%, Americas 46.5%, Asia/Pacific 24.4%, Europe 28.4%
Avnet, inc.	BBB-	Technology	USA	Africa and Middle East 4.2%, Americas 39.8%, Asia/Pacific 30.2%, Europe 25.8% (*)
Bae Systems plc	BBB	Aerospace and Defense	UK	Africa and Middle East 22.3%, Americas 38.6%, Asia/Pacific 4.7%, Europe 34.4%
Baker Hughes Incorporated	Α	Energy	USA	Africa and Middle East 6.4%, Americas 45.5%, Asia/Pacific 25.8%, Europe 22.3% (*)
Baxter International inc.	A-	Other	USA	Africa and Middle East 0.6%, Americas 52.4% (North Amer 43%), Asia/Pacific 19.3%, Europe 27.7%
Bayer Aktiengesellschaft	A-	Pharmaceuticals	Germany	Africa and Middle East 9%, Americas 35.1%, Asia/Pacific 21.6%, Europe 34.3%
Bayerische Motoren Werke Aktiengesellschaft	A+	Automotive	Germany	Africa and Middle East 4.6%, Americas 23.3%, Asia/Pacific 26.6%, Europe 45.5%
Borgwarner inc.	BBB+	Automotive	USA	Africa and Middle East 1.1%, Americas 34.5%, Asia/Pacific 26.1%, Europe 38.2% (*)
BP PLC	A+	Energy	UK	Africa and Middle East 5%, Americas 39%, Asia/Pacific 19.5%, Europe 36.5%
Bristol-Myers Squibb Company	A+	Pharmaceuticals	USA	Africa and Middle East 4.6%, Americas 54.2% (USA 49%), Asia/Pacific 20.3%, Europe 20.9%
British American Tobacco plc	BBB+	Consumer products	UK	Africa and Middle East 19.9%, Americas 20.8%, Asia/Pacific 28%, Europe 31.3%
Canon inc.	AA	Manufacturing	Japan	Africa and Middle East 0.7%, Americas 30.1%, Asia/Pacific 40.9%, Europe 28.2%
Caterpillar inc.	Α	Manufacturing	USA	Africa and Middle East 5.5%, Americas 55.6% (North Amer 46.6%), Asia/Pacific 20.5%, Europe 18.4% (*)
Citigroup inc.	BBB+	Financial Institution	USA	Africa and Middle East 3.3%, Americas 57.4% (North Amer 42.4%), Asia/Pacific 17.9%, Europe 10%, Other 11.5%
Continental Aktiengesellschaft	BBB+	Automotive	Germany	Africa and Middle East 2.6%, Americas 28.1%, Asia/Pacific 19.9%, Europe 49.4%
Credit Suisse Group ag	BBB+	Financial Institution	Switzerland	Africa and Middle East 4%, Americas 35.6%, Asia/Pacific 12%, Europe 48.4%
Daimler ag	Α	Automotive	Germany	Africa and Middle East 3.2%, Americas 31.2%, Asia/Pacific 22.7%, Europe 42.9% (*)
Diageo plc	A-	Consumer products	UK	Africa and Middle East 15.2%, Americas 42.2%, Asia/Pacific 18.8%, Europe 23.4%, Other 0.3% (*)
E. I. Du Pont de Nemours and Company	A-	Chemicals	USA	Africa and Middle East 5.5%, Americas 53.1% (North Amer 42.4%), Asia/Pacific 25.8%, Europe 22.3% (*)
Eastman Chemical Company	BBB	Chemicals	USA	Africa and Middle East 6.2%, Americas 51% (North Amer 45%), Asia/Pacific 23.4%, Europe 19.4%
GKN Holdings plc	BBB-	Automotive	UK	Africa and Middle East 1.8%, Americas 38.2%, Asia/Pacific 13.8%, Europe 46.2%
Glaxosmithkline plc	A+	Pharmaceuticals	UK	Africa and Middle East 6.5%, Americas 41.7%, Asia/Pacific 25%, Europe 26.9%
Halliburton Company	BBB+	Energy	USA	Africa and Middle East 5.4%, Americas 54.3% (USA 41%), Asia/Pacific 23.6%, Europe 16.7% (*)
Hannover Rueck SE	AA-	Financial Institution	Germany	Africa and Middle East 5.4%, Americas 33.2%, Asia/Pacific 22.7%, Europe 38.6%
Heidelbergcement ag	BBB-	Manufacturing	Germany	Africa and Middle East 4.6%, Americas 31.8%, Asia/Pacific 32.4%, Europe 31.2%
Heineken n.v.	BBB+	Consumer products	Netherlands	Africa and Middle East 10.5%, Americas 25%, Asia/Pacific 13.6%, Europe 50%, Other 0.4% (*)
Henkel ag & co. kgaa	Α	Consumer products	Germany	Africa and Middle East 8%, Americas 26.3%, Asia/Pacific 16.9%, Europe 48%, Other 0.7%
Hewlett-Packard Company	BBB	Technology	USA	Africa and Middle East 6.6%, Americas 44.4%, Asia/Pacific 27.6%, Europe 21.5% (*)
Honda Motor co., Itd.	A+	Automotive	Japan	North America 48.55%, Asia/Pacific 42.44%, Europe 4.41%, Other 4.60% (*)
Johnson Controls, inc.	BBB+	Automotive	USA	Africa and Middle East 3.7%, Americas 50.6% (USA 43%), Asia/Pacific 18.7%, Europe 27% (*)
Kering	BBB	Other	France	Africa and Middle East 20.5%, Americas 26.3%, Asia/Pacific 35.1%, Europe 33.6% (*)
Komatsu ltd.	Α	Manufacturing	Japan	Africa and Middle East 8.4%, Americas 35.7%, Asia/Pacific 45.1%, Europe 10.7% (*)

Company	S&P Rating	Industry	Domicile	Geographical Revenues Exposure
Koninklijke DSM n.v.	A-	Chemicals	Netherlands	Africa and Middle East 4.1%, Americas 36.7%, Asia/Pacific 25.6%, Europe 33.7%
Koninklijke Philips n.v.	BBB+	Manufacturing	Netherlands	Africa and Middle East 7.4%, Americas 39.4%, Asia/Pacific 26.5%, Europe 26.8%
Lafargeholcim Itd	BBB	Manufacturing	Switzerland	Africa and Middle East 10.3%, Americas 32.6%, Asia/Pacific 31.8%, Europe 25.3%
Linde Aktiengesellschaft	A+	Chemicals	Germany	Africa and Middle East 3.8%, Americas 32.8%, Asia/Pacific 26.9%, Europe 36.5%
Marsh & Mclennan Companies, inc.	A-	Financial Institution	USA	Africa and Middle East 4.9%, Americas 54.6% (USA 48.8%), Asia/Pacific 10.1%, Europe 30.4%
Mcdonald's Corporation	BBB+	Other	USA	Africa and Middle East 2.1%, Americas 39.9%, Asia/Pacific 24.9%, Europe 33.1%
Mondelez International, inc.	BBB	Consumer products	USA	Africa and Middle East 6.5%, Americas 40.4%, Asia/Pacific 14.4%, Europe 38.8%
Nestle s.a.	AA	Consumer products	Switzerland	Africa and Middle East 8.6%, Americas 41.4%, Asia/Pacific 23%, Europe 26.9%
Nissan Motor co., ltd.	A-	Automotive	Japan	Africa and Middle East 4.4%, Americas 52.9% (North Amer 44.6%), Asia/Pacific 28.4%, Europe 14.3% (*)
Nokia oyj	BB+	Telecommunications	Finland	Africa and Middle East 10.4%, Americas 20.5%, Asia/Pacific 38.6%, Europe 30.5%
Pernod Ricard	BBB-	Consumer products	France	Africa and Middle East 1.1%, Americas 28.5%, Asia/Pacific 39.3%, Europe 31.1% (*)
Pfizer inc.	AA	Pharmaceuticals	USA	Africa and Middle East 4.5%, Americas 50.5% (North Amer 46.8%), Asia/Pacific 22.8%, Europe 22.2%
PPG industries inc	A-	Chemicals	USA	Africa and Middle East 6.7%, Americas 54.3% (North Amer 44.7%), Asia/Pacific 16.2%, Europe 22.8% (*)
Ricoh Company, ltd.	A-	Manufacturing	Japan	Africa and Middle East 5.7%, Americas 31.4%, Asia/Pacific 44.3%, Europe 18.7% (*)
SabMiller plc	A-	Chemicals	UK	Africa 28.08%, Americas 40.94%, Asia/Pacific 15.11%, Europe 15.87% (*)
Sanofi	AA	Pharmaceuticals	France	Africa and Middle East 8.3%, Americas 46.1%, Asia/Pacific 18.3%, Europe 27.4%
Schneider Electric SE	A-	Manufacturing	France	Africa and Middle East 8.8%, Americas 33%, Asia/Pacific 26.6%, Europe 31.6% (*)
Scor SE	AA-	Financial Institution	France	Africa and Middle East 9.4%, Americas 43.5%, Asia/Pacific 15.5%, Europe 31.5%
Sealed Air Corporation	BB	Other	USA	Africa and Middle East 8%, Americas 51.5% (North Amer 41.6%) Asia/Pacific 13.9%, Europe 26.6%
Siemens Aktiengesellschaft	A+	Manufacturing	Germany	Africa and Middle East 10.5%, Americas 28.5%, Asia/Pacific 18.7%, Europe 42.3% (*)
Sodexo	A-	Other	France	Africa and Middle East 2.6%, Americas 44.7%, Asia/Pacific 10.9%, Europe 38%, Other 3.8% (*)
Softbank Group corp.	BB+	Telecommunications	Japan	Africa and Middle East 1%, Americas 47.8%, Asia/Pacific 48%, Europe 3.1% (*)
Solvay	BBB-	Chemicals	Belgium	Africa and Middle East 6.3%, Americas 32.9%, Asia/Pacific 27.8%, Europe 33.1%
Sony Corporation	BBB-	Manufacturing	Japan	Africa and Middle East 4.5%, Americas 25.2%, Asia/Pacific 47.1%, Europe 23.2% (*)
Starwood Hotels & Resorts Worldwide, inc.	BBB	Other	USA	USA 34.31%, Rest Americas 16.19%, Europe , Africa and Middle East 16.3%, Asia/Pacific 9.85%, Other 23.36%
Technip	BBB+	Energy	France	Europe, Russia and Central Asia 36.28%, Afirca 15.41%, Middle East 8.33%, Asia Pacific 15.91%, Americas 24.06%
Telefonaktiebolaget Ericsson	BBB	Telecommunications	Sweden	Africa and Middle East 20.3%, Americas 34.7%, Asia/Pacific 24.6%, Europe 20.4%
The Boeing Company	Α	Aerospace and Defense	USA	Africa and Middle East 16.7%, Americas 45.2%, Asia/Pacific 23.6%, Europe 14.6% (*)
The Dow Chemical Company	BBB	Chemicals	USA	Africa and Middle East 7.1%, Americas 42.6%, Asia/Pacific 27.8%, Europe 22.4%
The Goodyear Tire & Rubber Company	BB	Automotive	USA	Africa and Middle East 5.4%, Americas 53.9% (North Amer 46.7%), Asia/Pacific 13.6%, Europe 27.1% (*)
The Procter & Gamble Company	AA-	Consumer products	USA	Africa and Middle East 5.8%, Americas 52% (North Amer 43.8%), Asia/Pacific 19.2%, Europe 22.9% (*)
Transocean inc.	B+	Energy	USA	Africa and Middle East 7.6%, Americas 34.8%, Asia/Pacific 25.4%, Europe 32.2%
UBS AG	A+	Financial Institution	Switzerland	Africa and Middle East 5.5%, Americas 38.4%, Asia/Pacific 15.9%, Europe 40.2%
Unilever n.v.	A+	Consumer products	Netherlands	Africa and Middle East 8.2%, Americas 32.5%, Asia/Pacific 31.9%, Europe 27.4%
Valeo	BBB	Automotive	France	Africa and Middle East 5.6%, Americas 23.3%, Asia/Pacific 26.2%, Europe 44.9% (*)
Weatherford International Itd.	В	Energy	Switzerland	Africa and Middle East 21%, Americas 55.9% (North Amer 37.1%), Asia/Pacific 7.3%, Europe 15.8%
WPP 2005 limited	BBB	Other	UK	Africa and Middle East 4.7%, Americas 40.5%, Asia/Pacific 18.2%, Europe 36.6%

In the portfolio, Local Currency Long-Term ratings as for January 2017 go from AA (Canon, Nestle, Pfizer, and Sanofi) to B (Weatherford Int.) resulting the debt classification of these companies in 5 groups: High grade in 7 cases (9.3%), Upper medium investment grade for 30 firms (40%), Lower medium grade 30 times (40%), Non-investment grade speculative in 6 cases (8%) and Highly speculative grade in 2 companies (2.7%).

The 75 firms are distributed along 10 different sectors: 13.3% of them are included in the Automotive industry, 12% Chemicals, 12% Consumer Products, 9.3% Energy, 8% Financial Institutions (which includes 3 banks, 1 insurance firm and 2 reinsurance companies), 14.6% Manufacturing, 8% Pharmaceuticals, 4% Technology and 4% Telecommunications. 13.3% of the companies are aggregated as belonging to "Other" sectors as they carry out very different activities. Two of those companies belong to the Aerospace and Defense sector (The Boeing Co. and Bae Systems), while Retailing, Conglomerate, Media, Healthcare, Restaurants, Lodging, Packaging and Metals-Mining have only one component (Kering, Sodexo, WPP 2005, Baxter Int., McDonald's, Starwood Hotels, Sealed Air Corp. and Arcelormittal respectively).

In this heterogeneous sample, 26 firms have their fiscal domicile in the USA, 7 in Japan, 9 in Germany and in UK, 8 in France, 5 in Switzerland and in the Netherlands, 3 in Sweden and 1 in Belgium, Finland, and Luxembourg (35% America, 9% Asia and 56% Europe).

Table 9 reports summary statistics on 5-year CDS spreads for these companies.²³ We use end-of-day quotes in weekly basis (Wednesday's prices to avoid sharp movements due to irregular trading on, for example, derivatives expiration dates which usually are on Fridays).

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²³ According to previous literature, the 5-year maturity is the most widely traded. See Eichengreen, Mody, Nedeljkovic and Sarno (2012).

They were supplied by Credit Market Analysis (CMA) Data Vision. Spreads are denominated in basis points and are therefore free of units of account.

It is interesting to note that most companies have a CDS average spread bellow 100b.p. (being the lowest mean for Bristol-Myers), and that 35% of the average spreads range between 100.21 (Hewlett-Packard) and 434.642 (Goodyear). No CDS has a mean equal or above 500 b.p., which according to Pelizzon, Subrahmanyam, Tomio and Uno (2016) is the threshold used as an indicator by clearing houses in setting margins. However, the maximum reached by these premiums is above 500 b.p. in several cases (Volvo, Arcelormittal, Avnet, Borgwarner, BP, Citi, Continental, Daimler, GKN, Heidelbergcement, Johnson Controls, Kering, Lafargeholcim, Nissan Motors, Nokia, Pernod Ricard, Sealed Air, Softbank, Starwood Hotels, Dow Chemical, The Goodyear Tire and Rubber, Transocean, Valeo, Weatherford and WPP 2005) indicating that, as expected, in the sample timeframe there have been troubled periods (subprime crisis 2007-2009, and European sovereign crisis 2009-2015). In this sense, the highest quotation is for Heidelbergeement (5315,85 b.p. on December 12, 2008) and the lowest is the one quoted for Nestle (3.25 b.p. on June 13, 2007) and Canon (3.25 b.p. on June 27, 2007). It is interesting to note the high time-series variations in many cases, being the overall range average 497 b.p. As expected, the maximum range is 5286 b.p. for Heidelbergcement and the smallest 48 b.p. for Baxter International (who also show the highest and lowest standard deviation).

We also report the standard deviation, skewness and kurtosis. In terms of historical volatility the highest change is for the Heidelbergcement CDS, followed by the Transocean, Nokia, Nissan, Johnson Controls, Softbank and Continental CDS, whose variation coefficients, i.e. the ratio of the standard deviation to the mean, are all above 1. The lowest ratio is for the Baxter CDS, followed by Sodexo, Eastman Chemical, Diageo, DSM, Unilever,

British American Tobacco and McDonald's. All CDS spread distributions show a certain grade of skewness and the hypothesis of normality (Shapiro Wilks test) has been rejected in the CDS prices distribution for every company (see Appendix D).

In sum, we account with a large sample period that covers a wide number of global firms across many sectors, countries and ratings with quite different performance during the last 10 years.

Table 9: Descriptive statistics for weekly CDS prices.

This table reports descriptive statistics for weekly 5-year CDS spreads measured in basis points. The data source is Credit Market Analytics Data Vision through Bloomberg. The time series covers the period from January 2007 to November 2016.

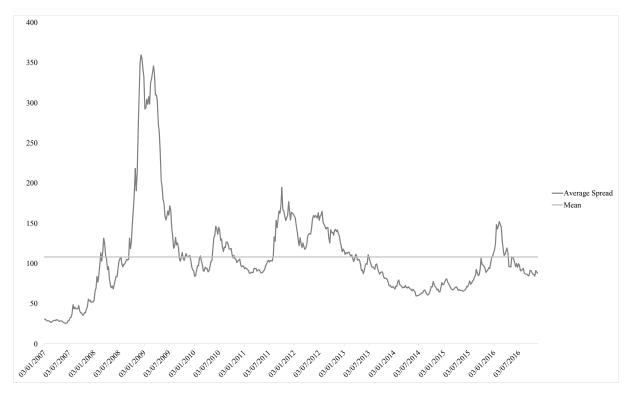
	ELECTROLUX	VOLVO	AKZO NOBEL	APACHE	ARCELORMITTAI
Maximum	203.269	606.314	200.444	354.202	1155.912
Minimum	22.566	19.938	20.879	13.340	23.23
Mean	76.512	152.523	75.728	84.842	314.28
Standard Deviation	32.252	105.062	31.436	56.159	202.22
Skewness	1.714	1.864	0.793	1.650	0.999
Kurtosis	3.517	4.113	0.382	3.193	1.77
Numb. Observ.	516	516	516	516	513
	ARROW ELEC.	ASTRAZENECA	AVNET	BAE SYSTEMS	BAKER HUGHES
Maximum	290.677	187.206	560.759	282.368	130.084
Minimum	35.170	4.456	42.510	13.934	13.299
Mean	106.697	50.070	136.721	90.796	54.439
Standard Deviation	45.211	27.644	76.342	45.860	23.719
Skewness	0.849	2.012	2.201	1.011	0.658
Kurtosis	0.347	6.497	7.026	1.379	0.094
Numb. Observ.	516	516	516	516	516
	BAXTER INT	BAYER	BMW	BORGWARNER	BP
Maximum	56.35	145.868	496.898	611.625	611.963
Minimum	8.751	143.808	8.893	21.833	3.667
Mean	30.071	55.463	91.065	97.519	75.99
Standard Deviation	9.064	22.491	72.013	78.414	62.891
Skewness	0.033	1.120	2.638	3.619	4.300
Kurtosis	-0.209	1.713	8.639	16.725	27.932
Numb. Observ.	516	516	516	516	516
	2212201 4 24522 241 4			0.750000.00	
Maximum	BRISTOL-MYERS SH A 68.632	169.596	179.900	CATERPILLAR 414.302	CITI 653.793
Minimum	7.927	19.545	3.250	12.572	7.438
Mean	29.323	55.964	33.986	78.952	144.327
Standard Deviation	12.280	21.055	23.810	52.378	100.993
Skewness	0.504	2.098	2.375	2.538	1.886
Kurtosis	0.039	7.240	8.396	9.077	5.251
Numb. Observ.	516	516	516	516	516
	CONTINENTAL	CDEDIT CHICCE	DAIAILED	DIACEO	F I DII DONT
Maximum	CONTINENTAL 1513.911	CREDIT SUISSE	DAIMLER 513.333	DIAGEO	E. I. DU PONT 195.025
	38.092	252.010 9.958	20.080	126.957 13.614	8.689
Minimum	271.114	97.526		58.820	53.869
Mean	271.114		96.160		
Standard Deviation Skewness	2.078	44.803 0.397	70.251 2.626	19.868 -0.147	25.661 1.838
Kurtosis	4.691	-0.048	9.058	-0.147	5.733
Numb. Observ.	516	-0.048 516	516	-0.130 516	5.73
	EASTMAN CHEM.	GKN HOLD	GLAXOSMITHKLINE	HALLIBURTON	HANNOVER RU
Maximum	195.092	1002.402	114.665	216.356	154.721
Minimum	30.835	36.960	4.918	14.425	8.500
Mean	83.631	191.970	43.566	64.763	73.785
Standard Deviation	27.491	149.092	18.201	34.705	33.955
Skewness	0.816	2.943	0.424	1.453	0.208
Kurtosis	1.916	10.463	1.783	3.046	-0.757
Numb. Observ.	516	516	516	516	516
	HEIDELBERGCEMENT	HEINEKEN	HENKEL & CO	HEWLETT-PACKARD	HONDA MOTOR
Maximum	4454.340	265.250	176.675	374.408	316.625
Minimum	30.400	31.886	10.417	8.250	4.217
	395.589	86.128	49.569	100.210	53.87
Mean	644.583	45.300	27.579	74.013	46.540
	044.303				
Mean Standard Deviation Skewness	4.021	1.456	1.313	1.123	2.984
Standard Deviation		1.456 1.925	1.313 2.763	1.123 0.962	2.98 ² 10.79 ²

Maniana	JOHNSON CONT.	KERING	KOMATSU	DSM	PHILIPS
Maximum Minimum	1014.020 18.566	701.815 33.344	158.251 7.031	141.056 22.728	161.939 14.213
Mean	119.092	141.976	43.080	56.213	64.746
Standard Deviation	134.760	116.993	26.403	18.947	27.989
Skewness	3.639	2.625	1.578	1.369	0.935
Kurtosis	15.526	7.524	3.175	2.837	0.599
Numb. Observ.	512	516	516	516	516
	LAFARGEHOLCIM	LINDE	MARSH & MCLENNAN	MCDONALD'S	MONDELEZ
Maximum	841.650	165.310	163.956	67.558	141.340
Minimum	19.000	15.931	16.004	9.788	12.985
Mean	163.378	49.979	58.395	31.312	53.812
Standard Deviation	128.209	22.293	31.081	11.953	22.208
Skewness	2.414	1.634	1.036	0.360	1.049
Kurtosis	7.296	4.864	0.331	-0.335	0.785
Numb. Observ.	516	516	516	516	516
	NESTLE	NISSAN MOTOR	NOKIA	PERNOD RICARD	PFIZER
Maximum	86.386	741.769	1230.020	746.015	123.300
Minimum	3.250	14.955	8.278	42.250	4.832
Mean	33.769	96.988	206.690	150.273	40.903
Standard Deviation	15.451	111.745	238.802	136.259	23.402
Skewness V vertexis	0.550	3.387	2.102	2.656	0.675
Kurtosis Numb. Observ.	0.792 516	12.608 516	3.978 516	7.411 516	0.397 513
Numb. Observ.	310	310	310	310	313
	PPG INDUSTRIES	RICOH	SABMILLER	SANOFI	SCHNEIDER ELEC.
Maximum	278.226	214.558	215.000	128.769	263.300
Minimum	16.225	4.917	26.480	9.071	18.200
Mean	65.930	48.523	80.183	49.135	72.536
Standard Deviation	44.706	38.123	40.207	21.238	42.506
Skewness Kurtosis	2.504 7.287	2.325 6.109	1.389	0.822 1.007	1.538 2.897
Numb. Observ.	516	516	1.927 440	516	516
ivania. Observ.	310	310	110	310	310
	SCOR	SEALED AIR	SIEMENS	SODEXO	SOFTBANK
Maximum	238.290	567.706	234.799	115.000	2266.667
Minimum	10.335	28.747	10.704	18.429	95.000
Mean Standard Deviation	94.999	181.257	59.674	58.304	328.114
Skewness	48.831 0.879	96.254 1.205	32.086 1.862	18.278 0.188	341.357 3.569
Kurtosis	0.476	1.722	5.813	-0.012	13.932
Numb. Observ.	516	516	516	516	516
	SOLVAY	SONY	STARWOOD HOTELS	TECHNIP	ERICSSON
Maximum	249.312	451.137	830.408	311.650	431.065
Minimum	10.063	8.829	15.492	20.300	20.587
Mean Standard Deviation	85.626 42.790	110.628 89.840	160.797	108.169 49.324	107.300
Skewness	0.870	1.593	149.106 2.517	0.979	67.475 1.988
Kurtosis	1.115	2.630	6.803	2.194	5.259
Numb. Observ.	516	516	516	516	516
	BOEING	DOW CHEMICAL	GOODYEAR	PROCTER & GAMBLE	TRANSOCEAN
Maximum	271.252	630.050	1600.960	150.000	2399.793
Minimum	7.789	14.450	151.675	6.460	19.662
Mean	58.474	117.339	434.642	39.281	338.998
0. 1 170 1.1			251.352	24.060	432.146
Standard Deviation	43.951	93.673	231.332	24.868	
Standard Deviation Skewness	43.951 2.109	93.673 3.166	1.396	1.996	2.456
Skewness	2.109	3.166	1.396	1.996	2.456
Skewness Kurtosis Numb. Observ.	2.109 5.709 516 UBS	3.166 12.306 516 UNILEVER	1.396 2.778 516 VALEO	1.996 4.982 516 WEATHERFORD	2.456 6.705 516 WPP 2005 LMTD
Skewness Kurtosis Numb. Observ.	2.109 5.709 516 UBS 347.229	3.166 12.306 516 UNILEVER 83.335	1.396 2.778 516 VALEO 719.728	1.996 4.982 516 WEATHERFORD 1373.227	2.456 6.705 516 WPP 2005 LMTD 611.097
Skewness Kurtosis Numb. Observ.	2.109 5.709 516 UBS 347.229 4.687	3.166 12.306 516 UNILEVER 83.335 12.400	1.396 2.778 516 VALEO 719.728 48.402	1.996 4.982 516 WEATHERFORD 1373.227 23.761	2.456 6.705 516 WPP 2005 LMTD 611.097 21.930
Skewness Kurtosis Numb. Observ. Maximum Minimum Mean	2.109 5.709 516 UBS 347.229 4.687 97.323	3.166 12.306 516 UNILEVER 83.335 12.400 33.956	1.396 2.778 516 VALEO 719.728 48.402 165.554	1.996 4.982 516 WEATHERFORD 1373.227 23.761 253.441	2.456 6.705 516 WPP 2005 LMTD 611.097 21.930 109.728
Skewness Kurtosis Numb. Observ. Maximum Minimum Mean Standard Deviation	2.109 5.709 516 UBS 347.229 4.687 97.323 58.562	3.166 12.306 516 UNILEVER 83.335 12.400 33.956 11.886	1.396 2.778 516 VALEO 719.728 48.402 165.554 113.267	1.996 4.982 516 WEATHERFORD 1373.227 23.761 253.441 244.669	2.456 6.705 516 WPP 2005 LMTD 611.097 21.930 109.728 93.405
Skewness Kurtosis Numb. Observ. Maximum Minimum Mean Standard Deviation Skewness	2.109 5.709 516 UBS 347.229 4.687 97.323 58.562 1.116	3.166 12.306 516 UNILEVER 83.335 12.400 33.956 11.886 1.140	1.396 2.778 516 VALEO 719.728 48.402 165.554 113.267 2.259	1.996 4.982 516 WEATHERFORD 1373.227 23.761 253.441 244.669 2.013	2.456 6.705 516 WPP 2005 LMTD 611.097 21.930 109.728 93.405 2.784
Skewness Kurtosis Numb. Observ. Maximum Minimum Mean Standard Deviation	2.109 5.709 516 UBS 347.229 4.687 97.323 58.562	3.166 12.306 516 UNILEVER 83.335 12.400 33.956 11.886	1.396 2.778 516 VALEO 719.728 48.402 165.554 113.267	1.996 4.982 516 WEATHERFORD 1373.227 23.761 253.441 244.669	2.456 6.705 516 WPP 2005 LMTD 611.097 21.930 109.728 93.405

Figure 13 tracks the time average spreads for the whole sample. After the bankruptcy of Lehman Brothers in September 2008, CDS spreads rise sharply reaching the highest level. The average premium stays at high levels during the U.S. Great Recession, which ends mid 2009. Spreads go then back and stay around their mean with a new (but not as strong as the former) rise between August 2011 and August 2012 (during the European Sovereign Crisis). Another price increase takes place in 2016 1Q when crude oil prices plummet to multi-year lows due to the demand and supply mismatch worldwide and a series of bankruptcies and poor financial results by some of the largest oil and gas players in the US.

Figure 13: Evolution of spreads on CDS (mean, basis points).

This figure depicts the evolution of the CDS average spread between January 2007 and November 2016. The lowest average takes place in 2007, June 6th (25.62 b.p.) while the maximum level is reached on 2008, October 12th (359.60 b.p.).



By looking at this graph, we would expect to be the US companies to be the ones which experience the price increase in 2008-2009, the European ones which have more volatile CDS premia during 2011-2012 and the energy firms to rise more in 2016.

Figure 14 confirms graphically the descriptive statistics data in Table 9, however it reveals surprising facts: The most explosive movements by the end of 2008 and the beginning of 2009 are for Heidelbergcement (Manufacturing, Germany, BBB-) and Softbank Group (Telecommunications, Japan, BB+), followed by Continental (Automotive, Germany, BBB+) and Goodyear (Automotive, USA, BB). From 2012 2Q until the start of 2013 4Q it is Nokia's CDS (Telecommunications, Finland, BB+) which shows a fiery rise. As expected, from the end of 2014 until the end of the sample timeframe, Transocean (Energy, USA, B+) experiences a violent increment followed by Weatherford (Energy, USA, B) and Arcelormittal (Metals and Mining, Luxembourg, BB).

Figure 14: CDS spreads of the firms that conform the global corporates portfolio.

This figure shows the evolution of the corporates CDS premia from January 2007 to November 2016. The firms not displayed follow a very similar path as the less volatile companies of this graph.

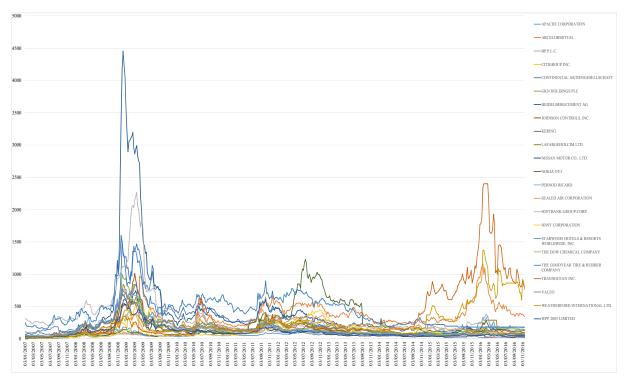


Figure 14 suggests a strong co-movement in CDS spreads across firms which invites us to further explore the possibility of a joint performance of the risk premia. While the focus of Billio's et al. (2012) work is on four sectors with extensive ties between them (hedge funds, banks, broker/dealers and insurance companies), the goal is to understand if there are also unobserved factors between other sectors composed by global companies which could provide evidence of an existing non-financial corporate credit risk.

4.3. Empirical estimations

For the purpose, we suggest two methods to capture the connectedness between the firms and the sectors they belong to. First we use principal components analysis (PCA) to estimate the relevance of common factors driving the changes of the CDS spreads of these firms. This method is going to help us to identify the most useful variables in the dataset and reduce the sample into manageable factors. We then determine the relative timing of the variables to understand if they exhibit significant lead-lag relationships through a Vector Autoregression (VAR) and Granger-causality test.

According to Chan-Lau (2006) the simplest proxy for systematic default risk is the spread of a credit derivatives index, which comprises a large cross section of firms. However, these spreads also react to changes in idiosyncratic default risk. We therefore use principal component analysis to extract the systematic component of the default risk of multinational firms, as in Díaz et al. (2013) for European investment-grade firms.

We use PCA to extract the common factors underlying weekly variations in the CDS spreads. If they move together, it can be inferred that there is a latent risk of failure that is not driven by sector or country specific factors but by global ones. Through a few unobserved

common factors we aim to capture the covariance among the series and to understand the fraction of the total variation which is explained by each factor.

For this purpose, we use weekly variations instead of weekly prices following an extent empirical work on default risk (e.g. Longstaff et al. 2011; Eichengreen et al., 2012; Ang and Longstaff 2013). Although Dieckmann and Plank (2012) cite Cremers, Driessen and Maenhout (2008) to remind that they do not find strong econometric evidence for a unit root in levels of credit spreads in the corporate debt context, they find that in their sovereign CDS sample 55% of the countries appear non-stationary and finally opt to analyze the data in changes as well as levels. In this study we choose changes of spreads to avoid any problems related to explosive quotations in times of crisis, or the small sample non-stationarity property (although we believe that the 2007-2016 is long enough) as noted by Dieckmann and Plank (2012), and to avoid any heterogeneity problem of level spread and volatility across firms (Diaz, Groba and Serrano, 2013). In sum, as stated by Pedrosa and Roll (1998), we feel it is safer to use changes instead of levels. Table 10 reports summary statistics on 5-year CDS spread changes, where the Jaque-Bera Lagrange multiplier statistics reject the null hypothesis of a normal distribution in all cases.

Table 10: Descriptive statistics for 5-year CDS spread changes.

This table includes a summary of the main statistics for weekly 5-year CDS spread changes, from January 2007 to November 2016.

	ELECTROLUX	VOLVO	AKZO NOBEL	APACHE	ARCELORMITTAL
Maximum	0.464	0.412	0.473	1.094	11.711
Minimum	-0.275	-0.302	-0.259	-0.316	-0.199
Mean	0.004	0.007	0.005	0.009	0.025
Standard deviation	0.082	0.095	0.084	0.105	0.524
Skewness	1.138	1.119	1.029	2.728	21.737
Kurtosis	5.140	2.881	4.121	23.149	485.050
Jarque-Bera probabi	0.0000	0.0000	0.0000	0.0000	0.0000
затчие-вета рговавт	0.0000	0.0000	0.0000	0.0000	0.0000
	ARROW ELECTR.	ASTRAZENECA	AVNET	BAE SYSTEMS	BAKER HUGHES
Maximum	0.459	0.685	0.492	0.557	1.267
Minimum	-0.251	-0.286	-0.222	-0.343	-0.692
Mean	0.005	0.007	0.005	0.006	0.005
Standard deviation	0.092	0.083	0.088	0.083	0.095
Skewness	1.125	3.096	1.510	1.394	4.275
Kurtosis	3.317	20.632	5.682	6.599	67.667
Jarque-Bera probabi	0.0000	0.0000	0.0000	0.0000	0.0000
q = p			5.0000		5.555
	BAXTER INT	BAYER	BMW	BORGWARNER	ВР
Maximum	0.542	0.474	0.760	0.473	1.449
Minimum	-0.352	-0.269	-0.274	-0.244	-0.260
Mean	0.005	0.005	0.009	0.004	0.012
Standard deviation	0.078	0.080	0.105	0.077	0.118
Skewness	1.847	1.285	1.828	1.752	5.040
Kurtosis	10.635	4.860	9.149	7.800	48.983
Jarque-Bera probabi	0.0000	0.0000	0.0000	0.0000	0.0000
surque Beru probubi	0.0000	0.0000	0.0000	0.0000	0.0000
	BRISTOL-MYERS	BRITISH AMERICAN TOBACCO	CANON	CATERPILLAR	CITI
Maximum	0.663	0.346	0.700	0.634	1.080
Minimum	-0.296	-0.247	-0.295	-0.305	-0.555
Mean	0.005	0.004	0.008	0.008	0.012
Standard deviation	0.084	0.068	0.105	0.102	0.129
Skewness	2.006	1.145	2.423	1.362	2.516
Kurtosis	12.832	4.869	11.047	5.721	17.540
Jarque-Bera probabi	0.0000	0.0000	0.0000	0.0000	0.0000
	CONTINENTAL	CREDIT SUISSE	DAIMLER	DIAGEO	E. I. DU PONT
Maximum	0.418	0.963	0.759	0.606	0.491
Minimum	-0.294	-0.339	-0.299	-0.260	-0.251
Mean	0.004	0.011	0.005	0.006	0.006
Standard deviation	0.092	0.110	0.105	0.079	0.085
Skewness	1.020	2.131	1.374	2.659	1.275
Kurtosis	3.261	14.040	6.977	16.607	4.839
Jarque-Bera probabi	0.0000	0.0000	0.0000	0.0000	0.0000
	EASTMAN CHEM.	GKN HOLD	GLAXOSMITHKLINE	HALLIBURTON	HANNOVER RU
Maximum	0.491	0.575	0.745	0.879	0.642
Minimum	-0.302	-0.342	-0.224	-0.364	-0.330
Mean	0.005	0.006	0.007	0.007	0.009
		0.091	0.077	0.100	0.109
Standard deviation	0.085				
Standard deviation	1.002	1.208	3.883	2.550	1.217
Standard deviation Skewness Kurtosis			3.883 27.429	2.550 17.341	
Standard deviation Skewness Kurtosis	1.002	1.208			4.892
Standard deviation Skewness Kurtosis Jarque-Bera probabi	1.002 4.625 0.0000	1.208 5.745 0.0000	27.429 0.0000	17.341 0.0000	4.892 0.0000
Standard deviation Skewness Kurtosis Jarque-Bera probabi HEID	1.002 4.625 0.0000 ELBERGCEMENT	1.208 5.745 0.0000 HEINEKEN	27.429 0.0000 HENKEL & CO	17.341 0.0000 HEWLETT-PACKARD	4.892 0.0000 HONDA MOTOR
Standard deviation Skewness Kurtosis Jarque-Bera probabi HEID Maximum	1.002 4.625 0.0000 ELBERGCEMENT 0.869	1.208 5.745 0.0000 HEINEKEN 0.519	27.429 0.0000 HENKEL & CO 0.993	17.341 0.0000 HEWLETT-PACKARD 0.714	4.892 0.0000 HONDA MOTOR 0.759
Standard deviation Skewness Kurtosis Jarque-Bera probabi HEID Maximum Minimum	1.002 4.625 0.0000 ELBERGCEMENT 0.869 -0.286	1.208 5.745 0.0000 HEINEKEN 0.519 -0.242	27.429 0.0000 HENKEL & CO 0.993 -0.285	17.341 0.0000 HEWLETT-PACKARD 0.714 -0.411	4.892 0.0000 HONDA MOTOR 0.759 -0.368
Standard deviation Skewness Kurtosis Jarque-Bera probabi HEID Maximum Minimum Mean	1.002 4.625 0.0000 ELBERGCEMENT 0.869 -0.286 0.007	1.208 5.745 0.0000 HEINEKEN 0.519 -0.242 0.003	27.429 0.0000 HENKEL & CO 0.993 -0.285 0.004	17.341 0.0000 HEWLETT-PACKARD 0.714 -0.411 0.009	4.892 0.0000 HONDA MOTOR 0.759 -0.368 0.008
Standard deviation Skewness Kurtosis Jarque-Bera probabi HEID Maximum Minimum Mean Standard deviation	1.002 4.625 0.0000 ELBERGCEMENT 0.869 -0.286 0.007 0.113	1.208 5.745 0.0000 HEINEKEN 0.519 -0.242 0.003 0.062	27.429 0.0000 HENKEL & CO 0.993 -0.285 0.004 0.082	17.341 0.0000 HEWLETT-PACKARD 0.714 -0.411 0.009 0.095	4.892 0.0000 HONDA MOTOR 0.759 -0.368 0.008 0.114
Standard deviation Skewness Kurtosis Jarque-Bera probabi HEID Maximum Minimum Mean Standard deviation Skewness	1.002 4.625 0.0000 ELBERGCEMENT 0.869 -0.286 0.007 0.113 2.434	1.208 5.745 0.0000 HEINEKEN 0.519 -0.242 0.003 0.062 2.726	27.429 0.0000 HENKEL & CO 0.993 -0.285 0.004 0.082 4.047	17.341 0.0000 HEWLETT-PACKARD 0.714 -0.411 0.009 0.095 1.175	4.892 0.0000 HONDA MOTOR 0.759 -0.368 0.008 0.114 2.313
Standard deviation Skewness Kurtosis Jarque-Bera probabi HEID Maximum	1.002 4.625 0.0000 ELBERGCEMENT 0.869 -0.286 0.007 0.113	1.208 5.745 0.0000 HEINEKEN 0.519 -0.242 0.003 0.062	27.429 0.0000 HENKEL & CO 0.993 -0.285 0.004 0.082	17.341 0.0000 HEWLETT-PACKARD 0.714 -0.411 0.009 0.095	1.217 4.892 0.0000 HONDA MOTOR 0.759 -0.368 0.008 0.114 2.313 12.073 0.0000

	JOHNSON CONT.	KERING	KOMATSU	DSM	PHILIPS
Maximum	0.440	0.447	0.911	0.506	161.939
Minimum	-0.623	-0.240	-0.295	-0.249	14.213
Mean	0.005	0.004	0.007	0.004	64.746
Standard deviation	0.090	0.082	0.110	0.076	0.074
Skewness	0.058	1.300	3.981	1.412	0.935
Kurtosis	10.395	4.440	26.070	6.719	0.599
Jarque-Bera probabi	0.0000	0.0000	0.0000	0.0000	0.0000
	LAFARGEHOLCIM	LINDE	MARSH & MCLENNAN	MCDONALD'S	MONDELEZ
Maximum	0.615	0.696	0.540	0.468	0.733
Minimum	-0.591	-0.259	-0.270	-0.233	-0.242
Mean	0.008	0.003	0.002	0.005	0.006
Standard deviation	0.099	0.084	0.067	0.074	0.080
Skewness	1.269	2.177	1.383	1.351	2.569
Kurtosis	8.581	13.769	11.141	6.604	17.808
Jarque-Bera probabi	0.0000	0.0000	0.0000	0.0000	0.0000
	NESTLE	NISSAN MOTOR	NOKIA OYJ	PERNOD RICARD	PFIZER
Maximum	0.633	0.748	0.653	0.490	1.280
Minimum	-0.270	-0.442	-0.592	-0.179	-0.265
Mean	0.007	0.006	0.010	0.003	0.007
Standard deviation	0.082	0.107	0.093	0.069	0.090
Skewness	2.383	1.816	1.000	1.457	5.915
Kurtosis	14.669	11.476	12.293	7.207	77.976
Jarque-Bera probabi	0.0000	0.0000	0.0000	0.0000	0.0000
	PPG INDUSTRIES	RICOH	SABMILLER	SANOFI	SCHNEIDER ELEC.
Maximum	0.370	1.153	0.254	0.585	0.391
Minimum	-0.294	-0.296	-0.177	-0.279	-0.220
Mean	0.003	0.007	-0.001	0.005	0.002
Standard deviation	0.067	0.105	0.055	0.078	0.065
Skewness	0.600	3.055	0.928	1.721	1.700
Kurtosis	4.688	28.829	3.779	9.869	8.671
Jarque-Bera probabi	0.0000	0.0000	0.0000	0.0000	0.0000
	SCOR	SEALED AIR	SIEMENS	SODEXO	SOFTBANK
Maximum	SCOR 0.663	SEALED AIR 0.641	SIEMENS 0.399	SODEXO 0.436	SOFTBANK 0.693
Maximum Minimum					
	0.663	0.641	0.399	0.436	0.693
Minimum	0.663 -0.276	0.641 -0.251	0.399 -0.253	0.436 -0.252	0.693 -0.365
Minimum Mean	0.663 -0.276 0.007	0.641 -0.251 0.006	0.399 -0.253 0.005	0.436 -0.252 0.004 0.070	0.693 -0.365 0.002
Minimum Mean Standard deviation	0.663 -0.276 0.007 0.083 1.880	0.641 -0.251 0.006 0.082 2.159	0.399 -0.253 0.005 0.075 1.153	0.436 -0.252 0.004 0.070 1.502	0.693 -0.365 0.002 0.079
Minimum Mean Standard deviation Skewness	0.663 -0.276 0.007 0.083	0.641 -0.251 0.006 0.082	0.399 -0.253 0.005 0.075	0.436 -0.252 0.004 0.070	0.693 -0.365 0.002 0.079 1.796
Minimum Mean Standard deviation Skewness Kurtosis	0.663 -0.276 0.007 0.083 1.880 11.451	0.641 -0.251 0.006 0.082 2.159 14.515	0.399 -0.253 0.005 0.075 1.153 5.041	0.436 -0.252 0.004 0.070 1.502 6.865	0.693 -0.365 0.002 0.079 1.796 15.000
Minimum Mean Standard deviation Skewness Kurtosis	0.663 -0.276 0.007 0.083 1.880 11.451	0.641 -0.251 0.006 0.082 2.159 14.515	0.399 -0.253 0.005 0.075 1.153 5.041	0.436 -0.252 0.004 0.070 1.502 6.865	0.693 -0.365 0.002 0.079 1.796 15.000
Minimum Mean Standard deviation Skewness Kurtosis	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000	0.693 -0.365 0.002 0.079 1.796 15.000
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.0002	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000 BOEING	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000 DOW CHEMICAL	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000 GOODYEAR	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000 PROCTER & GAMBLE	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000 TRANSOCEAN
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000 BOEING 0.467	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000 DOW CHEMICAL 1.262	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000 GOODYEAR 0.491	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000 PROCTER & GAMBLE 0.814	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000 TRANSOCEAN 1.128
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000 BOEING 0.467 -0.267	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000 DOW CHEMICAL 1.262 -0.314	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000 GOODYEAR 0.491 -0.252	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000 PROCTER & GAMBLE 0.814 -0.230	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000 TRANSOCEAN 1.128 -0.420
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Minimum Mean	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000 BOEING 0.467 -0.267 0.006	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000 DOW CHEMICAL 1.262 -0.314 0.009	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000 GOODYEAR 0.491 -0.252 0.002	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000 PROCTER & GAMBLE 0.814 -0.230 0.004	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000 TRANSOCEAN 1.128 -0.420 0.012
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000 BOEING 0.467 -0.267 0.006 0.083	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000 DOW CHEMICAL 1.262 -0.314 0.009 0.115	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000 GOODYEAR 0.491 -0.252 0.002 0.079	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000 PROCTER & GAMBLE 0.814 -0.230 0.004 0.070	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000 TRANSOCEAN 1.128 -0.420 0.012 0.120
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000 BOEING 0.467 -0.267 0.006 0.083 1.014	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000 DOW CHEMICAL 1.262 -0.314 0.009 0.115 3.214	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000 GOODYEAR 0.491 -0.252 0.002 0.079 1.263	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000 PROCTER & GAMBLE 0.814 -0.230 0.004 0.070 4.256	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000 TRANSOCEAN 1.128 -0.420 0.012 0.120 3.016
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000 BOEING 0.467 -0.267 0.006 0.083 1.014 5.469	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000 DOW CHEMICAL 1.262 -0.314 0.009 0.115 3.214 29.226	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000 GOODYEAR 0.491 -0.252 0.002 0.079 1.263 5.545	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000 PROCTER & GAMBLE 0.814 -0.230 0.004 0.070 4.256 41.438	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000 TRANSOCEAN 1.128 -0.420 0.012 0.120 3.016 21.632
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000 BOEING 0.467 -0.267 0.006 0.083 1.014 5.469	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000 DOW CHEMICAL 1.262 -0.314 0.009 0.115 3.214 29.226	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000 GOODYEAR 0.491 -0.252 0.002 0.079 1.263 5.545	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000 PROCTER & GAMBLE 0.814 -0.230 0.004 0.070 4.256 41.438	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000 TRANSOCEAN 1.128 -0.420 0.012 0.120 3.016 21.632
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000 BOEING 0.467 -0.267 0.006 0.083 1.014 5.469 0.0000	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000 DOW CHEMICAL 1.262 -0.314 0.009 0.115 3.214 29.226 0.0000	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000 GOODYEAR 0.491 -0.252 0.002 0.079 1.263 5.545 0.0000	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000 PROCTER & GAMBLE 0.814 -0.230 0.004 0.070 4.256 41.438 0.0000	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000 TRANSOCEAN 1.128 -0.420 0.012 0.120 3.016 21.632 0.0000
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000 BOEING 0.467 -0.267 0.006 0.083 1.014 5.469 0.0000	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000 DOW CHEMICAL 1.262 -0.314 0.009 0.115 3.214 29.226 0.0000 UNILEVER	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000 GOODYEAR 0.491 -0.252 0.002 0.079 1.263 5.545 0.0000	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000 PROCTER & GAMBLE 0.814 -0.230 0.004 0.070 4.256 41.438 0.0000	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000 TRANSOCEAN 1.128 -0.420 0.012 0.120 3.016 21.632 0.0000 WPP 2005 LMTD
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000 BOEING 0.467 -0.267 0.006 0.083 1.014 5.469 0.0000 UBS	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000 DOW CHEMICAL 1.262 -0.314 0.009 0.115 3.214 29.226 0.0000 UNILEVER 0.405	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000 GOODYEAR 0.491 -0.252 0.002 0.079 1.263 5.545 0.0000 VALEO 0.430	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000 PROCTER & GAMBLE 0.814 -0.230 0.004 0.070 4.256 41.438 0.0000 WEATHERFORD INT 1.121	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000 TRANSOCEAN 1.128 -0.420 0.012 0.120 3.016 21.632 0.0000 WPP 2005 LMTD 0.544
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000 BOEING 0.467 -0.267 0.006 0.083 1.014 5.469 0.0000 UBS 1.477 -0.318	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000 DOW CHEMICAL 1.262 -0.314 0.009 0.115 3.214 29.226 0.0000 UNILEVER 0.405 -0.282	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000 GOODYEAR 0.491 -0.252 0.002 0.079 1.263 5.545 0.0000 VALEO 0.430 -0.372	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000 PROCTER & GAMBLE 0.814 -0.230 0.004 0.070 4.256 41.438 0.0000 WEATHERFORD INT 1.121 -0.230	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000 TRANSOCEAN 1.128 -0.420 0.012 0.120 3.016 21.632 0.0000 WPP 2005 LMTD 0.544 -0.220
Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Standard deviation Skewness Kurtosis Jarque-Bera probabi Maximum Minimum Mean Maximum Minimum Minimum Minimum Minimum Minimum Minimum Minimum Minimum Minimum Mean	0.663 -0.276 0.007 0.083 1.880 11.451 0.0000 SOLVAY 0.683 -0.328 0.007 0.090 1.946 10.018 0.0000 BOEING 0.467 -0.267 0.006 0.083 1.014 5.469 0.0000 UBS 1.477 -0.318 0.012	0.641 -0.251 0.006 0.082 2.159 14.515 0.0000 SONY 0.758 -0.410 0.008 0.113 1.532 7.872 0.0000 DOW CHEMICAL 1.262 -0.314 0.009 0.115 3.214 29.226 0.0000 UNILEVER 0.405 -0.282 0.004	0.399 -0.253 0.005 0.075 1.153 5.041 0.0000 STARWOOD HOTELS 1.019 -0.481 0.002 0.094 2.138 29.043 0.0000 GOODYEAR 0.491 -0.252 0.002 0.079 1.263 5.545 0.0000 VALEO 0.430 -0.372 0.004	0.436 -0.252 0.004 0.070 1.502 6.865 0.0000 TECHNIP 0.580 -0.272 0.005 0.072 2.247 14.994 0.0000 PROCTER & GAMBLE 0.814 -0.230 0.004 0.070 4.256 41.438 0.0000 WEATHERFORD INT 1.121 -0.230 0.011	0.693 -0.365 0.002 0.079 1.796 15.000 0.0000 ERICSSON 0.565 -0.325 0.006 0.080 1.312 8.187 0.0000 TRANSOCEAN 1.128 -0.420 0.012 0.120 3.016 21.632 0.0000 WPP 2005 LMTD 0.544 -0.220 0.004
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To explore how closely the spreads for the various corporate CDS move together, we measure Spearman rank correlations for weekly changes in the premia, which can be found in Appendix E. All of them turn out to be positive and significant at a 1% level suggesting that the spread changes are driven by common factors.

Prior to the extraction of the factors, we assess the suitability of the data for factor analysis. These tests include Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. Authors such as Williams, Onsman and Brown (2010), consider a KMO index above 0.50 as indicating that data are suitable for factor analysis. On the other hand, the null hypothesis of the Bartlett's Test of Sphericity states that the observed correlation matrix is equal to the identity matrix (lack of sufficient correlation between the variables), which in the study is always rejected confirming that the observed correlation matrix is statistically different from a singular matrix and linear combinations exist (Beavers et al., 2013).

The results from the principal components analysis are shown in Table 11. They exhibit a first factor explaining 42.3 percent of the variation in spreads, which can be identified as a European factor.²⁴ The second principal component explains an additional 4.2 percent of the variation and is primarily a European Automotive factor. The third one explains an additional 3.7 percent and correlates best with the U.S. Energy sector. The fourth principal component explains an additional 3 percent of the variation and represents a part of the US market. The fifth principal component explains an additional 2.5 percent and is related to the US Automotive sector. Together, the first three principal components explain a 50.18 percent of the total variation in CDS spreads and 10 common factors drive 65 percent of the movement of the risk premium in the 75 firms sample.

²⁴ See Table 19 for detailed factors components.

Since the purpose is to find out if there is a global economic risk underlying multinational corporations and since the financial sector has been broadly analysed in this sense, we next perform a similar PCA but excluding the 6 banks and insurance companies. This analysis points out a first principal component explaining 42.7 percent of the variation in spreads, a second one explaining an additional 4.3 percent of the variation and a third principal component explaining an additional 3.9 of the variation. Together, the first three principal components explain the 50.94 percent of the total variation in CDS spreads and are primarily a general European, European Automotive and Japanese factor respectively. The fourth principal component is more related to the US Energy sector while the fifth one to other US industries. Results confirm that ten common factors drive 65.5 percent of the risk premium movement in the subsample.

Table 11: Principal Component Analysis

PCA for extracting the common factors underlying weekly variations in the CDS spreads.

	75 firms	69 firms
PC 1 (%)	42.296	42.719
PC 2 (%)	4.186	4.307
PC 3 (%)	3.698	3.916
PC 4 (%)	2.974	3.119
PC 5 (%)	2.535	2.715
PC 6 (%)	2.224	2.066
PC 7 (%)	1.910	1.882
PC 8 (%)	1.683	1.693
Cum Var (%)	61.506	62.417
KMO	0.967	0.968
Bartlett Sig	0.000	0.000

These results evidence that changes in CDS premia evolve together and highlight a risk of default that is not explained by sector or country specific factors but by global ones. They are

in line with Diaz et al. (2013) who find a first component explaining the 56% of the variation in spread changes, and with Berndt and Obreja (2010) who note a first factor explaining 53% of CDS weekly returns. However, it must be noted that both studies deal with European companies, without assessing multinationality, for shorter periods of time (2006-2010 and 2003-2008 respectively), and that in Diaz et al. (2013) all companies are investment grade firms, being therefore more homogeneous than the sample analysed here, which comprises all kinds of credit qualities, over a longer time period, that includes periods of crisis and financial calm.

Anyhow, we find interesting that there is a dominant factor which drives the spreads of multinational companies across all countries and sectors, which is consistent with the existence of a global credit risk component and which corroborates the findings of Longstaff and Rajan (2008) regarding an industry and economywide default risk accounting for one-third of the total CDX index spread.

4.4. Sector Analysis

Following Diaz et al. (2013) who suggest the importance of sectors when it comes to compare the level and behavior of CDS premia, Table 12 details the components of each group and Table 13 summarizes the main statistics for the CDS spreads by industry.

Table 12: Sectors components

The table shows each of the 75 firms of the sample in the industry they belong to.

Auto	Chemical	Consumer	Energy	Manufacturing	
Daimler	Akzo Nobel	Henkel Baker Hughes		Caterpillar	
Nissan Motor	E. I. Du Pont	Electrolux BP		Komatsu	
BMW	DSM	Diageo Weatherford		Ricoh	
Honda Motor	PPG	Unilever Transocean		Schneider Electr.	
Goodyear	Sabmiller	Nestle	Nestle Apache		
GKN	Linde	Procter & Gamble	Halliburton	Canon	
Valeo	Eastman	Mondelez	Technip	Volvo	
Borgwarner	Dow Chemical	Pernod Ricard	•		
Continental	Continental Solvay Britis			Heidelbergcement	
Johnson Controls		Heineken		Sony	
				Philips	
Other	Pharma	Technology	Telecomm.	Fin. Inst.	
Bae Systems	Astrazeneca	Hewlett Packard	Nokia	Marsh & Mclennan	
Baxter	Bayer	Arrow Electr.	Softbank	UBS	
Sodexo	Bristol Myers S.	Avnet	Ericsson	Hannover Rueck	
Arcelormittal	Glaxosmithkline			Scor	
Sealed Air	Pfizer			Citigroup	
Kering	Sanofi			Credit Suisse	
Starwood Hotels	S				
Boeing					
WPP 2005					
Mcdonald's					

Table 13: Main statistics for the 5-year CDS spreads across sectors.Sectoral CDS are characterized by different levels of risk.

	Auto	Chemical	Consumer	Energy	Manufact.
Maximum	1600.96	630.05	746.02	2399.79	4454.34
Minimum	4.22	8.69	3.25	3.67	3.25
Mean	161.83	74.18	63.66	140.09	111.24
Standard deviation	186.40	48.42	59.79	217.66	227.12
Coefficient of variation	1.15	0.65	0.94	1.55	2.04
Skewness	2.97	4.20	5.85	5.08	11.35
Kurtosis	11.56	34.00	50.91	34.14	161.62
Observations	5156	4568	5125	3612	5676
Missing values	4	76	35	0	0
Zero increment (%)	7.76	3.22	3.90	5.92	2.55
	Other	Pharma	Technology	Telecomm.	Fin. Inst.
Maximum	1155.91	187.21	560.76	2266.67	653.79
Minimum	7.79	4.46	8.25	8.28	4.69
Mean	117.59	44.75	114.54	214.03	94.39
Standard deviation	129.29	22.98	68.60	259.93	63.74
Coefficient of variation	1.10	0.51	0.60	1.21	0.68
Skewness	2.75	1.28	1.68	3.96	2.46
Kurtosis	9.96	3.81	5.36	20.75	12.18
Observations	5157	2577	1548	1548	3096
Missing values	3	3	0	0	0
Zero increment (%)	3.45	7.26	2.20	1.23	2.78

We note that a typical Telecommunications firm has the widest average spread although the highest maximum price was quoted in the Manufacturing industry. This sector also records the highest coefficient of variation and the least normal distribution, as represented by the highest skewness and kurtosis. Figures suggest that in the 2007-2016 timeframe, the Telecommunications, Automotive and Energy sectors where the most risky as stated by their high average spreads. By contrast, Pharma seems to be the less volatile sector, with the lowest average spread (followed by the Consumer and Chemical industries) and with the most normal-like distribution. These results are in line with Narayan, Narayan and Prabheesh

(2014) findings for data spanning between 2004 to 2012 where the Healthcare and Consumer staples sectors appear to show the narrowest average spreads.

To make the sector study complete, we next analyse the relevance of common factors driving the variation in the CDS spreads in each industry.

Results in Table 14 show a strong first principal component that drives the behavior of each industry when taking into account global corporates, ranging between 47.46% ("Other") and 79.14% (Technology). The fact that the "Other" sector, which is a catch-all one for multinational firms which do not belong to another industry with enough representations, shows a strong unobserved factor generating common movements in the spreads changes, provides support for a global credit risk component. It is also relevant to underscore that the Technology industry (79.14%) shows a stronger first principal component driving its behavior than the Financial Industry (62.92%) whose communalities are broadly accepted. Even the rest of the sectors show a co-movement at a similar level. Figure 15 depicts the first three principal components that drive the behavior of each industry.

Table 14: Principal sector components analysis results.

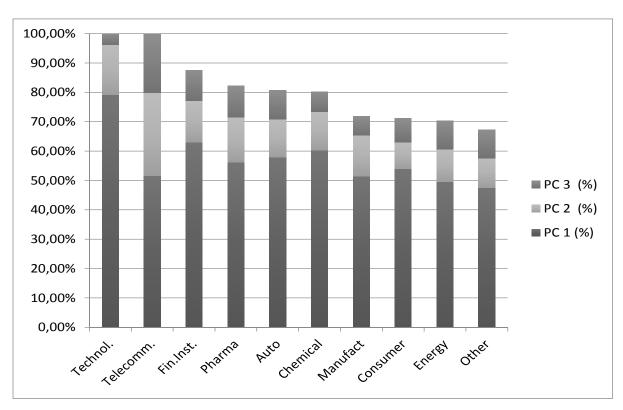
This table reports summary statistic for PCA of the correlation matrix of weekly changes in 5-year CDS spreads for the different industries comprising the sample and ranging from 2007 to 2016.

	Auto	Chemical	Consumer	Energy	Manufact
PC 1 (%)	57.915	60.191	53.971	49.471	51.509
PC 2 (%)	12.911	13.264	9.098	11.209	13.848
PC 3 (%)	9.878	6.729	8.111	9.714	6.452
Cum Var (%	80.704	80.184	71.180	70.394	71.809
KMO	0.865	0.906	0.932	0.863	0.918
Bartlett Sig	0.000	0.000	0.000	0.000	0.000

	Other	Pharma	Technol. T	elecomm.	Fin. Inst.
PC 1 (%)	47.457	56.131	79.144	51.586	62.921
PC 2 (%)	10.048	15.354	16.995	28.249	14.210
PC 3 (%)	9.684	10.748	3.861	20.165	10.371
Cum Var (%	67.189	82.233	100.000	100.000	87.502
KMO	0.905	0.834	0.662	0.578	0.849
Bartlett Sig	0.000	0.000	0.000	0.000	0.000

Figure 15: Three principal components by sector.

This figure shows the first three principal components that drive the behavior of each industry making evident the existence of a strong unobserved factor, which generates common movements in the spreads changes.



To provide a better understanding of the components of each sector we compute the correlations between the original data for every firm and each principal component. In the case of the Auto, Chemical, Manufacturing and "Other" segments, two main components are extracted (PC1 and PC2). In the rest of the sectors, one principal component (PC1) includes all firms of the industry.

In the Automotive industry, the PC1 is strongly correlated with 5 European and 2 American firms, while the PC2 is more related to Japanese corporates (and 1 American company). This suggests that the first is a European factor (and that U.S. Goodyear and Johnson Controls vary together with it) while the second is a Japanese one which includes U.S. Borgwarner. Furthermore, figures evidence that the first principal component correlates most strongly with the German companies (Daimler 0.872, BMW 0.866 and Continental 0.818) and the second component with Nissan (0.893), followed by Honda (0.879).

Regarding the Chemical sector, the first principal component moves with changes in the European industry as it is highly correlated to every European firm, correlating most strongly with the continental firms (Akzo Nobel 0.874, Linde 0.859, DSM 0.840, Solvay 0.837) and less with the UK Sabmiller. The PC2 suggests that the 4 U.S. corporates vary together led by Eastman Chemical (0.848).

PC1 of the Manufacturing segment can be viewed as a measure of the European market as it is highly correlated to the 6 European corporates that form this sector, and, with the lowest coefficient, to U.S. Caterpillar. PC2 is a measure of the Japanese industry.

The catch-all "Other" sector shows a PC1 which is primarily a measure of the European market (WPP 2005 0.842, Sodexo 0.828, Kering 0.816 and Bae Systems 0.804), although also

correlated to U.S. firms. Interestingly, the Luxembourger Steel corporation does not correlate to this PC1 and therefore is a PC2 itself.

In the remaining industries, one principal component (PC1) includes all firms due to their high correlation with the synthetic component. The Consumer factor correlates most to the European Packaged Goods companies (Unilever, Nestlé and Henkel) and the Tobacco firm British American Tobacco. The Energy factor correlates strongly with the U.S. Transocean, Halliburton and Apache companies. The Pharma component is mainly a European factor as it varies most with the changes in Sanofi, Bayer, Astrazeneca and Glaxosmithkline. The Technology and the Telecommunications subsamples are configured by only 3 firms being Avnet and Arrow Electronics more representative in the former (where all of them are USA based companies) and Ericsson and Nokia (the Europeans in contrast to the Japanese firm) in the latter. Finally, the companies in the Financial sector vary together but due to the higher correlation of the Swiss entities, it is concluded that it is primarily a measure of the Swiss financial segment and that the other European firms (Hannover Ru. and Scor) move in a more similar way than the U.S. Citigroup and Marsh and McLennan.

We do not find important differences between the factors in what concerns credit ratings. All of them have high correlation to firms with diverse credit quality, except the "Other" PC2 which is composed by only one firm (Arcelormittal, Non-investment grade). The latter, together with the Energy factor (from Highly Speculative to Upper Medium Grade) and the Telecomm component (Non-investment and Lower Medium Grade) are the factors with lower credit ratings. The factor associated to higher credit quality is Pharma (High and Upper Medium Grade) followed by Financial Institutions and Consumer Products (from High to Lower Medium Grade).

To explore how closely the first principal components of the different industries move together, Table 15 reports the Spearman correlations. 73% of the pairwise correlations between the industries PC1s show a strong or very strong, and the remaining 27% a moderate strength level of correlation.²⁵

Table 15: Principal components correlations (Spearman)

Principal components correlations (Spearman) for the sample (75 companies), subsample (non-financial 69 firms) and sectoral PCs. * and ** indicate significance at the 5% and 1% level, respectively.

	PC1_75	PC1_69	PC1 Auto	PC2 Auto	PC1 Chemical	PC2 Chemical	PC1 Consumer	PC1 Energy
PC1_75	1							
PC1_69	.968(**)	1						
PC1 Auto	.352(**)	.373(**)	1					
PC2 Auto	.098 (*)	.087	054	1				
PC1 Chemical	.778(**)	.790(**)	.539(**)	.208(**)	1			
PC2 Chemical	068	059	.391(**)	.224(**)	076	1		
PC1 Consumer	.608(**)	.618(**)	.744(**)	.313(**)	.725(**)	.389(**)	1	
PC1 Energy	.289(**)	.322(**)	.574(**)	.353(**)	.486(**)	.409(**)	.715(**)	1
PC1 Manufact.	.565(**)	.582(**)	.753(**)	.149(**)	.673(**)	.374(**)	.818(**)	.663(**)
PC2 Manufact.	125(**)	107 (*)	024	.542(**)	.064	.144(**)	.124(**)	.173(**)
PC1 Other	.481(**)	.500(**)	.740(**)	.303(**)	.643(**)	.477(**)	.882(**)	.701(**)
PC2 Other	035	012	.128(**)	.236(**)	.147(**)	.426(**)	.194(**)	.271(**)
PC1 Pharma	.587(**)	.597(**)	.657(**)	.323(**)	.703(**)	.350(**)	.823(**)	.631(**)
PC1 Technol.	.244(**)	.249(**)	.622(**)	.282(**)	.416(**)	.478(**)	.672(**)	.576(**)
PC1 Telecom.	.408(**)	.398(**)	.556(**)	.348(**)	.541(**)	.249(**)	.695(**)	.580(**)
PC1 Fin.Inst.	.340(**)	.455(**)	.686(**)	.210(**)	.582(**)	.382(**)	.757(**)	.640(**)

	PC1 Manufact.	PC2 Manufact.	PC1 Other	PC2 Other	PC1 Pharma	PC1 Technol.	PC1 Telecom.	PC1 Fin.Inst.
PC1 Manufact.	1							
PC2 Manufact.	142(**)	1						
PC1 Other	.808(**)	.138(**)	1					
PC2 Other	.191(**)	.141(**)	.302(**)	1				
PC1 Pharma	.733(**)	.154(**)	.824(**)	.214(**)	1			
PC1 Technol.	.643(**)	.180(**)	.746(**)	.299(**)	.643(**)	1		
PC1 Telecom.	.644(**)	.212(**)	.647(**)	.160(**)	.638(**)	.584(**)	1	
PC1 Fin.Inst.	.712(**)	.138(**)	.748(**)	.173(**)	.677(**)	.587(**)	.575(**)	1

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²⁵ Previous literature describes the strength of the correlation using the following guide for the absolute value of p: .00-.19 "very weak" .20-.39 "weak" .40-.59 "moderate" .60-.79 "strong" .80-1.0 "very strong (e.g. Starmer et al., 2015).

Correlations are significant at a 1% in all cases but for the sectors PC2. The Japanese Automotive industry (PC2 Auto) shows no significant correlation to the European Automotive segment (PC1 Auto) and to the 69 non-financial corporate portfolio. It also exhibits a 5% significant correlation to the 75 corporate portfolio. On the other hand, the US Chemical sector (PC2 Chemical) shows no significant correlation to the European Chemical segment (PC1 Chemical) and to the global 75 and 69 corporate portfolios. The Japanese Manufacturing industry (PC2 Manufact.) shows no significant correlation to the European Automotive segment (PC1 Auto) and to the European Chemical segment (PC1 Chemical). It also exhibits a 5% significant correlation to the 69 non-financial corporate portfolio. At last, the "Other" PC2, which consists solely of Arcelormittal, does not correlate to the rest of the firms (PC1_75 and PC1_69). In sum, PC2s do not correlate to their same industry PC1s (which is consistent to the goal of PCA of converting a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables) and the Japanese factors show a lower correlation to the global portfolios. In all other cases, correlations are positive, significant at 1% level and show a strong to very strong level.

Dynamics between industries

After measuring the degree of connectedness between the firms in each industry, we next perform a Vector Autoregressive Analysis (VAR) and use Granger-causality networks to model the dynamics between sectors (using their first principal component PC1) and to explore the lead lag relationship between them. Following Billio et al. (2012) and suggested by other authors before, the degree of Granger causality between sectors can be viewed as a proxy for credit risk spillover effects among them. The purpose is to study the relationships

between the global industries and their directionality to be able to interpret the so called global credit risk.

We first prove for stationarity in the sectors PC1s to avoid the possibility of spurious relationships between variables because of common trends. By applying the Johansen test to the sectors PC1 to look for cointegration, all of them are found to be stationary.

The Final Prediction Error (FPE) and the Akaike's Information Criterion (AIC) are used as the lag length selection criteria in the analysis, proving that no more than one lag (in weekly basis) is determinant. We also perform F-tests of the null hypotheses that the coefficients are equal to zero, i.e. there is no Granger-causality between sectors. Results are shown in Table 16.

Table 16: P-values of linear Granger-causality tests.

The table depicts P-values of linear Granger-causality tests for first principal components of each sector composing the sample of the most global corporates. Statistics that are significant at the 1%, 5% and 10% level are shown in bold.

					TO:					
FROM:	Auto	Chemical	Consumer	Energy	Manufact.	Other	Pharma	Technol.	Telecomm.	Fin. Inst.
Auto		0.557	0.163	0.046	0.410	0.710	0.848	0.395	0.526	0.408
Chemical	0.050		0.125	0.757	0.386	0.048	0.090	0.239	0.978	0.985
Consumer	0.453	0.001		0.422	0.059	0.014	0.074	0.013	0.019	0.187
Energy	0.166	0.191	0.946		0.135	0.769	0.451	0.192	0.035	0.722
Manufact.	0.206	0.862	0.930	0.518		0.979	0.552	0.614	0.376	0.765
Other	0.965	0.002	0.004	0.142	0.088		0.009	0.810	0.107	0.010
Pharma	0.035	0.000	0.002	0.001	0.005	0.002		0.024	0.003	0.001
Technol.	0.305	0.046	0.236	0.020	0.239	0.389	0.264		0.725	0.209
Telecomm.	0.333	0.935	0.046	0.038	0.550	0.075	0.057	0.206		0.318
Fin. Inst.	0.423	0.179	0.020	0.958	0.024	0.002	0.078	0.405	0.263	

P-values of the linear Granger-causality test evidence that there are important lead/lag relationships between many of these global sectors constituted by multinational companies.

We find feedback loops between Telecommunications (European, Non-investment Grade factor) and the Consumer Products sector (European, Upper Medium Grade factor) and between Telecommunications and Energy (U.S., Lower Medium Grade factor). It also reveals that the "Other" segment (European, Lower Medium Grade factor) maintains a feedback relationship with the Chemical, Consumer Products, Pharmaceutical and Financial Institutions industries (all of them European factors with the highest investment grades ranging from Lower Medium to High Grade). Unexpectedly, the "Other" sector and Pharma are found to Granger-cause Financial Institutions.

The most interesting and somehow puzzling result in this sample is the fact that the Pharma sector (European, with the highest quality) appears to lead all other industries. This evidences that this industry is playing a main role in the transmission of global economic risk to the rest of the Economy. According to the European Commission, the EU Pharmaceutical sector is essential to achieve a competitive knowledge-based economy. ²⁶ It is one of Europe's top performing high-technology sectors and a research-based industry, key asset of the European economy. In 2015, around €31,500 million were invested in R&D in Europe (it is the industry with highest R&D intensity). The European sector employs 725,000 people directly and around 2.5 million people indirectly. The revenue of the worldwide Pharma market has grown from \$390 billion in 2001 to \$1 trillion in 2015. ²⁷ North America accounts for 49% share of the market, while Europe and Japan for 22% and 8% respectively. In 2013,

²⁶ http://ec.europa.eu/growth/sectors/healthcare es

²⁷ https://www.statista.com/statistics/263102/pharmaceutical-market-worldwide-revenue-since-2001/

the total spending (public and private) on healthcare as a percentage of GDP at market prices was 9%, 16% and 10% in Europe, USA and Japan respectively.²⁸

In sum, results and figures evidence that it is necessary to deepen in the links between the pharma sector and the remaining industries and that further research regarding this issue should be undertaken.

4.5. Dynamics between global credit risk and market risk.

Following the identification of common factors across firms and sectors that might drive their default premia and with the goal of going further in a better interpretation of those first factors, we next aim to understand the relationship between credit risk and market risk. The former is the fear regarding the future economic health of these firms and sectors, while the latter carries systematic risk. Both affect each other (Jarrow and Turnbull, 2000).

For this purpose we run the correlation of each first common factors (from the 2 portfolios as well as from the 10 sectors) with changes in the CBOE implied volatility index (VIX) to understand which portion of this co-movement is attributable to VIX. This is in line with Hammoudeh, Liu, Chang, and McAleer (2013) who explores the risk feedbacks between oil-related CDS spreads and VIX.²⁹

We also compute correlations with another global equity indicator, the MSCI ACWI index,³⁰ and with two other CDS indices: iTraxx and CDX.³¹

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²⁸ http://www.efpia.eu

²⁹ The VIX index measures expectations of volatility of the S&P 500 index over one month. It typically moves in an adverse direction to the stock markets and is known as a fear indicator. Fernandes, Medeiros and Scharth (2014) for detailed information.

³⁰ The MSCI ACWI equity index comprises 2.484 large and mid cap entities across 23 Developed Markets and 23 Emerging Markets countries, covering approximately 85% of the global investable equity opportunity set. Visit https://www.msci.com/documents/10199/a71b65b5-d0ea-4b5c-a709-24b1213bc3c5 for broader information.

³¹ The iTraxx and CDX indices comprise 125 equally weighted European/U.S. (respectively) CDS on investment grade entities.

Table 17: Spearman rank correlations.

The table shows the correlations between the changes in credit indices (iTraxx and CDX), the equity index ACWI, the volatility VIX index and the first factor of each of the sectors and portfolios (composed by 75 companies and by the 69 non-financial ones). ** indicates significance at the 1% level.

	iTraxx	CDX	ACWI	VIX	75	69
iTraxx	1					
CDX	.887(**)	1				
ACWI	.753(**)	767(**)	1			
VIX	.595(**)	.610(**)	726(**)	1		
75	.393(**)	.300(**)	290(**)	.170(**)	1	
69	.459(**)	.352(**)	334(**)	.213(**)	.968(**)	1
Auto	.739(**)	.722(**)	623(**)	.437(**)	.352(**)	.373(**)
Chemical	.594(**)	.519(**)	470(**)	.311(**)	.778(**)	.790(**)
Consumer	.784(**)	.738(**)	652(**)	.459(**)	.608(**)	.618(**)
Energy	.638(**)	.651(**)	533(**)	.351(**)	.289(**)	.322(**)
Manufact.	.741(**)	.702(**)	562(**)	.400(**)	.565(**)	.582(**)
Other	.765(**)	.767(**)	621(**)	.448(**)	.481(**)	.500(**)
Pharma	.681(**)	.648(**)	539(**)	.397(**)	.587(**)	.597(**)
Technol.	.619(**)	.657(**)	513(**)	.376(**)	.244(**)	.249(**)
Telecom.	.607(**)	.553(**)	516(**)	.336(**)	.408(**)	.398(**)
Financial	.828(**)	.764(**)	635(**)	.468(**)	.340(**)	.455(**)

As shown in Table 17, correlations are significant at a 1% in all cases. As expected, MSCI ACWI correlates negatively to all other variables, which is consistent with the strong negative link between CDS spread changes and stock returns stated by previous literature (e.g. Norden and Weber, 2009).

Regarding market risk indices, figures evidence that ACWI shows a stronger correlation (coefficient) to all the PCA common factors than VIX does. On the other hand, those principal components exhibit a similar correlation strength to both credit risk indices (which is not surprising given that iTraxx and CDX show a 0,887 correlation with a 1% significant level).

The positive significant coefficients between VIX and the PC1s confirm the expectations about changes in global credit risks being positively related to changes in the volatility index. It confirms Collin-Dufresne, Goldstein, and Martin (2001) and Blanco et al. (2005) findings about implied stock volatilities being an important explanatory variable for changes in credit spreads. However, this relationship is not very strong (0.17).

Interestingly, the Energy sector is not the highest correlated to VIX neither. Hammoudeh et al. (2013) find that the "fear" index hit its historic high immediately after the oil price reached its historic peak in July 2008, but sectors such as Financial Institutions (0.47) "Other" (0.45), Consumer (0.46), Automotive (0.44), Manufacturing (0.40), Pharma (0.40) and Technology (0.38) industries show a stronger Spearman coefficient than the Energy group (0.35). This, once again, corroborates the global risk that drives the spreads of the CDS of the multinational companies, which are therefore less conditioned by sectorial risks.

We next perform a VAR analysis and Granger-causality test to identify the network of statistically significant Granger-causal relations among the risk premiums of each sector and portfolio and the credit and market risk indices. Results are shown in Table 18, while Figure 16 depicts the relationships at a 1% significance level

Table 18: P-values of linear Granger-causality tests from credit and market risk indices to the different portfolios and industries and viceversa.

The table depicts P-values of linear Granger-causality tests from the iTraxx, CDX, VIX and ACWI indices to the first principal components of each sample and sector, as well as from the first principal components of each sector and portfolio to the iTraxx, CDX, VIX and ACWI indices. Statistics that are significant at 1%, 5% and 10% level are shown in bold.

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FROM:	75	69	Auto	Chemical	Consumer	Energy
iTraxx	0.138	0.047	0.231	0.023	0.149	0.316
CDX	0.759	0.759	0.882	0.376	0.124	0.363
VIX	0.000	0.000	0.001	0.000	0.085	0.239
ACWI	0.001	0.000	0.237	0.004	0.012	0.002

TO:

FROM:	Manufact.	Other	Pharma	Technol.	Telecom.	Fin.Inst.
iTraxx	0.646	0.702	0.049	0.931	0.035	0.285
CDX	0.026	0.49	0.248	0.982	0.328	0.049
VIX	0.045	0.431	0.227	0.899	0.141	0.518
ACWI	0.013	0.069	0.251	0.001	0.066	0.472

FROM:

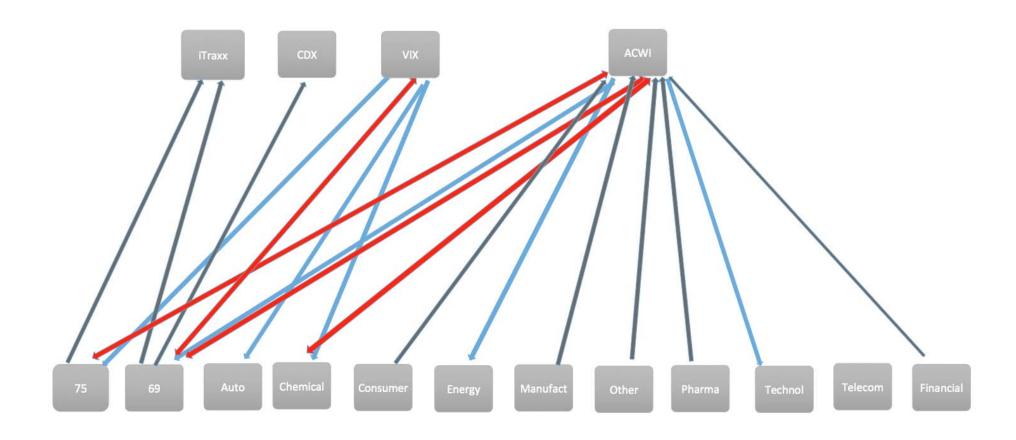
TO:	75	69	Auto	Chemical	Consumer	Energy
iTraxx	0.006	0.001	0.075	0.014	0.441	0.033
CDX	0.015	0.009	0.130	0.055	0.299	0.487
VIX	0.013	0.006	0.742	0.015	0.708	0.873
ACWI	0.000	0.000	0.455	0.000	0.000	0.166

FROM:

TO:	Manufact.	Other	Pharma	Technol.	Telecom.	Fin.Inst.
iTraxx	0.632	0.330	0.594	0.601	0.638	0.148
CDX	0.197	0.600	0.253	0.466	0.194	0.011
VIX	0.540	0.663	0.512	0.977	0.182	0.203
ACWI	0.000	0.000	0.000	0.026	0.471	0.000

Figure 16: Granger-causality relationships at a 1% significance level.

This graph shows the Granger-causality relationships between the different indices and the portfolios/industries that are significant at 1% level. In black color are shown the portfolios Granger-causing indices. In blue, indices Granger-causing portfolios/industries. In red, feedback loops between both, indices and portfolios, are depicted.



When taking into account up to the 10% significance level, we note that regarding credit risk indices, the iTraxx index is leading a higher number of portfolios than the CDX index does. This is no surprise as the PC1s have been used and those where mainly European factors. This also stands for the other round relationship. Furthermore, both indices lag a higher number of portfolios/industries than they lead, revealing that the PC1s of the portfolios/sectors provide statistically significant information about future values of those indices.

Regarding the market risk indices, both VIX and ACWI show a loop relationship with the two corporate portfolios. Besides this, the ACWI index shows an informational loop with almost all the PC1s too, providing evidence of the tight relationship between sectorial credit risk factors and the portfolio formed with 85% of the global investable equities.

In addition to these two-way relationships, the Granger-causality test proves that VIX leads the Automotive sector while this leads iTraxx. On the other hand, ACWI leads the Energy segment while the latter also leads iTraxx. Regarding the Pharma industry, it lags iTraxx but leads ACWI. There is evidence that the Telecommunications industry leads both, iTraxx and ACWI. Finally, the CDX index leads the Financial sector while this leads ACWI.

In any case, it is evidenced that the global industries have more significant feedback loops with the ACWI global market risk index than with the well-known volatility indicator.

We also find that regarding the 75 firms and the non-financial portfolios, the null hypotheses of coefficients being equal to zero is always rejected, and therefore, we can state that the global companies in the sample Granger cause all global indices, the European and US credit risk ones as well as the market risk indicators (measured in terms of volatility as well as in equity prices).

4.6. A diversified portfolio for international investors

The results obtained so far lead us to propose an alternative strategy to constitute an international and sectorally diversified investment portfolio. It will be formed by a reduced number of assets that also exhibit credit quality diversity, thus limiting the market risk level and facing up the already evidenced global credit risk.

Recent evidence in financial markets suggests that the benefits of international diversification have declined in the post-2000 period. In a globalized world, where geographical divisions are becoming less relevant, diversification opportunities are scarcer and harder to achieve. In fact, this reduction in the potential for diversification entails a greater risk in investments (Cotter, Gabriel and Roll, 2016).

As already stated, in opposition to publications related to systemic risk in financial markets, there has been a scarce number of articles published in relation to systematic global risk and therefore, to the implications for the investor of a more integrated and less diversified world.

Some studies have focused on the advantages of investing in emerging markets, which continue to have the greatest benefits of diversification (Beckaert and Harvey, 2014; or Berger, Pukthuanthong and Yang, 2011), and others have analysed the integration of some type of financial asset in the markets or have studied diversification indices (Cotter et al., 2016).

The cited Cotter et al. (2016) article points to the high level of credit risk in the markets as a cause of the decline in diversification capacity. Based on this line, we estimate the diversification potential of a portfolio exposed to credit risk, considering the set of multinational companies that meet globalization requirements. Therefore, we contribute to fill

the existing gap in the literature regarding international diversification, offering a simple way to diversify systematic risk in portfolios exposed to credit risks.

After obtaining the common factors that affect the credit risk of multinational companies through a principal component analysis (PCA) and detecting a high degree of communality consistent with previous studies, we now use these factors to select the companies that will form a diversified portfolio. According to Roll (2013), portfolio managers should go beyond the correlations and look at the common factors that affect the risks; this is because, although the correlations between two assets may be low, the common factors affecting those two assets may be the same and therefore the benefits of diversification null. However, the factors obtained reflect the underlying risks to which financial assets are exposed. If, for two given assets, these factors are the same, we find that combining these assets does not reduce systematic risk. Thus, assets that provide different idiosyncratic (or specific) risk, and therefore depend on different factors, are needed.

We follow this new approach to international diversification and provide a new application, demonstrating clearly the benefits that it has for global investors. We study how to achieve an optimal diversification by using the common factors that we have found to drive the changes in the CDS of multinational companies.

The set of multinational companies with geographically highly delocalized revenues should in itself constitute a portfolio with diversified risk. Investing in these assets does not carry a specific geographic risk since their incomes do not come only from the country where they are domiciled but from many other places. Therefore, an investor eager to maintain a well-diversified portfolio could opt for the set of the largest global companies. However, as the number of the entities is high, investing in all of them could lead to excessive fees payment and high management needs. Furthermore, and as explained before, an investor

would also be investing in companies whose exposure to the underlying risks is very similar and consequently enhancing the vulnerability of the portfolio. For this reason we go beyond simple diversification based on correlations and deepen in the selection criteria of companies considering global credit risk.

The PCA completed in Section 4.3. helps us to extract a few factors that account for much of the overall variability and thus reduce the dimensionality of the initial group of multinationals to a small but highly diversified portfolio. The factors obtained by the PCA are orthogonal to each other, and therefore independent, reflecting the structure in which the overall credit risk is summarized.

By transforming the sample of companies into a portfolio with lower number of assets, we retain those that contribute the most to the variance and are represented in different factors, leaving aside those companies that are redundant for diversification purposes.

The results of the PCA of the CDS of the 75 companies are again shown in Table 19, this time exhibiting all the components of each factor. The first factor reflects the highest possible proportion of the original variability. The second reflects the maximum possible variability not included in the first one, and so on. In this way, companies are grouped into 11 easily interpretable factors with which we collect 66% of the variability in the sample.

Table 19: 75 CDS Principal Component Analysis and composition of each factor

The table shows the common factors that underlie the weekly price changes of the 75 CDS. The main components or factors are a linear combination of the original values, and are independent of each other. The Kaiser-Meyer-Olkin (KMO) measures of sampling adequacy and Bartlett's sphericity test evaluate the adequacy of the analysis. Both confirm that the data are suitable for factor analysis.

PCA	Components from highest to lowest factorial load
42.296	Linde, Henkel, Akzo Nobel, Bayer, Unilever, DSM, Solvay and 21 companies more*
4.186	BMW, Daimler, Valeo, Continental, GKN and Volvo
3.698	Transocean, BP, Halliburton, Apache, Weatherford and Baker Hughes
2.974	Bristol-Myers, Pfizer, Baxter, McDonald's, Procter&Gamble, Mondelez and Boeing
2.535	Johnson Controls, Borgwarner, Goodyear, Starwood Hotels, Caterpillar and PPG
2.224	Nissan Motor, Honda Motor, Sony, Komatsy and Softbank
1.910	Avnet, Arrow, Sealed Air, Hewlett-Packard, Eastman, El Du Pont and Dow Chemical
1.683	UBS, Credit Suisse, Scor, Hannover Ru. and Citigroup
1.601	Ricoh and Canon
1.477	Heineken and Marsh & Mclennan
1.354	Arcelormittal
65.938	
0.967	
0.000	
	42.296 4.186 3.698 2.974 2.535 2.224 1.910 1.683 1.601 1.477 1.354 65.938 0.967

The remaining 21 companies in PC1, from the highest to the lowest factorial load, are: Astrazeneca, Bae Systems, Nestle, Sanofi, Diageo, Sodexo, WPP 2005 limited, Philips, Kering, Glaxosmithkline, Pernod Ricard, Technip, Lafargeholcim, Schneider Electric, Siemens, Electrolux, British American Tobacco, SabMiller, Heidelbergcement, Ericsson and Nokia.

We are now in position to propose a suitable strategy to design a portfolio of international and sectorally diversified assets, with a variety of credit qualities, with a low number of securities and a controlled market risk level. Each of the 11 factors is going to be associated to the company that in each principal component has the greater factorial load, i.e., those with a stronger relationship to the principal component to which they are associated. The diversified portfolio is thus composed of 11 companies specified in Table 20, and whose low stock price changes correlations are shown in Table 21.

Table 20: Highly diversified international portfolio

Data for geographic revenues exposure are 2015 year-end figures in almost all cases. (*) stands for 2016 data.

Company	Rating	Sector	Domicile	Geographic Revenues Exposure	Factor Loadings
Linde	A+	Chemicals	Germany	Africa and Middle East 3.8%. Americas 32.8%. Asia/Pacific 26.9%. Europe 36.5%	0.784
BMW	A+	Automotive	Germany	Africa and Middle East 4.6%. Americas 23.3%. Asia/Pacific 26.6%. Europe 45.5%	0.730
BP	A+	Energy	UK	Africa and Middle East 5%. Americas 39%. Asia/Pacific 19.5%. Europe 36.5%	0.687
Bristol-Myers	A+	Pharmaceuticals	USA	Africa and Middle East 4.6%. Americas 54.2% (USA 49%). Asia/Pacific 20.3%. Europe 20.9%	0.734
Johnson Controls	BBB+	Automotive	USA	Africa and Middle East 3.7%. Americas 50.6% (USA 43%). Asia/Pacific 18.7%. Europe 27% (*)	0.702
Nissan Motor	A-	Automotive	Japan	Africa and Middle East 4.4%. Americas 52.9% (USA 39.9%. Canada 4.7%). Asia/Pacific 28.4%. Europe 14.3% (*	0.837
Avnet	BBB-	Technology	USA	Africa and Middle East 4.2%. Americas 39.8%. Asia/Pacific 30.2%. Europe 25.8% (*)	0.672
UBS	A+	Fin. Inst.	Switzerland	Africa and Middle East 5.5%. Americas 38.4%. Asia/Pacific 15.9%. Europe 40.2%	0.778
Ricoh	A-	Manufacturing	Japan	Africa and Middle East 5.7%. Americas 31.4%. Asia/Pacific 44.3%. Europe 18.7% (*)	0.653
Heineken	BBB+	Consumer	Netherlands	Africa and Middle East 10.5%. Americas 25%. Asia/Pacific 13.6%. Europe 50%. Unspecified 0.4% (*)	0.570
Arcelormittal	BB	Other	Luxembourg	Africa and Middle East 10.5%. Americas 39.1%. Asia/Pacific 5%. Europe 45.4% (*)	0.902

Table 21: Spearman's correlation coefficients between stock price changes.

All of them are significant at the 1% level.

	Linde	BMW	BP	Bristol-Myers	lohnson Control	s Nissan Motor	Avnet	UBS	Ricoh	Heineken	Arcelormittal
Linde	1										
BMW	0.5230	1									
ВР	0.3918	0.4193	1								
Bristol-Myers	0.2645	0.2633	0.2098	1							
Johnson Controls	0.3322	0.3435	0.2822	0.3873	1						
Nissan Motor	0.1278	0.1392	0.1015	0.0374	0.0657	1					
Avnet	0.3172	0.3637	0.2639	0.3512	0.5072	0.0915	1				
UBS	0.4352	0.5286	0.3994	0.2514	0.3563	0.1984	0.3750	1			
Ricoh	0.1315	0.1350	0.1380	0.0412	0.0720	0.5860	0.1002	0.1899	1		
Heineken	0.3888	0.3839	0.2908	0.2200	0.2394	0.1255	0.2299	0.3080	0.1329	1	
Arcelormittal	0.4558	0.5120	0.4840	0.2046	0.3412	0.1337	0.3587	0.4857	0.1419	0.2578	1

We now verify the effectiveness of this portfolio in relation to the reduction of investment risk. To do this, we will use the prices of the stocks, in local currency, of these companies (not the CDS). Following Markowitz (1952), we calculate the portfolio risk with the standard deviation of the yields of these companies' shares from the variance-covariance matrix and the correlation coefficients of the yields of the 11 stocks. By doing so, we will be able to compare the risk-return binomial of the portfolio, which is representative of global credit risk, with other equity indexes and verify its effectiveness in terms of risk diversification. In particular, we will take as a reference the MSCI ACWI (USD) global index. As stated before, this index reflects the evolution of 2,477 companies in 23 developed markets and 23 emerging countries and covers approximately 85% of companies globally investable.

The portfolio risk, consisting of 11 securities, between 2007 and 2016, turns out to be 20.45% in terms of annualized volatility, slightly higher than the MSCI ACWI index, which shows a 17.63%volatility. In terms of performance, the portfolio has an annualized return of + 2.43% higher than the + 1.01% of the ACWI index (see Table 22 and Figure 16).

In order to achieve a holistic view of the effectiveness of the portfolio proposed, we compare the results with those of the most widely used equity indices in the financial world, Eurostoxx 50 and S&P 500, geographically located in the Euro zone in the first case and in the United States in the second (see Table 22). It is found that a small, internationally and sectorally diversified portfolio, which reflects the overall credit risk structure, presents less market risk than traditional equity indices, without sacrificing profitability.

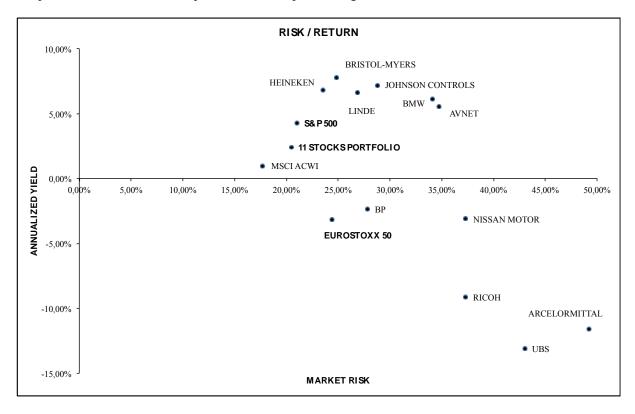
Table 22: Risk and returns

This table shows both, the risk and the return of the global portfolio and the main equity indexes between January 3, 2007 and November 18, 2016.

	Market	Annualized	Total Return
	Risk	Return	3 Jan 2007 - 18 Nov 2016
Linde	26.84%	6.66%	94.80%
BMW	34.09%	6.13%	86.16%
BP	27.84%	-2.33%	-21.12%
Bristol-Myers	24.84%	7.77%	115.65%
Johnson Controls	28.77%	7.18%	103.65%
Nissan Motor	37.30%	-3.10%	-27.53%
Avnet	34.71%	5.54%	76.81%
UBS	43.03%	-13.08%	-75.60%
Ricoh	37.34%	-9.13%	-62.47%
Heineken	23.55%	6.82%	97.34%
Arcelormittal	49.23%	-11.61%	-72.14%
11 stocks portfolio	20.45%	2.43%	27.87%
MSCI ACWI	17.63%	1.01%	10.87%
Eurostoxx 50	24.43%	-3.14%	-27.87%
S&P 500	21.02%	4.31%	54.02%

Figure 17: Risk and returns

The graph shows the volatility-profitability profile of the different securities and portfolios. It depicts the power of the international portfolio with exposure to global credit risk.



In sum, results highlight that as a result of the informative power of multinational corporative CDS regarding global credit risk and of the strength of the factor analysis technique, it is possible to take advantage of existing diversification possibilities and to reduce market risk in investments.

Third part: Conclusions, Contributions and Future Research

5. Concluding Remarks

Occasionally, a powerful financial innovation appears. But it is not easy to find a financial innovation as versatile, as diverse, and, above all, as meaningful as the Credit Default Swap (CDS).

Through the literature on financial risks that uses CDS during the 2000-2015 period, we have followed the concerns of researchers, regulators and financial-market participants; i.e. we have followed the financial history of the early 21st century, which has already experienced remarkable fluctuations.

Using a systematic bibliometric approach, trendsetting papers on CDS and financial risks were identified. Built on this approach, we have drawn a conceptual map, primarily motivated by the chronological appearance of the various permutations of CDS, and then grouped the breakthrough literature into different clusters.

We have noted how the credit derivative contract has evolved from being the perfect product to manage credit risks in times of volatility and uncertainty to playing a prominent role in increasing the fragility of the financial system. But overall, we have corroborated its usefulness as price for several kinds of financial risk. In this context, contagion, risk spillover and systemic risk have emerged as areas of remarkable worriedness and literary productivity between 2011 and 2015, that is, after the fall of Lehman Brothers, the subprime crisis, and the sovereign debt crisis. However, the study points to the fact that those risks are still unsolved financial dangers.

The relevance of CDS has then being confirmed by exploiting the results of a search on title textual analysis to explore interactions between the CDS notional amounts and the level of research activity over the 2001 - 2015 time frame. During the 2001-2010 period both variables are found to measure a common underlying factor, i.e. the relevance of the CDS market, being volumes the leading variable. We also document a structural break in this relationship around the Dodd-Frank reform, as the effects of the post crisis regulation changed the activity standards in the CDS market. During the 2011-2015 period, the trading volume in credit derivative markets notably decreased, while research activity remained stable and high, showing evidence of divergence between both variables. When measuring the contribution of each of the two variables to the revelation of the common fundamental we only find weak evidence of informational dominance from volumes to papers in this second subperiod.

Anyhow, CDS spreads remain key indicators of credit quality available for a large number of firms and sovereigns. Moreover, we may be witnessing the threshold of a new market revival with the Trump era, as the US president plans to repeal the financial regulations imposed under 2010 Dodd-Frank law.³² In this context, academic literature contributes to the regulation policy debate involving position limits in the CDS market.

Finally, we have also pretended to deepen in CDS spreads as indicator of global credit risk. While globalization has turned the corporate sector out considerably complex, the extant literature regarding financial risks is scarce when it comes to analyse global risks in other sectors than the financial system.

Although stocks belonging to different sectors should be characterized by different levels of risk, a latent risk of failure driven by global factors becomes apparent. Global corporates

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 $^{^{32}\} http://www.wsj.com/articles/donald-trump-took-aim-at-dodd-frank-on-the-stump-1478691726$

CDS co-move driven by common determinants, suggesting the existence of a credit global risk. Therefore, the global portfolio is found to proxy a non-financial worldwide credit risk.

While assessing the dynamics between global sectors and their relevance in predictive causality terms, we report the leadership of the Pharmaceutical industry.

Additionally, the results confirm a strong relationship between the global credit risk proxy and other credit risk measures as well as with global market risk indicators. These findings are in line with previous literature that proclaims links between stock volatility, stock returns and credit risk. Furthermore, the estimations provide evidence of the multinational corporate sector Granger-causing well-known market and credit risk indices.

Finally, we have reduced the sample of 75 highly diversified values to 11 factors that incorporate 66% of the information immersed in the original sample. Selecting the most informative company of each factor, we have followed Markowitz's theory of diversification (1952) and have analysed the market risk of a portfolio with global credit risk. The findings confirm that the market risk assumed by the globalized portfolio that incorporates credit risk between 2007 and 2016 (20.45%) was lower than when investing in the 50 stocks of the Eurostoxx 50 index (24.43%) or in the SandP500 index (21.02%), preserving a return of 27.87%. In other words, the investment diversification is still beneficial in terms of market risk reduction and the attainment of profitability, even under the evidence of the existence of a global credit risk.

5.1. Contributions

With this work, we aim to help filling some gaps regarding current financial risks. Specifically, we deepen into CDS markets and into global credit risk, but also involving market risk. The findings are relevant to regulators, academics and investors such as investment fund and pension fund managers by contributing to the existing literature in many different ways:

First, by using CDS as a guide to disentangle the field of financial risks, we organize and structure the financial risks' issues that have concerned researchers and policy makers in the early 21st century. By doing so, we evidence the still unsolved threats.

Second, we contribute to the revelation of the CDS market as a variable of scientific interest by means of an informational leadership analysis, where the level of publication activity is proxied applying textual analysis. To our knowledge, this is the first study to relate trading and publication activity and to use textual analysis beyond the framework of event studies. By doing so, we shed light to the ongoing debate regarding trading position limits.

Third, we go further into the research regarding the factors that explain CDS spreads and complement the systemic financial risk analysis by providing evidence of an existing non-financial global corporate credit risk. Unlike previous literature regarding corporate CDS spreads, the sample comprises underlying companies with fiscal domicile in 11 different countries (3 continents) and with investment and non-investment credit quality grade, over a ten-year period. As far as we are concerned, this study is the first to capture the main common factors that drive the credit risk of the worldwide largest multinational firms and the relevance of the causal relationships among them.

Fourth, we highlight the relevance of analysing the risk spillover between non-financial industries, where literature is scarce, by exploring the credit risk feedbacks between global sectors. Results evidence the existence of a predictive relation between many of the global sectors worthwhile to be taken into account as the lead/lag relations turn out to be important. Moreover, the Pharma sector needs to be analysed in detail, as it appears to Granger-cause all other industries.

Fifth, the results confirm the links between stock volatility, stock returns and credit risk suggested by previous literature while analysing the interrelations between the global credit risk and the global market risk.

Finally, we contribute to market risk diversification theory by confirming that it is still beneficial even under the evidence of a global credit risk. Furthermore, we propose a simple method of diversifying international portfolios and apply it in the current globalized environment achieving a well-diversified portfolio, with reduced market risk and convenient profitability.

5.2. Future Research

We present future research lines centred in three main paths:

On the one hand, we understand that the results in this paper regarding the influence of CDS might be extended to address the impact of looser regulation under the Trump era. We contend that the academic literature should aim to contribute to the regulation policy debate involving position limits in the CDS market. By doing so, future research could be useful for finding the way to keep on benefiting from the added value of CDS while helping to reduce

the negative consequences of its missuse. In this sense, it could lead to reshape the CDS trading volumes trend towards higher outstanding amounts.

On the other hand, the findings demonstrate the relevance and informative power of multinational corporate CDS regarding global credit risk. These results encourage further investigation to deepen in the risk spillover along our globalized world, which is characterized by a complex network of interactions. The suitability of broader analysis of that intricate system of connections, with special attention to risk in the Pharma sector is also suggested, as well as the need of watching out the complex links between this segment and the remaining industries. Therefore, deeper mapping and monitoring of the relationships between sectors may provide a valuable guidance to minimize risk contagion.

Finally, in order to achieve high-diversified portfolios that reduce market risk although facing credit risk, further research aiming to attain a more advanced technique to detect the most important companies in each factor of a PCA might be a relevant step to be taken.

References

- Acharya, V. V., Schaefer, S. M., and Zhang, Y. (2015). Liquidity risk and correlation risk: A clinical study of the general motors and ford downgrade of may 2005. Available at SSRN: http://ssrn.com/abstract=1074783.
- Acharya, V., Drechsler, I. and Schnabl, P. (2014). A pyrrhic victory? Bank bailouts and sovereign credit risk. The Journal of Finance 69, 2689-2739. DOI: 10.1111/jofi.12206.
- Allen, F. (2001). Presidential address: Do financial institutions matter? The Journal of Finance, 56(4), 1165-1175.
- Alper, C. E., Forni, L. and Gerard, M. (2013). Pricing of sovereign credit risk: Evidence from advanced economies during the financial crisis. International Finance 16, 161-188. DOI: 10.1111/j.1468-2362.2013.12028.x.
- Alter, A. and Schüler, Y. S. (2012). Credit spread interdependencies of European states and banks during the financial crisis. Journal of Banking and Finance 36, 3444-3468.
- Ang, A. and Longstaff, F. A. (2013). Systemic sovereign credit risk: Lessons from the US and europe. Journal of Monetary Economics 60, 493-510. DOI:10.1016/j.jmoneco.2013.04.009.
- Arce O., Mayordomo S. and Peña, J.I. (2013). Credit-risk valuation in the sovereign CDS and bonds markets: Evidence from the euro area crisis. Journal of International Money and Finance, 35:124-145. DOI:10.1016/j.jimonfin.2013.01.006.
- Aretz, K. and Pope, P. F. (2013). Common factors in default risk across countries and industries. European Financial Management 19, 108-152. DOI: 10.1111/j.1468-036X.2012.571.x.
- Arora, N., Gandhi, P. and Longstaff, F. A. (2012). Counterparty credit risk and the credit default swap market. Journal of Financial Economics 103, 280-293. DOI:10.1016/j.jfineco.2011.10.001.
- Augustin P., Subrahmanyam M.G., Tang D.Y. and Wang S.Q. (2016). Credit Default Swaps: Past, Present, and Future. Annual Review of Financial Economics, 8:175–196. DOI: 10.1146/annurev-financial-121415-032806.
- Azar O.H. (2004). Rejections and the importance of first response times. International Journal of Social Economics, 31(3):259-274. DOI: 10.1108/03068290410518247.
- Badaoui, S., Cathcart, L. and El-Jahel, L. (2013). Do sovereign credit default swaps represent a clean measure of sovereign default risk? A factor model approach. Journal of Banking and Finance, 37, 2392-2407. DOI:10.1016/j.jbankfin.2013.01.038.
- Battistini, N., Pagano, M. and Simonelli, S. (2014). Systemic risk, sovereign yields and bank exposures in the euro crisis. Economic Policy 29, 203-251. DOI: 10.1111/1468-0327.12029.

- Beavers A.S, Lounsbury J.W., Richards J.K., Huck S.W., Skolits G.J. and Esquivel S.L. (2013). Practical Considerations for Using Exploratory Factor Analysis in Educational Research. Practical Assessment, Research and Evaluation. Volume 18, Number 6, March 2013
- Bedendo, M. and Colla, P. (2015). Sovereign and corporate credit risk: Evidence from the eurozone. Journal of Corporate Finance 33, 34-52. DOI:10.1016/j.jcorpfin.2015.04.006.
- Beirne, J. and Fratzscher, M. (2013). The pricing of sovereign risk and contagion during the European sovereign debt crisis. Journal of International Money and Finance, 34, 60-82. DOI:10.1016/j.jimonfin.2012.11.004.
- Bekaert, G. and Harvey, C. (2014). Emerging Equity Markets in a Globalizing World. Network for Studies on Pensions, Aging and Retirement, DP 05/2014-024.
- Berger, D., Pukthuanthong, K., and Yang, J.J. (2011). International Diversification with Frontier Markets. Journal of Financial Economics, 101, 227-242.
- Berndt, A., and Obreja, I. (2010). Decomposing european CDS returns. Review of Finance, 14(2), 189-233.
- Berndt, A. and Obreja, I., 2007. The pricing of risk in European credit and corporate bond markets. European Central Bank. Working Paper Series 805.
- Bertoni, F. and Lugo, S. (2014). The effect of sovereign wealth funds on the credit risk of their portfolio companies. Journal of Corporate Finance 27, 21-35. DOI:10.1016/j.jcorpfin.2014.04.004.
- Billio, M., Getmansky, M., Lo, A. W., and Pelizzon, L. (2010). Measuring systemic risk in the finance and insurance sectors. NBER Working Paper.
- Billio M., Getmansky M., Lo A.W. and Pelizzon L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. Journal of Financial Economics, 104(3):535-559. DOI: 10.1016/j.jfineco.2011.12.010.
- Björk B. and Solomon D. (2013). The publishing delay in scholarly peer-reviewed journals. Journal of Informetrics, 7(4):914-923. DOI: 10.1016/j.joi.2013.09.001.
- Blanco, R., Brennan, S. and Marsh, I. W. (2005). An empirical analysis of the dynamic relation between investment grade bonds and credit default swaps. The Journal of Finance 60, 2255-2281. DOI: 10.1111/j.1540-6261.2005.00798.x.
- Brigo D. and Chourdakis K. (2009). Counterparty risk for credit default swaps: Impact of spread volatility and default correlation. International Journal of Theoretical and Applied Finance, 12(07):1007-1026. DOI: 10.1142/S0219024909005567.
- Brown, C. and Hao, C. (2012). Treating uncertainty as risk: The credit default swap and the paradox of derivatives. Journal of Economic Issues 46, 303-312. DOI: 10.2753/JEI0021-3624460205.

- Brunnermeier, M. K., Crockett, A., Goodhart, C. A., Persaud, A., and Shin, H. S. (2009). The fundamental principles of financial regulation. Geneva Report on the World Economy.
- Calice, G., Ioannidis, C. and Williams, J. (2012). Credit derivatives and the default risk of large complex financial institutions. Journal of Financial Services Research 42, 85-107. DOI: 10.1007/s10693-011-0121-z.
- Caporin, M., Pelizzon, L., Ravazzolo, F. and Rigobon, R. (2013). Measuring sovereign contagion in Europe. National Bureau of Economic Research, No. 18741. DOI: 10.3386/w18741.
- Castren, O., Dees, S., and Zaher, F. (2008). Global macro-financial shocks and expected default frequencies in the euro area. ECB Working Paper NO 875
- Castrén, O. and Kavonius, I. K. (2009). Balance sheet interlinkages and macro-financial risk analysis in the euro area (ECB Working Paper ed.) European Central Bank.
- Chan-Lau, J. A. (2006). Is systematic default risk priced in equity returns? A cross-sectional analysis using credit derivatives prices. International Monetary Fund 148.
- Chen, H., Cummins, J. D., Viswanathan, K. S. and Weiss, M. A. (2014). Systemic risk and the interconnectedness between banks and insurers: An econometric analysis. Journal of Risk and Insurance 81, 623-652. DOI: 10.1111/j.1539-6975.2012.01503.x.
- Chen, R., Cheng, X. and Wu, L. (2013). Dynamic interactions between interest-rate and credit risk: Theory and evidence on the credit default swap term structure*. Review of Finance, 17(1), 403-441. DOI: 10.1093/rof/rfr032.
- Chen, R., Fabozzi, F. J., Pan, G. and Sverdlove, R. (2006). Sources of credit risk: Evidence from credit default swaps. The Journal of Fixed Income 16, 7-21. DOI: 10.3905/jfi.2006.670090.
- Collin-Dufresne, P., Goldstein, R.S. and Martin, J.S. (2001). The Determinants of Credit Spread Changes. The Journal of Finance 61(6). DOI: 10.1111/0022-1082.00402
- Corzo, M. T., Gomez, J. and Lazcano, L. (2014). Financial crises and the transfer of risk between the private and public sectors: Evidence from European financial markets. The Spanish Review of Financial Economics 12, 1-14. DOI: 10.1016/j.srfe.2013.09.001.
- Cotter, J., Gabriel, S.A. and Roll, R. (2016). Nowhere to Run, Nowhere to Hide: Asset Diversification in a Flat World. Available at SSRN: https://ssrn.com/abstract=2852164 or https://ssrn.com/abstract=2852164 or https://ssrn.com/abstract=2852164 or http://dx.doi.org/10.2139/ssrn.2852164
- Cremers, K. J. M., Driessen, J. and Maenhout, P. (2008), 'Explaining the level of credit spreads: option- implied jump risk premia in a firm value model', The Review of Financial Studies 21(5), 2209–2242
- Das, S. R. and Hanouna, P. (2006). Credit default swap spreads. Journal of Investment Management 4(3), 93.

- Das, S. R., Hanouna, P. and Sarin, A. (2009). Accounting-based versus market-based cross-sectional models of CDS spreads. Journal of Banking and Finance 33, 719-730. DOI: 10.1016/j.jbankfin.2008.11.003.
- De Bandt, O. and Hartmann, P, (2000). Systemic risk: A survey. ECB working paper ed. European Central Bank.
- De Bruyckere, V., Gerhardt, M., Schepens, G. and Vander Vennet, R. (2013). Bank/sovereign risk spillovers in the European debt crisis. Journal of Banking and Finance 37, 4793-4809. DOI:10.1016/j.jbankfin.2013.08.012.
- Delatte, A., Gex, M.and López-Villavicencio, A. (2012). Has the CDS market influenced the borrowing cost of European countries during the sovereign crisis? Journal of International Money and Finance 31, 481-497. DOI:10.1016/j.jimonfin.2011.10.008.
- Demirgüç-Kunt, A. and Huizinga, H. (2013). Are banks too big to fail or too big to save? International evidence from equity prices and CDS spreads. Journal of Banking and Finance 37, 875-894. DOI:10.1016/j.jbankfin.2012.10.010.
- Díaz, A., Groba, J. and Serrano, P. (2013). What drives corporate default risk premia? Evidence from the CDS market. Journal of International Money and Finance 37, 529-563. DOI:10.1016/j.jimonfin.2013.07.003.
- Dieckmann, S. and Plank, T. (2012). Default risk of advanced economies: An empirical analysis of credit default swaps during the financial crisis. Review of Finance 16, 903-934. DOI: 10.1093/rof/rfr015.
- Draghi, M., Giavazzi, F. and Merton, R. C. (2003). Transparency, risk management and international financial fragility. National Bureau of Economic Research, working paper 9806. DOI: 10.3386/w9806.
- Duffee, G. R. and Zhou, C. (2001). Credit derivatives in banking: Useful tools for managing risk? Journal of Monetary Economics 48, 25-54. DOI: 10.1016/S0304-3932(01)00063-0.
- Duffie D., Scheicher M. and Vuillemey G. (2015). Central clearing and collateral demand. Journal of Financial Economics, 116(2):237-256. DOI: http://dx.doi.org/10.1016/j.jfineco.2014.12.006
- Düllmann, K. and Sosinska, A. (2007). Credit default swap prices as risk indicators of listed German banks. Financial Markets and Portfolio Management 21, 269-292. DOI: 10.1007/s11408-007-0053-7.
- Dunbar, K. (2008). US corporate default swap valuation: The market liquidity hypothesis and autonomous credit risk. Quantitative Finance 8, 321-334. DOI: 10.1080/14697680701397927.
- Eichengreen, B., Mody, A., Nedeljkovic, M., and Sarno, L. (2012). How the subprime crisis went global: Evidence from bank credit default swap spreads. Journal of International Money and Finance, 31(5), 1299-1318.

- Ejsing, J. and Lemke, W. (2011). The janus-headed salvation: Sovereign and bank credit risk premia during 2008–2009. Economics Letters 110, 28-31. DOI: 10.1016/j.econlet.2010.10.001.
- Engle R.F. and Granger C.W. (1987). Co-integration and error correction: Representation, estimation, and testing. Econometrica: Journal of the Econometric Society, 55(2):251-276.
- Fabozzi, F. J., Cheng, X. and Chen, R. (2007). Exploring the components of credit risk in credit default swaps. Finance Research Letters 4, 10-18. DOI: 10.1016/j.frl.2006.10.002.
- Feldhütter, P., and Nielsen, M. S. (2012). Systematic and idiosyncratic default risk in synthetic credit markets. Journal of Financial Econometrics, 10(2), 292-324. DOI: 10.1093/jjfinec/nbr011.
- Fernandes, M., Medeiros, M.C. and Scharth, M. (2014). Modeling and predicting the CBOE market volatility index. Journal of Banking and Finance. 40: 1-10. DOI: https://doi.org/10.1016/j.jbankfin.2013.11.004
- Figuerola-Ferretti I. and Gonzalo J. (2010). Modelling and measuring price discovery in commodity markets. Journal of Econometrics, 158(1):95-107. DOI: http://dx.doi.org/10.1016/j.jeconom.2010.03.013
- Forte, S., and Lovreta, L. (2015). Time- varying credit risk discovery in the stock and CDS markets: Evidence from quiet and crisis times. European Financial Management 21, 430. DOI: 10.1111/j.1468-036X.2013.12020.x.
- Fung, H., Wen, M. and Zhang, G. (2012). How does the use of credit default swaps affect firm risk and value? Evidence from US life and Property/Casualty insurance companies. Financial Management 41, 979-1007. DOI: 10.1111/j.1755-053X.2012.01203.x.
- Gapen, M. T., Xiao, Y., Gray, D. F. and Lim, C. H. (2008). Measuring and analyzing sovereign risk with contingent claims (IMF Staff Papers Vol. 55 No.1 ed.) International Monetary Fund Working Paper. http://dx.doi.org/10.5089/9781451861747.001
- Gauthier, C., and Souissi, M. (2012). Understanding systemic risk in the banking sector: A MacroFinancial risk assessment framework. Bank of Canada Review, 29-38.
- Ghosh, A. R., Ostry, J. D., and Qureshi, M. S. (2013). Fiscal space and sovereign risk pricing in a currency union. Journal of International Money and Finance, 34, 131-163. http://dx.doi.org/10.1016/j.jimonfin.2012.11.008
- Gray, D. F., and Malone, S. W. (2008). Macrofinancial risk framework linked to macroeconomic models. Macrofinancial Risk Analysis, , 203-218.
- Gray, D. F., Merton, R. C., and Bodie, Z. (2006). A New Framework for Analyzing and Managing Macrofinancial Risks of an Economy. National Bureau of Economic Research.

- Groba, J., Lafuente, J. A., and Serrano, P. (2013). The impact of distressed economies on the EU sovereign market. Journal of Banking and Finance, 37(7), 2520-2532. http://dx.doi.org/10.1016/j.jbankfin.2013.02.003
- Haerri, M., Morkoetter, S. and Westerfeld, S. (2015). Sovereign Risk and the Pricing of Corporate Credit Default Swaps. The Journal of Credit Risk. http://dx.doi.org/10.2139/ssrn.2554483
- Hammoudeh, S., Bhar, R. and Liu, T. (2013). Relationships between financial sectors' CDS spreads and other gauges of risk: Did the great recession change them? Financial Review, 48(1), 151-178. DOI: 10.1111/j.1540-6288.2012.00350.x
- Hammoudeh, S., Liu, T. Chang, C. and McAleer, M. (2013). Risk spillovers in oil-related CDS, stock and credit markets. Energy Economics 36, 526-535.
- Hricko, D. C. T., Aunon-Nerin, D., and Huang, Z. (2003). Analyzing credit risk in default swap transaction data: Is fixed-income markets' information sufficient to evaluate credit risk? National Centre of Competence in Research Financial Valuation and Risk Management, Working Paper,
- Huang, A. Y., and Cheng, C. (2013). Information risk and credit contagion. Finance Research Letters, 10(3), 116-123. http://dx.doi.org/10.1016/j.frl.2013.06.002
- Hui C. and Chung T. (2011). Crash risk of the euro in the sovereign debt crisis of 2009–2010. Journal of Banking and Finance, 35:2945-2955. http://dx.doi.org/10.1016/j.jbankfin.2011.03.020
- Janus, T., Jinjarak, Y., and Uruyos, M. (2013). Sovereign default risk, overconfident investors and diverse beliefs: Theory and evidence from a new dataset on outstanding credit default swaps. Journal of Financial Stability, 9, 330-336. http://dx.doi.org/10.1016/j.jfs.2012.11.007
- Jarrow, R. A., and Turnbull, S.M. (2000). The intersection of market credit risk. Journal of Banking and Finance 24, 271-299.
- Jarrow, R. A., and Yildirim, Y. (2002). Valuing default swaps under market and credit risk correlation. The Journal of Fixed Income, 11(4), 7-19. http://dx.doi.org/10.3905/jfi.2002.319308
- Jorion, P., and Zhang, G. (2007). Good and bad credit contagion: Evidence from credit default swaps. Journal of Financial Economics, 84(3), 860-883. http://dx.doi.org/10.1016/j.jfineco.2006.06.001
- Jorion, P., and Zhang, G. (2009). Credit contagion from counterparty risk. Journal of Finance, 64(5), 2053-2087. http://dx.doi.org/10.1111/j.1540-6261.2009.01494.x
- Kim, D. H., Loretan, M., and Remolona, E. M. (2010). Contagion and risk premia in the amplification of crisis: Evidence from asian names in the global CDS market. Journal of Asian Economics, 21(3), 314-326. http://dx.doi.org/10.1016/j.asieco.2009.07.010

- Kim, M. A., and Kim, T. S. (2004). Credit default swap valuation with counterparty default risk and market risk. Journal of Risk, 6, 49-80.
- Kress, J. C. (2011). Credit default swap clearinghouses and systemic risk: Why centralized counterparties must have access to central bank liquidity. Harvard Journal on Legislation, 48 (1). http://ssrn.com/abstract=1583912
- Laeven, L., and Valencia, F. (2012). Systemic banking crises database: An update. International Monetary Fund working paper.
- Lehmann, B. N. (2002). Some desiderata for the measurement of price discovery across markets. Journal of Financial Markets, 5, 259–276. http://dx.doi.org/10.1016/S1386-4181(02)00025-3
- Leung, K. S., and Kwok, Y. K. (2009). Counterparty risk for credit default swaps: Markov chain interacting intensities model with stochastic intensity. Asia-Pacific Financial Markets, 16(3), 169-181. http://dx.doi.org/10.1007/s10690-009-9091-7
- Li, J., and Zinna, G. (2014). How much of bank credit risk is sovereign risk? evidence from the eurozone. Banca D'Italia, Eurosistema Working Papers, http://dx.doi.org/10.2139/ssrn.2571288
- Longstaff, F. A., and Rajan, A. (2008). An empirical analysis of the pricing of collateralized debt obligations. The Journal of Finance, 63(2), 529-563.
- Longstaff, F. A., Mithal, S., and Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? new evidence from the credit default swap market. Journal of Finance, 60(5), 2213-2253. http://dx.doi.org/10.1111/j.1540-6261.2005.00797.x
- Longstaff, F. A., Pan, J., Pedersen, L. H., and Singleton, K. J. (2011). How sovereign is sovereign credit risk? American Economic Journal: Macroeconomics. http://dx.doi.org/10.1257/mac.3.2.75
- Loon, Y. C., and Zhong, Z. K. (2014). The impact of central clearing on counterparty risk, liquidity, and trading: Evidence from the credit default swap market. Journal of Financial Economics, 112, 91-115. http://dx.doi.org/10.1016/j.jfineco.2013.12. 001
- Loughran T. and McDonald B. (2011). When is a liability not a liability? textual analysis, dictionaries, and 10-Ks. The Journal of Finance, 66(1):35-65. DOI: 10.1111/j.1540-6261.2010.01625.x.
- MacKinnon J. (1991). Critical Values for Cointegration Tests, in R. Engle and C. W. Granger, eds., Long-run Economic Relationship: Readings in Cointegration: Oxford University Press.
- Markose, S., Giansante, S., and Shaghaghi, A. R. (2012). 'Too interconnected to fail'financial network of US CDS market: Topological fragility and systemic risk. Journal of Economic Behavior and Organization, 83(3), 627-646. http://dx.doi.org/10.1016/j.jebo.2012.05.016

- Markowitz H. (1952). Portfolio selection. The Journal of Finance, 7(1):77-91. DOI: 10.1111/j.1540-6261.1952.tb01525.x.
- Merton, R. C., Billio, M., Getmansky, M., Gray, D., Lo, A. W., and Pelizzon, L. (2013). On a new approach for analyzing and managing macrofinancial risks. Financial Analysts Journal, 69(2), 22-33. http://dx.doi.org/10.2469/faj.v69.n2.5
- Naifar, N. (2011). What explains default risk premium during the financial crisis? evidence from japan. Journal of Economics and Business, 63(5), 412-430. http://dx.doi.org/10.1016/j.jeconbus.2010.09.003
- Narayan P.K., Narayan S. and Prabheesh K. (2014). Stock returns, mutual fund flows and spillover shocks. Pacific-Basin Finance Journal, 29:146-162. DOI: 10.1016/j.pacfin.2014.03.007.
- Nashikkar, A., Subrahmanyam, M. G., and Mahanti, S. (2011). Liquidity and arbitrage in the market for credit risk. Journal of Financial and Quantitative Analysis, 46(3), 627-656. http://dx.doi.org/10.1017/S002210901100007X
- Nijskens, R., and Wagner, W. (2011). Credit risk transfer activities and systemic risk: How banks became less risky individually but posed greater risks to the financial system at the same time. Journal of Banking and Finance, 35, 1391-1398. http://dx.doi.org/10.1016/j.jbankfin.2010.10.001
- Norden L. and Weber M. (2009). The comovement of credit default swap, bond and stock markets: An empirical analysis. European Financial Management, 15(3):529-562. DOI: 10.1111/j.1468-036X.2007.00427.x.
- Ohno, S. (2013). European sovereign risk: The knock-on effects of default risk across the public and financial sectors. Public Policy Review, 9(1), 139-170.
- Oldani C. (2011). The management of greek sovereign risk. The IUP Journal of Financial Risk Management. Dec2011, 8(4):25-36.
- Otero J. and Smith J. (2000). Testing for cointegration: Power versus frequency of observation—further monte carlo results. Economics Letters, 67(1):5-9. DOI: http://dx.doi.org/10.1016/S0165-1765(99)00245-1.
- Pedrosa M. and Roll R. (1998) Systematic Risk in Corporate Bond Credit Spreads. The Journal of Fixed Income December 1998, Vol. 8, No. 3: pp. 7-26 DOI: 10.3905/jfi.1998.408249
- Pelizzon, L., Subrahmanyam, M.G., Tomio, D. and Uno, J. (2016) Sovereign credit risk, liquidity, and ECB intervention: Deus ex machina? SAFE Working Paper Series, No. 95. http://dx.doi.org/10.2139/ssrn.2587786
- Pu, X., and Zhao, X. (2012). Correlation in credit risk changes. Journal of Banking and Finance, 36, 1093-1106. http://dx.doi.org/10.1016/j.jbankfin.2011.11.002

- Remolona, E. M., Scatigna, M., and Wu, E. (2008). A ratings based approach to measuring sovereign risk. International Journal of Finance and Economics, 13(1), 26-39. http://dx.doi.org/10.1002/ijfe.357
- Revoltella, D., Mucci, F., and Mihaljek, D. (2010). Properly pricing country risk: A model for pricing long-term fundamental risk applied to central and eastern european countries. Financial Theory and Practice, 34(3), 219-245.
- Rodríguez-Moreno, M., and Peña, J. I. (2013). Systemic risk measures: The simpler the better? Journal of Banking and Finance, 37(6), 1817-1831. http://dx.doi.org/10.1016/j.jbankfin.2012.07.010
- Roll, R. (2013). Volatility, Correlation and Diversification in a Multi-factor World. Journal of Portfolio Management, 38 (2), 11-18.
- Schweikhard, F. A., and Tsesmelidakis, Z. (2011). The impact of government interventions on CDS and equity markets. Finance Meeting EUROFIDAI-AFFI, Paris, December, http://dx.doi.org/10.2139/ssrn.1943546
- Sharma, S. D. (2013). Credit default swaps: Risk hedge or financial weapon of mass destruction? Economic Affairs, 33(3), 303-311. http://dx.doi.org/10.1111/ecaf.12029
- Subrahmanyam, M. G., Tang, D. Y., and Wang, S. Q. (2014). Does the tail wag the dog?: The effect of credit default swaps on credit risk. Review of Financial Studies, 27(10), 2927. http://dx.doi.org/10.1093/rfs/hhu038
- Suh, S., Jang, I., and Ahn, M. (2013). A simple method for measuring systemic risk using credit default swap market data. Journal of Economic Development, 38(4), 75-100. DOI:10.1007/978-81-322-2541-6_11
- Starmer H.M., Quon, H., Kumar, R., Alcorn, S., Murano, E., Jones, B., Humbert, I. (2015). The Effect of Radiation Dose on Swallowing: Evaluation of Aspiration and Kinematic Dysphagia 30 (4), 430-7. DOI: 10.1007/s00455-015-9618-1
- Tang, D. Y., and Yan, H. (2010). Market conditions, default risk and credit spreads. Journal of Banking and Finance, 34, 743-753. http://dx.doi.org/10.1016/j.jbankfin.2009.05.018
- Tetlock P.C., Saar-Tsechansky M. and Macskassy S. (2008). More than words: Quantifying language to measure firms' fundamentals. The Journal of Finance, 63(3):1437-1467. DOI: 10.1111/j.1540-6261.2008.01362.x.
- Trujillo-Ponce, A., Samaniego-Medina, R., and Cardone-Riportella, C. (2014). Examining what best explains corporate credit risk: Accounting-based versus market-based models. Journal of Business Economics and Management, 15(2), 253-276. http://dx.doi.org/10.2139/ssrn.2072176
- Weithers, T. (2007). Credit derivatives, macro risks, and systemic risks. Economic Review-Federal Reserve Bank of Atlanta, 92(4), 43.

- Williams B., Onsman A. and Brown T. (2010). Exploratory factor analysis: A five-step guide for novices. Journal of Emergency Primary Health Care (JEPHC), Vol. 8, Issue 3, 2010 Article 990399
- Yang, J., and Zhou, Y. (2013). Credit risk spillovers among financial institutions around the global credit crisis: Firm-level evidence. Management Science, 59(10), 2343-2359. http://dx.doi.org/10.1287/mnsc.2013.1706
- Zhang B., Zhou H. and Zhu H. (2009). Explaining credit default swap spreads with the equity volatility and jump risks of individual firms. Review of Financial Studies, 22(12):5099-5131. http://dx.doi.org/10.1093/rfs/hhp004.

Appendix A: Different Impact Indices

The JCR Impact Factor (ISI Web of Knowledge) is the average number of times articles from the journal published in the past two years have been cited in the JCR year. It is calculated by dividing the number of citations in the JCR year by the total number of articles published in the two previous years.

SJR (Scopus) is a measure of scientific influence of scholarly journals that accounts for both the number of citations received by a journal and the importance or prestige of the journals where such citations come from. It is a size-independent indicator and it ranks journals by their 'average prestige per article'.

SNIP (Scopus) Source Normalized Impact per Paper (SNIP) measures contextual citation impact by weighting citations based on the total number of citations in a subject field. The impact of a single citation is given higher value in subject areas where citations are less likely, and vice versa. It is defined as the ratio of a journal's citation count per paper and the citation potential in its subject field.

AJG (Association of Business Schools) classifies journals into 4 categories (4: journals that publish the most original and best-executed research. 1: journals that publish research of a recognised but more modest standard in their field) plus a Journal of Distinction category (4*), which recognises the quality of those journals ranked as a top class journal in at least 3 out of 5 international listings consulted.

H5 index (Google Scholar) is the h-index (an index that attempts to measure both the productivity and citation impact of the work of a scientist or journal) for articles published in the last 5 complete years. It is the largest number h such that h articles published in 2010-2014 have at least h citations each.

Appendix B: identifying top papers in the bibliometric analysis

WoS:

Title	"Risk""
and Topic	"Credit default swap*" OR "CDS"
Timespan	2000-2015
Domain	Social Sciences
Research Areas	Business, Economics
Found	164 documents

Scopus

title-abs-key	"Risk*"
and title-abs-key	"Credit default swap*" OR "CDS"
pub year	2000-2015
subject area	Economics, Econometrics and Finance
Found	477 documents

EBSCO:

Title	"Risk*"
and abstract	"Credit default swap*" OR "CDS"
Timespan	2000-2015
Limited to	Peer-reviewed articles
Found	582 documents

DIALNET:

Documents search	"Risk*" AND ("CDS" OR "Credit default swap*")
Document type	Journal article
Timespan	2000-2015
Found	38 documents

Updated to December 31st, 2015

Appendix C: Selected articles regarding financial risks guided by CDS

					JOURNAL					ART	ICLE
	AUTHOR	Title	YEAR	JOURNAL	JCR	SJR	SNIP	AJG	Н5-	No	No
					2014	2014	2014	2015	index	citations	citations
									GS	WoS	Scopus
									2015		
1	Acharya, V.	Liquidity risk and correlation	2015	QUARTERLY JOURNAL							
	V., Schaefer,	risk: A clinical study of the		OF FINANCE							
	S. M., and	general motors and ford									
	Zhang, Y.	downgrade of may 2005									
2	Acharya, V.,	A pyrrhic victory? bank bailouts	2014	JOURNAL OF FINANCE	5.424	17.138	5.609	4*	108	11	19
	Drechsler, I.,	and sovereign credit risk.									
	and Schnabl,										
	P.										
3	Alper, CE.,	Pricing of sovereign credit risk:	2013	INTERNATIONAL	0.697	0.383	0.593			0	0
	Forni, L. and	Evidence from advanced		FINANCE							
	Gerard, M.	economies during the financial									
		crisis.									
4	Alter, A., and	Credit spread interdependencies	2012	JOURNAL OF BANKING	1.299	1.059	1.587	3	73	32	23
	Schüler, Y. S.	of European states and banks		and FINANCE							
		during the financial crisis.									
5	Ang, A., and	Systemic sovereign credit risk:	2013	JOURNAL OF	1.726	4.779	1.952	4	50	17	17
	Longstaff, F.	Lessons from the US and europe		MONETARY							
	A.			ECONOMICS							
6	Arce, O.,	Credit-risk valuation in the	2013	JOURNAL OF	2.117	1.114	1.418	3	45	4	8
	Mayordomo,	sovereign CDS and bonds		INTERNATIONAL							
	S., and Peña,	markets: Evidence from the		MONEY AND FINANCE							
	J. I.	euro area crisis									
7	Aretz, K., and	Common factors in default risk	2013	EUROPEAN	1.158	0.926	1.746	3	30	4	5
	Pope, P. F.	across countries and industries.		FINANCIAL							
				MANAGEMENT							
8	Arora, N.,	Counterparty credit risk and the	2012	JOURNAL OF	4.047	10.116	4.200	4*	113	20	25
	Gandhi, P.,	credit default swap market.		FINANCIAL							
	and			ECONOMICS							
	Longstaff, F.										
	A.										

9	Badaoui, S.,	Do sovereign credit default	2013	JOURNAL OF BANKING	1.299	1.059	1.587	3	73	7	6
	Cathcart, L.,	swaps represent a clean measure		and FINANCE							
	and El-Jahel,	of sovereign default risk? A									
	L.	factor model approach.									
10	Battistini, N.,	Systemic risk, sovereign yields	2014	ECONOMIC POLICY	2.485	3.768	2.819			5	8
	Pagano, M.	and bank exposures in the euro									
	and	crisis									
	Simonelli, S.	C11515									
1.1			2015	VOLUMNAL OF	1 102	1.516	1.520	ļ	46		
11	Bedendo, M.	Sovereign and corporate credit	2015	JOURNAL OF	1.193	1.516	1.528	4	46	0	0
	and Colla. P.	risk: Evidence from the		CORPORATE FINANCE							
		Eurozone									
12	Beirne, J., and	The pricing of sovereign risk	2013	JOURNAL OF	2.117	1.114	1.418	3	45	34	40
	Fratzscher,	and contagion during the		INTERNATIONAL							
	M.	European sovereign debt crisis.		MONEY AND FINANCE							
13	Berndt, A.	The pricing of risk in European	2007	ECB WORKING PAPER					57		
	and Obreja, I.	credit and corporate bond									
		markets									
14	Bertoni, F.	The effect of sovereign wealth	2014	JOURNAL OF	1.193	1.516	1.528	4	46	2	3
	and Lugo, S	funds on the credit risk of their		CORPORATE FINANCE							
		portfolio companies									
15	Blanco, R.,	An empirical analysis of the	2005	JOURNAL OF FINANCE	5.424	17.138	5.609	4*	108	183	232
	Brennan, S.,	dynamic relation between									
	and Marsh, I.	investment - grade bonds and									
	W.										
1.6		credit default swaps.	2000	DATE DATE OF THE STATE OF THE S		0.515	0.015		20		25
16	Brigo, D. and	Counterparty risk for credit	2009	INTERNATIONAL		0.715	0.815		20		37
	Chourdakis,	default swaps: Impact of spread		JOURNAL OF							
	K.	volatility and default correlation		THEORETICAL AND							
				APPLIED FINANCE							
17	Brown, C.	Treating Uncertainty as Risk:	2012	JOURNAL OF	0.573	0.431	0.663	2		5	5
	and Hao, C.	The Credit Default Swap and		ECONOMIC ISSUES							
		the Paradox of Derivatives.									
18	Calice, G.,	Credit derivatives and the	2012	JOURNAL OF	1.200	0.874	1.153	3	19	2	2
	Ioannidis, C.,	default risk of large complex		FINANCIAL SERVICES							
	and Williams,	financial institutions.		RESEARCH							
	J.										
19	Caporin, M.,	Measuring sovereign contagion	2012	CAMP WORKING				+	1		
	Pelizzon, L.,	in Europe		PAPER							
	,,	· r ·									

1	Ravazzolo, F.										
	and Rigobon,										
	R.										
20	Chan-Lau, J.	Is systematic default risk priced	2006	IMF WORKING PAPER							
	A.	in equity returns? A cross-									
		sectional analysis using credit									
		derivatives prices									
21	Chen, H.,	Systemic risk and the	2014	JOURNAL OF RISK	1.075	1.465	1.540	3	27	3	10
	Cummins, J.	interconnectedness between		AND INSURANCE							
	D.,	banks and insurers: An									
	Viswanathan,	econometric analysis.									
	K. S., and										
	Weiss, M. A.										
22	Chen, R.,	Dynamic interactions between	2012	REVIEW OF FINANCE	2.012	3.796	1.620	4	40	6	6
	Cheng, X.,	interest-rate and credit risk:									
	and Wu, L.	Theory and evidence on the									
	,	credit default swap term									
		structure.									
23	Chen, R.,	Sources of Credit Risk:	2006	THE JOURNAL OF		0,321	0,505				
	Fabozzi,F.,	□Evidence from Credit Default		FIXED INCOME		.,-	.,				
	Pan,G. and	Swaps									
	Sverdlove, R.	Swaps									
24	Cook, Fu and	The effect of liquidity and	2014	JOURNAL OF BANKING	1.299	1.059	1.587	3	73	0	0
24	Tang	solvency risk on the inclusion of	2014	and FINANCE	1.2))	1.037	1.367		73	o o	0
	rang	bond covenants		and Phyance							
25	C T	Financial crises and the transfer	2014	SPANISH REVIEW OF		0.220	0.202				0
25	Corzo, T.,		2014			0.228	0.302				0
	Gómez, J. and	of risk between the private and		FINANCIAL							
	Lazcano, L.	public sectors: Evidence from		ECONOMICS							
26	C 1 + W	European financial markets The "forward premium puzzle"	2012	TOTAL OF	2 117	1 114	1 410	2	45	10	0
26	Coudert, V.	•	2013	JOURNAL OF	2.117	1.114	1.418	3	45	10	9
	and Mignon,	and the sovereign default risk		INTERNATIONAL							
	V.			MONEY AND FINANCE							
27	Das, S. R.,	Credit default swap spreads.	2006	JOURNAL OF							
	and Hanouna,			INVESTMENT							
	Р.			MANAGEMENT							
28	Das, S. R.,	Accounting-based versus	2009	JOURNAL OF BANKING	1.299	1.059	1.587	3	73	24	33
	Hanouna, P.,	market-based cross-sectional		and FINANCE							

	and Sarin, A.	models of CDS spreads.									
29	De	Bank/sovereign risk spillovers	2013	JOURNAL OF BANKING	1.299	1.059	1.587	3	73	13	13
	Bruyckere,	in the European debt crisis.		and FINANCE							
	V., Gerhardt,										
	M., Schepens,										
	G., and										
	Vander										
	Vennet, R.										
30	Delatte, Gex	Has the CDS market influenced	2012	JOURNAL OF	2.117	1.114	1.418	3	45	13	18
	and Lopez-	the borrowing cost of European		INTERNATIONAL							
	Villavicencio	countries during the sovereign		MONEY AND FINANCE							
		crisis?									
31	Demirgüç-	Are banks too big to fail or too	2013	JOURNAL OF BANKING	1.299	1.059	1.587	3	73	19	19
	Kunt, A., and	big to save? International		and FINANCE							
	Huizinga, H.	evidence from equity prices and									
		CDS spreads.									
32	Díaz, A.,	What drives corporate default	2013	JOURNAL OF	2.117	1.114	1.418	3	45	1	2
	Groba, J., and	risk premia? evidence from the		INTERNATIONAL							
	Serrano, P.	CDS market.		MONEY AND FINANCE							
33	Dieckmann,	Default risk of advanced	2012	REVIEW OF FINANCE	2.012	3.796	1.620	4	40	21	23
	S., and Plank,	economies: An empirical									
	T.	analysis of credit default swaps									
		during the financial crisis.									
34	Draghi, M.,	Transparency, risk management	2003	NBER WORKING					163		
	Giavazzi, F.,	and international financial		PAPER							
	and Merton,	fragility									
	R. C.										
35	Duffee, G. R.,	Credit derivatives in banking:	2001	JOURNAL OF	1.726	4.779	1.952	4	50	42	52
	and Zhou, C.	Useful tools for managing risk?		MONETARY							
				ECONOMICS							
36	Düllmann, K.,	Credit default swap prices as	2007	FINANCIAL MARKETS		0.478	0.600		12		7
	and Sosinska,	risk indicators of listed german		AND PORTFOLIO							
	A.	banks.		MANAGEMENT							
37	Dunbar, K	US Corporate Default Swap	2008	QUANTITATIVE	0.653	0.608	0.968	3	33	3	4
		Valuation: The Market		FINANCE							
		Liquidity Hypothesis and									
		Autonomous Credit Risk									
			L		<u> </u>	<u> </u>		<u> </u>			

38	Ejsing, J., and	The janus-headed salvation:	2011	ECONOMICS LETTERS	0.510	0.660	0.686		38	26	25
	Lemke, W.	Sovereign and bank credit risk									
		premia during 2008–2009.									
39	Fabozzi,F.,	Exploring the components of	2007	FINANCE RESEARCH	0.646	0.415	0.848		13		11
	Cheng, X. and	credit risk in credit default		LETTERS							
	Chen, R.	swaps.									
40	Feldhütter, P.,	Systematic and idiosyncratic	2012	JOURNAL OF	1.302	1.607	1.219	3	23	4	5
	and Nielsen,	default risk in synthetic credit		FINANCIAL							
	M. S.	markets.		ECONOMETRICS							
41	Forte, S., and	Time- varying credit risk	2015	EUROPEAN	1.158	0.926	1.746	3	30	0	0
	Lovreta, L.	discovery in the stock and CDS		FINANCIAL							
		markets: Evidence from quiet		MANAGEMENT							
		and crisis times.									
42	Fung, H.,	How does the use of credit	2012	FINANCIAL	1.000	1.123	0.976	3	30	2	4
	Wen, M., and	default swaps affect firm risk		MANAGEMENT							
	Zhang, G.	and value? evidence from US									
		life and Property/Casualty									
		insurance companies.									
43	Gapen, M. T.,	Measuring and analyzing	2008	IMF WORKING PAPER /						7	8
	Xiao, Y.,	sovereign risk with contingent		IMF STAFF Papers							
	Gray, D. F.,	claims									
	and Lim, C.										
	H.										
44	Ghosh, A. R.,	Fiscal space and sovereign risk	2013	JOURNAL OF	2.117	1.114	1.418	3	45	4	7
	Ostry, J. D.,	pricing in a currency union.		INTERNATIONAL							
	and Qureshi,			MONEY AND FINANCE							
	M. S.										
45	Groba, J.,	The impact of distressed	2013	JOURNAL OF BANKING	1.299	1.059	1.587	3	73	8	8
	Lafuente, J.	economies on the EU sovereign		and FINANCE							
	A., and	market.									
	Serrano, P.										
46	Haerri, M.,	Sovereign risk and the pricing	2015	JOURNAL OF CREDIT	0.312			1		0	
	Morkoetter,	of corporate credit default		RISK							
	S. and	swaps									
	Westerfeld, S.										
47	Hammoudeh,	Relationships between Financial	2013	FINANCIAL REVIEW		0.318	0.573	3	18		
	S., Bhar, R.	Sectors' CDS Spreads and									

	and Liu, T.	Other Gauges of Risk: Did the	1						1		
		Great Recession Change Them?									
48	Hricko, T.,	Analyzing credit risk in default	2003	NCCRFVRM WORKING							
	Cossin, D.,	swap transaction data: Is fixed-		PAPER							
	Aunon-Nerin,	income markets' information									
	D., and	sufficient to evaluate credit									
	Huang, Z.	risk?									
49	Huang, A. Y.,	Information risk and credit	2013	FINANCE RESEARCH	0.646	0.415	0.848		13	0	0
	and Cheng, C	contagion.		LETTERS							
50	Hui, C., and	Crash risk of the euro in the	2011	JOURNAL OF BANKING	1.299	1.059	1.587	3	73	16	18
	Chung, T.	sovereign debt crisis of 2009–		and FINANCE							
		2010.									
51	Janus, T.,	Sovereign default risk,	2013	JOURNAL OF	1.506	1.370	1.852	3	32	1	1
	Jinjarak, Y.,	overconfident investors and		FINANCIAL STABILITY							
	and Uruyos,	diverse beliefs: Theory and									
	M.	evidence from a new dataset on									
		outstanding credit default									
		swaps.									
52	Jarrow, R. A.,	Valuing default swaps under	2002	THE JOURNAL OF		0,321	0,505				
	and Yildirim,	market and credit risk		FIXED INCOME							
	Y.	correlation.									
53	JORION, P.,	Credit contagion from	2009	JOURNAL OF FINANCE	5.424	17.138	5.609	4*	108	60	76
	and ZHANG,	counterparty risk.									
	G.										
54	Jorion, P., and	Good and bad credit contagion:	2007	JOURNAL OF	4.047	10.116	4.200	4*	113	79	109
	Zhang, G.	Evidence from credit default		FINANCIAL							
		swaps.		ECONOMICS							
55	Kim, D.,	Contagion and risk premia in	2010	JOURNAL OF ASIAN		0.400	0.827	1	25		7
	Loretan, M.	the amplification of crisis:		ECONOMICS							
	and	Evidence from Asian names in									
	Remolona, E	the global CDS market									
56	Kim, M. A.,	Credit default swap valuation	2004	JOURNAL OF RISK	0.303				12		
	and Kim, T.	with counterparty default risk									
	S.	and market risk.									
57	Kress, J.	Credit default swaps,	2011	HARVARD JOURNAL	0.519	0.441	0.354			12	10
		clearinghouses, and systemic		ON LEGISLATION							
		risk: why centralized									
			<u> </u>			<u> </u>		<u> </u>	<u> </u>		

		counterparties must have access									
		to central bank liquidity									
58	Leung, KS	Counterparty risk for credit	2009	ASIA-PACIFIC		0.208	0.405	2			14
	and Kwok,	default swaps: Markov chain		FINANCIAL MARKETS							
	YK	interacting intensities model									
		with stochastic intensity									
59	Li, J., and	How Much of Bank Credit Risk	2014	BANCA D'ITALIA,							
	Zinna, G.	is Sovereign Risk? Evidence		EUROSISTEMA							
		from the Eurozone		WORKING PAPERS							
60	Longstaff, F.	Corporate yield spreads: Default	2005	JOURNAL OF FINANCE	5.424	17.138	5.609	4*	108	284	348
	A., Mithal, S.,	risk or liquidity? new evidence									
	and Neis, E.	from the credit default swap									
		market.									
61	Longstaff, F.	How Sovereign is Sovereign	2011	AMERICAN ECONOMIC	3.780	7.675	3.554		50	93	125
	A., Pan, J.,	Credit Risk?		JOURNAL-							
	Pedersen, L.			MACROECONOMICS							
	H., and										
	Singleton, K.										
	J.										
62	Loon, Y. C.,	The impact of central clearing	2014	JOURNAL OF	4.047	10.116	4.200	4*	113	1	2
	and Zhong, Z.	on counterparty risk, liquidity,		FINANCIAL							
	K.	and trading: Evidence from the		ECONOMICS							
		credit default swap market.									
63	Markose, S.,	'Too interconnected to	2012	JOURNAL OF	1.297	1.032	1.080		46	13	21
	Giansante, S.,	fail'financial network of US		ECONOMIC BEHAVIOR							
	and	CDS market: Topological		and ORGANIZATION							
	Shaghaghi, A.	fragility and systemic risk.									
	R.										
64	Merton, R. C.,	On a new approach for	2013	FINANCIAL ANALYSTS	1.548	2.116	1.429	3	26	2	5
	Billio, M.,	analyzing and managing		JOURNAL							
	Getmansky,	macrofinancial risks.									
	M., Gray, D.,										
	Lo, A. W.,										
	and Pelizzon,										
	L.										
65	Naifar, N	What explains default risk	2011	JOURNAL OF		0.319	0.822	1	18		4
		premium during the financial		ECONOMICS AND							
<u> </u>	J	I	<u> </u>	l .	l	<u> </u>	l	1	l	1	

66		=		BUSINESS							
	Nashikkar,	Liquidity and arbitrage in the	2011	JOURNAL OF	1.566	3.355	1.948	4	51	6	8
	A.,	market for credit risk.		FINANCIAL AND							
	Subrahmanya			QUANTITATIVE							
	m, M. G., and			ANALYSIS							
	Mahanti, S.										
67	Nijskens, R.,	Credit risk transfer activities	2011	JOURNAL OF BANKING	1.299	1.059	1.587	3	73	16	21
	and Wagner,	and systemic risk: How banks		and FINANCE							
	W.	became less risky individually									
		but posed greater risks to the									
		financial system at the same									
		time.									
68	Ohno, S	European Sovereign Risk: The	2013	PUBLIC POLICY					9		
		Knock-on Effects of Default		REVIEW							
		Risk across the Public and									
		Financial Sectors									
69	Oldani, C.	The management of greek	2011	THE IUP JOURNAL OF							
		sovereign risk.		FINANCIAL RISK							
				MANAGEMENT							
70	Pu, X., and	Correlation in credit risk	2012	JOURNAL OF BANKING	1.299	1.059	1.587	3	73	5	6
	Zhao, X.	changes.		and FINANCE							
71	Remolona, E.	A ratings - based approach to	2008	INTERNATIONAL	0.837	0.511	0.862		19	2	6
	M., Scatigna,	measuring sovereign risk.		JOURNAL OF FINANCE							
	M., and Wu,			and ECONOMICS							
	E.										
72	Revoltella,	Properly pricing country risk: a	2010	FINANCIAL THEORY					9		
	D., Mucci, F.	model for pricing long-term		AND PRACTICE							
	and Mihaljek,	fundamental risk applied to									
	D	central and eastern European									
		countries									
73	Rodríguez-	Systemic risk measures: The	2013	JOURNAL OF BANKING	1.299	1.059	1.587	3	73	10	16
	Moreno, M.,	simpler the better?		and FINANCE							
	and Peña, J. I.										
74	Schweikhard,	The impact of government	2011	FINANCE MEETING							
	F. and	interventions on cds and equity		EUROFIDAI - AFFI,							
	Tsesmedlidak	markets		Paris. Availabe: SSRN							
	is, Z.			(Social Science Research							

				Network)							
75	Sharma, SD	Credit default swaps: risk hedge	2013	ECONOMIC AFFAIRS		0.252	0.505		10		0
		or financial weapon of mass									
		destruction?									
76	Subrahmanya	Does the tail wag the dog?: The	2014	REVIEW OF	3.174	10.726	3.299	4*	101	6	6
	m, M. G.,	effect of credit default swaps on		FINANCIAL STUDIES							
	Tang, D. Y.,	credit risk.									
	and Wang, S.										
	Q.										
77	Suh, S., Jang,	A simple method for measuring	2013	JOURNAL OF						0	
	I., and Ahn,	systemic risk using credit		ECONOMIC							
	M.	default swap market data.		DEVELOPMENT							
78	Tang, D. Y.,	Market conditions, default risk	2010	JOURNAL OF BANKING	1.299	1.059	1.587	3	73	38	42
	and Yan, H.	and credit spreads.		and FINANCE							
79	Trujillo-	Examining what best explains	2014	JOURNAL OF	0.723	0.411	0.728		19	1	3
	Ponce, A.,	corporate credit risk:		BUSINESS ECONOMICS							
	Samaniego-	accounting-based versus		AND MANAGEMENT							
	Medina, R.	market-based models									
	and Cardone-										
	Riportella, C										
80	Yang, J. and	Credit risk spillovers among	2013	MANAGEMENT	2.482	3.393	2.392		67	3	4
	Zhou, Y.	financial institutions around the		SCIENCE							
		global credit crisis: Firm-level									
		evidence.									
81	Zhang, BY.,	Explaining credit default swap	2009	REVIEW OF	3.174	10.726	3.299	4*	101	67	84
	Zhou, H., and	spreads with the equity		FINANCIAL STUDIES							
	Zhu, HB.	volatility and jump risks of									
		individual firms.									
	1	I	1	I .	1	I	I	1	1	1	I

Appendix D: Shapiro Wilks test of normality.

Normality test in the CDS price distributions. P-values reject the normality hypothesis in all cases.

	Shapiro-Wilks	Sig.		Shapiro-Wilks	Sig.
ELECTROLUX	0.763935134	0.000	DSM	0.860983235	0.000
VOLVO	0.780054884	0.000	PHILIPS	0.855116676	0.000
AKZO NOBEL	0.902516301	0.000	LAFARGEHOLCIM	0.737049603	0.000
APACHE	0.825411532	0.000	LINDE	0.876420431	0.000
ARCELORMITTAL	0.914463028	0.000	MARSH & MCLENNAN	0.9111996540	0.000
ARROW ELECTR.	0.914403028	0.000	MCDONALD'S	0.967377211	0.000
ASTRAZENECA	0.710041246	0.000	MONDELEZ INT	0.863944296	0.000
AVNET	0.802821258	0.000	NESTLE	0.921190308	0.000
BAE SYSTEMS	0.899890262	0.000	NISSAN MOTOR	0.588216558	0.000
BAKER HUGHES	0.906158794	0.000	NOKIA OYJ	0.710522745	0.000
BAXTER INT	0.963589973	0.000	PERNOD RICARD	0.663688637	0.000
BAYER	0.881693653	0.000	PFIZER	0.934527319	0.000
BMW	0.696251342	0.000	PPG INDUSTRIES	0.678400629	0.000
BORGWARNER	0.581086010	0.000	RICOH	0.678509164	0.000
BP	0.558306024	0.000	SABMILLER	0.877286446	0.000
BRISTOL-MYERS SQUIBB	0.965544829	0.000	SANOFI	0.905052323	0.000
BRITISH AMERICAN TOBACCO	0.752117429	0.000	SCHNEIDER ELECTRIC	0.841228685	0.000
CANON	0.732117429	0.000	SCOR	0.866181775	0.000
CATERPILLAR	0.7140117170	0.000	SEALED AIR	0.848447564	0.000
CITI	0.798233521	0.000	SIEMENS	0.784306581	0.000
CONTINENTAL	0.780412515	0.000	SODEXO	0.966810880	0.000
CREDIT SUISSE	0.937446420	0.000	SOFTBANK	0.537250214	0.000
DAIMLER	0.746312217	0.000	SOLVAY	0.888962135	0.000
DIAGEO	0.978878630	0.000	SONY	0.814541113	0.000
E. I. DU PONT DE NEMOURS	0.742538918	0.000	STARWOOD HOTELS	0.716218324	0.000
EASTMAN CHEMICAL	0.902822930	0.000	TECHNIP	0.868111203	0.000
GKN HOLD	0.664714124	0.000	ERICSSON	0.774456481	0.000
GLAXOSMITHKLINE	0.893465864	0.000	BOEING	0.790648323	0.000
HALLIBURTON	0.861659533	0.000	DOW CHEMICAL	0.618308834	0.000
HANNOVER RU	0.937032221	0.000	GOODYEAR TIRE & RUBBER	0.876424249	0.000
HEIDELBERGCEMENT	0.468668637	0.000	PROCTER & GAMBLE	0.780703219	0.000
HEINEKEN	0.853941059	0.000	TRANSOCEAN	0.685009507	0.000
HENKEL & CO	0.888823592	0.000	UBS	0.879154578	0.000
HEWLETT-PACKARD	0.903506338	0.000	UNILEVER	0.877865975	0.000
HONDA MOTOR	0.632999720	0.000	VALEO	0.794625696	0.000
JOHNSON CONTROLS	0.597303609	0.000	WEATHERFORD INT	0.739105625	0.000
KERING	0.680767483	0.000	WPP 2005 LMTD	0.684846513	0.000
KOMATSU	0.792815556	0.000	W11 2003 EW11D	0.004040313	0.000

Appendix E: Correlation matrix of weekly changes in 5-year CDS spreads.

The sample consists of weekly observations for the January 3, 2007 to November 16, 2016 period. ** indicates significance at the 1% level.

001131313 01	WCC	Kiy C	JUSCI	vatio	115 101	tiic sa	maar y	5, 2	007 10	11010	11100	1 10	, 20	ro per	iiou.	iiia	icates sig	511111	curre	c at ti	10 1 / 0	, 10 (01	•	
	Electrolux	Volvo	Akzo Nobel	Apache	Arcelormittal	Arrow Electr.	Astrazeneca	Avnet	Bae Systems	Baker Hughes	Baxter	Bayer	BMW	Borgwarner	BP	Bristol Myers S.	British Am. Tobacco	Canon	Caterpillar	Citigroup	Continental	Credit Suisse	Daimler Diage	eo El du pont
Electrolux	1																							
Volvo	.548(**)	1																						
Akzo Nobel	.608(**)	.648(**)	1																					
Apache	.336(**)	.406(**)	.428(**)	1																				
Arcelormittal	.412(**)	.502(**)	.497(**)	.355(**)	1																			
Arrow Electr.	.451(**)	.580(**)	.546(**)	.374(**)	.422(**)	1																		
	.501(**)	,			.402(**)	-	1																	
Astrazeneca		.573(**)	.616(**)	.397(**)		.483(**)																		
Avnet	.443(**)	.571(**)	.550(**)	.397(**)	.417(**)	.885(**)	.480(**)	1																
Bae Systems	.555(**)	.634(**)	.674(**)	.473(**)	.514(**)	.519(**)	.582(**)	.546(**)	1															
Baker Hughes	.342(**)	.444(**)	.408(**)	.520(**)	.381(**)	.362(**)	.358(**)	.420(**)	.411(**)	1														
Baxter	.376(**)	.385(**)	.441(**)	.308(**)	.316(**)	.426(**)	.335(**)	.438(**)	.429(**)	.339(**)	1													
Bayer	.587(**)	.652(**)	.753(**)	.364(**)	.462(**)	.525(**)	.641(**)	.542(**)	.677(**)	.378(**)	.464(**)													
BMW	.567(**)	.778(**)	.650(**)	.410(**)	.531(**)	.553(**)	.557(**)	.542(**)	.629(**)	.434(**)	.404(**)	.642(**)	1											
Borgwarner	.368(**)	.398(**)	.418(**)	.372(**)	.340(**)	.444(**)	.385(**)	.485(**)	.437(**)	.413(**)	.355(**)			1										
BP	.443(**)	.579(**)	.544(**)	.473(**)	.435(**)	.427(**)	.473(**)	.435(**)	.576(**)	.396(**)		.534(**)		.347(**)	1									
Bristol Myers S.	.376(**)	.390(**)	.429(**)	.321(**)	.315(**)	.452(**)	.307(**)	.498(**)	.457(**)	.388(**)		.445(**)		.382(**)	.381(**)	1								
British Am. Tobacco	.537(**)	.633(**)	.645(**)	.352(**)	.447(**)	.522(**)	.540(**)	.507(**)	.645(**)	.352(**)	.403(**)			.414(**)	.520(**)	.412(**)	1							
Canon	.293(**)		.268(**)	.210(**)	.234(**)	.241(**)	.245(**)	.264(**)	.296(**)	.194(**)	.178(**)			.338(**)	.274(**)	.234(**)	.242(**)	1						
Canon	.439(**)	.242(**)	.521(**)	.428(**)	.488(**)		.418(**)	.564(**)	.459(**)	.471(**)	.452(**)	.509(**)		.489(**)	.424(**)	.475(**)	.494(**)	.266(**)						
						.558(**)													1					
Citigroup	.421(**)	.519(**)	.481(**)	.342(**)	.425(**)	.474(**)	.427(**)	.492(**)	.480(**)	.412(**)	.368(**)	.464(**)		.354(**)	.476(**)	.367(**)	.493(**)	.305(**)	.515(**)	1				
Continental	.515(**)	.674(**)	.601(**)	.379(**)	.464(**)	.544(**)	.533(**)	.557(**)	.609(**)	.442(**)	.340(**)			.440(**)	.504(**)	.421(**)	.575(**)	.234(**)	.497(**)	.515(**)	1			
Credit Suisse	.499(**)	.631(**)	.590(**)	.402(**)	.466(**)	.490(**)	.496(**)	.487(**)	.578(**)	.437(**)	.380(**)	.579(**)	.660(**)	.359(**)	.563(**)	.394(**)	.595(**)	.252(**)	.446(**)	.599(**)	.619(**)	1		
Daimler	.567(**)	.781(**)	.669(**)	.403(**)	.538(**)	.585(**)	.554(**)	.572(**)	.633(**)	.457(**)	.391(**)	.650(**)	.902(**)	.452(**)	.540(**)	.444(**)	.648(**)	.326(**)	.538(**)	.553(**)	.739(**)	.661(**)	1	
Diageo	.588(**)	.645(**)	.654(**)	.407(**)	.467(**)	.488(**)	.521(**)	.496(**)	.649(**)	.398(**)	.450(**)	.662(**)	.675(**)	.401(**)	.577(**)	.434(**)	.651(**)	.297(**)	.487(**)	.511(**)	.624(**)	.608(**)	.691(**) 1	
El du pont	.431(**)	.442(**)	.486(**)	.391(**)	.332(**)	.487(**)	.387(**)	.508(**)	.471(**)	.454(**)	.468(**)	.462(**)	.441(**)	.406(**)	.439(**)	.492(**)	.409(**)	.169(**)	.546(**)	.478(**)	.433(**)	.450(**)	.448(**) .439(*	**) 1
Eastman	.442(**)	.504(**)	.482(**)	.395(**)	.385(**)	.566(**)	.387(**)	.560(**)	.441(**)	.424(**)	.428(**)	.478(**)	.540(**)	.445(**)	.424(**)	.459(**)	.465(**)	.230(**)	.571(**)	.497(**)	.493(**)	.488(**)	.543(**) .472(*	
GKN	.495(**)	.685(**)	.592(**)	.397(**)	.449(**)	.535(**)	.556(**)	.539(**)	.562(**)	.438(**)	334(**)		.724(**)	.408(**)	.493(**)	.400(**)	.551(**)	.253(**)	.478(**)	.506(**)	.690(**)	.623(**)	.712(**) .570(*	
Glaxosmithkline	.440(**)	.496(**)	.559(**)	.365(**)	.335(**)	.435(**)	.614(**)	.436(**)	.553(**)	.347(**)		.570(**)		.435(**)	.405(**)	.301(**)	.498(**)	.282(**)	.389(**)	.360(**)	.461(**)	.432(**)	.498(**) .527(*	
Halliburton	.347(**)	.420(**)	.404(**)	.569(**)	.374(**)	.399(**)	.403(**)	.444(**)	.447(**)	.576(**)		.403(**)		.380(**)	.439(**)	.416(**)	.365(**)	.212(**)	.414(**)	.423(**)	.426(**)	.416(**)	.438(**) .389(*	,
Hannover Rueck	.517(**)	.601(**)	.601(**)	.369(**)	.495(**)	.474(**)	.471(**)	.477(**)	.578(**)	.388(**)		.578(**)		.351(**)	.561(**)	.378(**)	.574(**)	.259(**)	.474(**)	.571(**)	.572(**)	.738(**)	.611(**) .625(*	
Heidelbergcement	.529(**)	.668(**)	.652(**)	.451(**)	.597(**)	.550(**)	.568(**)	.557(**)	.648(**)	.449(**)		.659(**)		.440(**)	.594(**)	.443(**)	.604(**)	.267(**)	.546(**)	.502(**)	.700(**)	.629(**)	.689(**) .605(*	, , ,
Heineken	.376(**)	.464(**)	.461(**)	.350(**)	.415(**)	.385(**)	.420(**)	.405(**)	.467(**)	.366(**)		.477(**)		.317(**)	.394(**)	.344(**)	.484(**)	.201(**)	.399(**)	.365(**)	.509(**)	.464(**)	.490(**) .502(*	
Henkel	.565(**)	.616(**)	.673(**)	.404(**)	.447(**)	.497(**)	.579(**)	.504(**)	.625(**)	.415(**)	.418(**)	.679(**)		.411(**)	.554(**)	.429(**)	.600(**)	.293(**)	.490(**)	.462(**)	.567(**)	.575(**)	.622(**) .595(*	
Hewlett Packard	.399(**)	.541(**)	.459(**)	.377(**)	.386(**)	.611(**)	.443(**)	.622(**)	.506(**)	.446(**)	.402(**)	.483(**)	.521(**)	.419(**)	.442(**)	.410(**)	.469(**)	.218(**)	.546(**)	.441(**)	.484(**)	.463(**)	.533(**) .489(*	**) .492(**)
Honda Motor	.280(**)	.321(**)	.326(**)	.245(**)	.269(**)	.283(**)	.295(**)	.333(**)	.376(**)	.239(**)	.257(**)	.371(**)	.349(**)	.341(**)	.309(**)	.280(**)	.337(**)	.422(**)	.324(**)	.305(**)	.300(**)	.261(**)	.327(**) .295(*	**) .230(**)
Johnson Controls	.451(**)	.518(**)	.515(**)	.453(**)	.460(**)	.505(**)	.465(**)	.546(**)	.529(**)	.488(**)	.417(**)	.497(**)	.546(**)	.636(**)	.474(**)	.459(**)	.510(**)	.320(**)	.592(**)	.491(**)	.502(**)	.466(**)	.559(**) .488(*	**) .494(**)
Kering	.605(**)	.705(**)	.671(**)	.444(**)	.523(**)	.535(**)	.558(**)	.546(**)	.660(**)	.422(**)	.376(**)	.687(**)	.723(**)	.442(**)	.557(**)	.424(**)	.670(**)	.309(**)	.542(**)	.526(**)	.688(**)	.648(**)	.727(**) .703(*	**) .455(**)
Komatsu	237(**)	.321(**)	.267(**)	.243(**)	266(**)	.334(**)	.229(**)	.330(**)	283(**)	.209(**)	260(**)	268(**)	.316(**)	.346(**)	238(**)	237(**)	.262(**)	.429(**)	.329(**)	.295(**)	261(**)	.259(**)	338(**) 261(*	**) .251(**)
DSM	.579(**)	.667(**)	.775(**)	.404(**)	.456(**)	.557(**)	.614(**)	.545(**)	.673(**)	.381(**)	.412(**)	.734(**)	.631(**)	.403(**)	.557(**)	.394(**)	.632(**)	.252(**)	.467(**)	.461(**)	.586(**)	.568(**)	.636(**) .651(*	**) .423(**)
Philips	.551(**)	.623(**)	.656(**)	.383(**)	.433(**)	.545(**)	.548(**)	.542(**)	.628(**)	.416(**)	.408(**)	.630(**)	.626(**)	.392(**)	.538(**)	.394(**)	.625(**)	.270(**)	.424(**)	.443(**)	.585(**)	.581(**)	.627(**) .640(*	
		.700(**)	.670(**)		.570(**)				.666(**)				.684(**)	.411(**)							.629(**)	.608(**)	.675(**) .621(*	
Lafargeholcim	.564(**)	,		.451(**)		.557(**)	.587(**)	.564(**)		.462(**)	.421(**)		,		.549(**)	.423(**)	.622(**)	.278(**)	.515(**)	.511(**)		,		
Linde	.575(**)	.653(**)	.727(**)	.353(**)	.455(**)	.491(**)	.618(**)	.503(**)	.655(**)	.338(**)			.611(**)	.404(**)	.510(**)	.411(**)	.673(**)	.248(**)	.457(**)	.443(**)	.559(**)	.551(**)	.622(**) .628(*	
Marsh & Mclennan	.329(**)	.409(**)	.407(**)	.410(**)	.322(**)	.433(**)	.366(**)	.446(**)	.406(**)	.413(**)	.388(**)			.370(**)	.367(**)	.411(**)	.394(**)	.173(**)	.420(**)	.393(**)	.404(**)	.408(**)	.446(**) .420(*	
Mcdonald's	.369(**)	.401(**)	.427(**)	.368(**)	.284(**)	.500(**)	.375(**)	.478(**)	.422(**)	.331(**)		.418(**)		.353(**)	.338(**)	.412(**)	.390(**)	.224(**)	.451(**)	.364(**)	.377(**)	.386(**)	.431(**) .385(*	
Mondelez	.402(**)	.442(**)	.467(**)	.376(**)	.313(**)	.508(**)	.373(**)	.495(**)	.455(**)	.470(**)		.443(**)		.446(**)	.284(**)	.452(**)	.398(**)	.221(**)	.499(**)	.393(**)	.418(**)	.388(**)	.505(**) .412(*	**) .497(**)
Nestle	.531(**)	.592(**)	.609(**)	.376(**)	.431(**)	.454(**)	.501(**)	.453(**)	.600(**)	.392(**)	.379(**)	.574(**)	.612(**)	.372(**)	.534(**)	.380(**)	.591(**)	.277(**)	.458(**)	.459(**)	.575(**)	.537(**)	.588(**) .618(*	**) .402(**)
Nissan Motor	.336(**)	.384(**)	.406(**)	.290(**)	.337(**)	.334(**)	.339(**)	.374(**)	.392(**)	.273(**)	.288(**)	.403(**)	.402(**)	.392(**)	.320(**)	.322(**)	.381(**)	.346(**)	.347(**)	.308(**)	.353(**)	.307(**)	.404(**) .383(*	**) .286(**)
Nokia	.418(**)	.506(**)	.548(**)	.388(**)	.390(**)	.451(**)	.464(**)	.478(**)	.492(**)	.380(**)	.326(**)	.537(**)		.339(**)	.517(**)	.346(**)	.501(**)	.242(**)	.396(**)	.384(**)	.447(**)	.459(**)	.506(**) .496(*	**) .381(**)
Pernod Ricard	.516(**)	.618(**)	.569(**)	.410(**)	.491(**)	.505(**)	.520(**)	.523(**)	.595(**)	.389(**)	398(**)	.630(**)	.648(**)	.394(**)	.517(**)	.458(**)	.600(**)	.298(**)	.524(**)	.450(**)	.611(**)	.597(**)	.651(**) .638(*	**) .433(**)
Pfizer	.315(**)	.345(**)	.397(**)	.288(**)	.286(**)	.397(**)	.352(**)	.438(**)	.407(**)	.353(**)		.423(**)		.402(**)	.332(**)	.599(**)	.388(**)	.149(**)	.438(**)	.368(**)	.377(**)	.366(**)	.381(**) .392(*	
PPG	.333(**)	.354(**)	.357(**)	.397(**)	.240(**)	.419(**)	.391(**)	.426(**)	.391(**)	.426(**)		.380(**)		.410(**)	.324(**)	.373(**)	.359(**)	.234(**)	.436(**)	.395(**)	.332(**)	.331(**)	.387(**) .303(*	
Ricoh	.233(**)	.292(**)	.271(**)	.252(**)	.295(**)	.305(**)	.270(**)	.320(**)	.291(**)	.259(**)		.281(**)		.321(**)	.287(**)	.299(**)	.242(**)	.405(**)	.255(**)	.328(**)	.257(**)	.273(**)	.304(**) .261(*	
Sabmiller	.449(**)	.546(**)												.395(**)						.439(**)				
			.551(**)	.373(**)	.452(**)	.404(**)	.451(**)	.426(**)	.567(**)	.406(**)		.511(**)			.522(**)	.447(**)	.540(**)	.235(**)	.432(**)		.496(**)	.448(**)		,,
Sanofi	.518(**)	.562(**)	.658(**)	.410(**)	.462(**)	.503(**)	.578(**)	.493(**)	.640(**)	.386(**)	.417(**)			.406(**)	.514(**)	.389(**)	.594(**)	.240(**)	.501(**)	.471(**)	.570(**)	.518(**)	.623(**) .570(*	
Schneider Electr.	.468(**)	.479(**)	.486(**)	.326(**)	.387(**)	.411(**)	.507(**)	.427(**)	.579(**)	.364(**)		.541(**)		.452(**)	.402(**)	.360(**)	.504(**)	.285(**)	.349(**)	.349(**)	.503(**)	.464(**)	.486(**) .473(*	
Scor	.423(**)	.510(**)	.535(**)	.355(**)	.366(**)	.398(**)	.429(**)	.428(**)	.494(**)	.411(**)	.329(**)			.347(**)	.481(**)	.362(**)	.504(**)	.309(**)	.419(**)	.470(**)	.479(**)	.636(**)	.488(**) .543(*	
Sealed Air	.448(**)	.462(**)	.524(**)	.365(**)	.396(**)	.586(**)	.418(**)	.584(**)	.473(**)	.398(**)	.378(**)	.489(**)	.526(**)	.448(**)	.463(**)	.418(**)	.474(**)	.229(**)	.549(**)	.393(**)	.498(**)	.452(**)	.528(**) .417(*	**) .496(**)
Siemens	.500(**)	.620(**)	.614(**)	.430(**)	.482(**)	.525(**)	.551(**)	.538(**)	.626(**)	.438(**)	.409(**)	.645(**)	.635(**)	.371(**)	.574(**)	.425(**)	.598(**)	.264(**)	.436(**)	.453(**)	.565(**)	.552(**)	.646(**) .617(*	**) .419(**)
Sodexo	.584(**)	.612(**)	.640(**)	.378(**)	.444(**)	.540(**)	.584(**)	.526(**)	.646(**)	.398(**)	.449(**)	.641(**)	.627(**)	.381(**)	.509(**)	.407(**)	.638(**)	.255(**)	.458(**)	.507(**)	.590(**)	.613(**)	.635(**) .688(*	**) .405(**)
Softbank	.241(**)	.322(**)	.284(**)	.258(**)	.293(**)	.277(**)	.224(**)	.307(**)	.325(**)	.238(**)	.202(**)	.275(**)	.315(**)	.322(**)	.290(**)	.248(**)	.292(**)	.277(**)	.341(**)	.257(**)	.313(**)	.239(**)	.357(**) .251(*	**) .283(**)
Solvay	.583(**)	.657(**)	.757(**)	.410(**)	.569(**)	.534(**)	.640(**)	.554(**)	.684(**)	.466(**)	.393(**)	.706(**)	.654(**)	.459(**)	.524(**)	.406(**)	.620(**)	.315(**)	.512(**)	.505(**)	.600(**)	.582(**)	.676(**) .650(*	
Sony	.314(**)	.378(**)	.401(**)	.301(**)	.336(**)	.337(**)	.322(**)	.386(**)	.428(**)	.267(**)	.307(**)		.392(**)	.378(**)	.362(**)	.359(**)	.355(**)	.372(**)	.365(**)	.351(**)	.350(**)	.321(**)	.390(**) .368(*	
		.468(**)			.390(**)						.443(**)			.477(**)									.497(**) .450(*	
Starwood Hotels	.405(**)	,	.471(**)	.396(**)		.545(**)	.426(**)	.542(**)	.478(**)	.426(**)		.441(**)			.388(**)	.449(**)	.454(**)	.220(**)	.520(**)	.436(**)	.469(**)	.395(**)		,,
Technip	.423(**)	.478(**)	.494(**)	.406(**)	.406(**)	.377(**)	.504(**)	.412(**)	.495(**)	.417(**)	.316(**)	.471(**)	.483(**)	.365(**)	.487(**)	.308(**)	.459(**)	.227(**)	.393(**)	.418(**)	.464(**)	.472(**)	.487(**) .457(*	
Ericsson	.490(**)	.560(**)	.566(**)	.379(**)	.419(**)	.508(**)	.541(**)	.527(**)	.552(**)	.388(**)				.326(**)	.478(**)	.378(**)	.541(**)	.230(**)	.433(**)	.444(**)	.582(**)	.494(**)	.595(**) .583(*	
Boeing	.381(**)	.438(**)	.506(**)	.414(**)	.346(**)	.522(**)	.421(**)	.549(**)	.477(**)	.459(**)		.493(**)		.407(**)	.382(**)	.497(**)	.491(**)	.231(**)	.642(**)	.422(**)	.487(**)	.467(**)	.509(**) .474(*	
Dow Chemical	.475(**)	.556(**)	.549(**)	.418(**)	.465(**)	.567(**)	.489(**)	.581(**)	.502(**)	.481(**)	.437(**)	.563(**)	.585(**)	.437(**)	.481(**)	.459(**)	.518(**)	.279(**)	.617(**)	.513(**)	.561(**)	.518(**)	.610(**) .508(*	**) .610(**)
Goodyear	.370(**)	.464(**)	.425(**)	.335(**)	.402(**)	.486(**)	.415(**)	.514(**)	.470(**)	.449(**)	.341(**)	.445(**)	.535(**)	.534(**)	.336(**)	.362(**)	.455(**)	.223(**)	.479(**)	.460(**)	.476(**)	.482(**)	.540(**) .434(*	**) .441(**)
Procter & Gamble	.244(**)	.367(**)	.359(**)	.373(**)	.366(**)	.434(**)	.352(**)	.465(**)	.408(**)	.345(**)	.392(**)	.380(**)	.366(**)	.377(**)	.366(**)	.416(**)	.384(**)	.197(**)	.406(**)	.349(**)	.338(**)	.316(**)	.387(**) .326(*	**) .369(**)
Transocean	.388(**)	.480(**)	.443(**)	.540(**)	.495(**)	.424(**)	.391(**)	.422(**)	.471(**)	.540(**)	.378(**)			.401(**)	.494(**)	.356(**)	.423(**)	.227(**)	.545(**)	.411(**)	.451(**)	.436(**)	.482(**) .418(*	
UBS	.490(**)	.642(**)	.600(**)	.385(**)	.481(**)	.464(**)	.475(**)	.469(**)	.579(**)	.417(**)	.344(**)			.346(**)	.580(**)	.365(**)	.595(**)	.276(**)	.436(**)	.627(**)	.621(**)	.856(**)	.630(**) .602(*	
Unilever	.529(**)	.574(**)	.619(**)	.341(**)	.438(**)	.495(**)	.521(**)	.479(**)	.586(**)	.350(**)	.432(**)			.451(**)	.487(**)	.417(**)	.617(**)	.308(**)	.459(**)	.446(**)	.539(**)	.530(**)	.596(**) .654(*	
Valeo	.524(**)	.674(**)	.573(**)	.374(**)	.433(**)	.549(**)	.521(**)	.550(**)	.538(**)	.431(**)	.323(**)			.423(**)	.468(**)	.367(**)	.511(**)	.241(**)	.456(**)	.474(**)	.701(**)	.560(**)	.698(**) .566(*	
Weatherford	.384(**)	489(**)	.573(**)	.555(**)	.433(**)	.397(**)	.461(**)	.550(**)	.538(**)	.528(**)	.323(**)			.423(**)	.472(**)	.367(**)	.430(**)	.241(**)	.456(**)	.474(**)	.701(**)	.428(**)	.450(**) .424(*	
					.472(**)		.593(**)																	,
WPP 2005	.551(**)	.647(**)	.660(**)	.414(**)	.484(**)	.526(**)	.593(**)	.539(**)	.674(**)	.421(**)	.432(**)	.680(**)	.672(**)	.370(**)	.551(**)	.450(**)	.611(**)	.262(**)	.474(**)	.489(**)	.622(**)	.627(**)	.682(**) .617(*	**) .418(**)

	Eastman	GKN	Glaxosmithkline	Halliburton	Hannover Rueck	Heidelbergcement	Heineken	Henkel	Hewlett Packard	Honda Motor	Johnson Controls	Kering	Komatsu	DSM	Philins	Lafargeholcim	Linde	Marsh & Mclennan	Mcdonald's	Mondelez	Nestle	Nissan Motor	Nokia	Pernod Ricard	Pfizer
Eastman	1																								
GKN	.507(**)	1																							
Glaxosmithkline	.386(**)	.528(**)	1																						
Halliburton	.475(**)	.443(**)	.365(**)	1																					
Hannover Rueck	.450(**)		.392(**)	.351(**)	1																				
Heidelbergcement	.544(**)		.472(**)	.445(**)	.608(**)	1																			
Heineken	.328(**)		.368(**)	.374(**)	.412(**)	.482(**)	1																		
Henkel	.454(**)		.539(**)	.417(**)	.552(**)	.591(**)	.443(**)	1																	
Hewlett Packard	.487(**)		.434(**)	.408(**)	.440(**)	.513(**)		.482(**)	1																
Honda Motor	.265(**)		.320(**)	.306(**)	.273(**)	.349(**)		.335(**)	.287(**)	1															
Johnson Controls	.537(**)		.451(**)	.435(**)	.469(**)	.553(**)	.435(**)		.493(**)	.359(**)	1														
Kering	.488(**)		.491(**)	.464(**)	.636(**)	.700(**)	.537(**)		.488(**)	.328(**)	.554(**)	1													
Komatsu DSM	.281(**)		.265(**) .582(**)	.228(**) .389(**)	.246(**) .603(**)	.315(**) .640(**)	.177(**) .469(**)	.677(**)	.331(**) .457(**)	.472(**) .300(**)	.349(**) .494(**)	.261(**)	.273(**)												
Philips	.447(**)		.482(**)	.397(**)	.566(**)	.610(**)		.572(**)	.480(**)	.333(**)	.486(**)	.636(**)		.682(**)	1										
Lafargeholcim		.638(**)	.562(**)	.492(**)	.595(**)	.737(**)		.619(**)	.534(**)	.345(**)	.504(**)				.644(**)	1									
Linde	.434(**)		.572(**)	.389(**)	.548(**)	.606(**)	.451(**)		.449(**)	.308(**)	.486(**)		.269(**)			.624(**)	1								
Marsh & Mclennan		.454(**)	.325(**)	.380(**)	.396(**)	.441(**)		.335(**)	.448(**)	.220(**)	.451(**)		.234(**)			.488(**)	.359(**)	1							
Mcdonald's	.453(**)		.396(**)	.394(**)	.355(**)	.361(**)	.275(**)		.478(**)	.245(**)	.411(**)		.297(**)			.400(**)	.407(**)	.340(**)	1						
Mondelez	.500(**)		.407(**)	.442(**)	.386(**)	.393(**)	.344(**)		.466(**)	.242(**)	.436(**)		.231(**)			.467(**)	.384(**)	.437(**)	.534(**)	1					
Nestle	.412(**)		.478(**)	.393(**)	.503(**)	.562(**)	.475(**)		.445(**)	.309(**)	.464(**)		.277(**)			.602(**)	.627(**)	.337(**)	.354(**)	.368(**)	1				
Nissan Motor	.304(**)	.332(**)	.388(**)	.320(**)	.304(**)	.379(**)	.262(**)	.415(**)	.311(**)	.712(**)	.425(**)	.393(**)	.496(**)	.373(**)	.363(**)	.425(**)	.375(**)	.239(**)	.289(**)	.324(**)	.383(**)	1			
Nokia	.342(**)	.449(**)	.419(**)	.358(**)	.503(**)	.517(**)	.377(**)	.476(**)	.452(**)	.311(**)	.471(**)	.510(**)	.304(**)	.503(**)	.559(**)	.526(**)	.487(**)	.378(**)	.290(**)	.338(**)	.434(**)	.304(**)	1		
Pernod Ricard	.508(**)	.572(**)	.451(**)	.401(**)	.554(**)	.679(**)	.523(**)	.566(**)	.481(**)	.299(**)	.530(**)	.694(**)	.265(**)	.578(**)	.549(**)	.653(**)	.589(**)	.428(**)	.377(**)	.422(**)	.564(**)	.340(**)	.470(**)	1	
Pfizer	.402(**)	.355(**)	.317(**)	.356(**)	.343(**)	.415(**)	.331(**)	.412(**)	.406(**)	.231(**)	.462(**)	.372(**)	.245(**)	.386(**)	.367(**)	.399(**)	.361(**)	.400(**)	.382(**)	.387(**)	.330(**)	.291(**)	.318(**)	.441(**)	1
PPG	.559(**)		.349(**)	.442(**)	.289(**)	.401(**)	.281(**)		.393(**)	.250(**)	.484(**)		.221(**)			.398(**)	.355(**)	.421(**)	.424(**)	.474(**)		.254(**)	.254(**)	.352(**)	.397(**)
Ricoh	.246(**)		.262(**)	.241(**)	.239(**)	.300(**)	.185(**)		.265(**)	.442(**)	.351(**)		.428(**)			.305(**)	.305(**)	.198(**)	.193(**)		.283(**)	.401(**)	.250(**)	.258(**)	.240(**)
Sabmiller	.411(**)		.335(**)	.381(**)	.455(**)	.565(**)		.489(**)	.427(**)	.240(**)	.531(**)		.255(**)			.525(**)	.516(**)	.335(**)	.347(**)		.521(**)	.320(**)	.475(**)	.591(**)	.402(**)
Sanofi	.422(**)		.515(**)	.384(**)	.535(**)	.587(**)		.599(**)	.484(**)	.338(**)	.493(**)		.318(**)			.597(**)	.663(**)	.427(**)	.416(**)		.586(**)	.384(**)	.522(**)	.535(**)	.385(**)
Schneider Electr.	.341(**)		.516(**)	.367(**)	.416(**)	.512(**)		.478(**)	.420(**)	.306(**)	.422(**)			.499(**)		.521(**)	.513(**)	.384(**)	.348(**)		.445(**)	.322(**)	.396(**)	.470(**)	.354(**)
Scor	.335(**)		.382(**) .395(**)	.327(**) .387(**)	.669(**)	.518(**) .559(**)		.483(**)	.386(**) .507(**)	.321(**)	.402(**)		.246(**)			.532(**) .511(**)	.475(**) .469(**)	.361(**)	.297(**)		.478(**)	.326(**) .297(**)	.448(**)	.482(**) .496(**)	.338(**) .362(**)
Sealed Air Siemens	.594(**) .455(**)		.450(**)	.460(**)	.444(**) .557(**)	.630(**)	.344(**) .487(**)		.495(**)	.268(**) .318(**)	.517(**) .487(**)		.285(**) .318(**)			.622(**)	.591(**)	.428(**) .443(**)	.444(**) .405(**)	.427(**) .444(**)		.370(**)	.576(**)	.556(**)	.373(**)
Sodexo	.437(**)		.562(**)	.376(**)	.615(**)	.617(**)		.627(**)	.510(**)	.297(**)	.456(**)		.256(**)			.630(**)	.633(**)	.389(**)	.458(**)		.599(**)	.356(**)	.463(**)	.596(**)	.373()
Softbank	.290(**)		.217(**)	.245(**)	.255(**)	.354(**)		.278(**)	.271(**)	.459(**)	.371(**)			.233(**)		.352(**)	.266(**)	.181(**)	.196(**)		.292(**)	.502(**)	.258(**)	.299(**)	.220(**)
Solvay	.469(**)		.590(**)	.458(**)	.593(**)	.648(**)		.699(**)	.511(**)	.357(**)	.542(**)		.293(**)			.716(**)	.711(**)	.439(**)	.372(**)		.594(**)	.438(**)	.519(**)	.595(**)	.407(**)
Sony	.336(**)		.354(**)	.325(**)	.344(**)	.383(**)		.369(**)	.338(**)	.559(**)	.448(**)			.369(**)		.384(**)	.365(**)	.265(**)	.276(**)		.329(**)	.654(**)	.320(**)	.330(**)	.295(**)
Starwood Hotels	.471(**)		.437(**)	.424(**)	.389(**)	.499(**)	.392(**)		.462(**)	.274(**)	.553(**)		.260(**)			.511(**)	.411(**)	.439(**)	.474(**)		.398(**)	.345(**)	.390(**)	.474(**)	.473(**)
Technip	.356(**)	.479(**)	.442(**)	.445(**)	.447(**)	.496(**)	.386(**)	.523(**)	.360(**)	.322(**)	.405(**)	.482(**)	.273(**)	.486(**)	.483(**)	.517(**)	.489(**)	.281(**)	.348(**)	.359(**)	.452(**)	.365(**)	.353(**)	.469(**)	.274(**)
Ericsson	.394(**)		.451(**)	.386(**)	.487(**)	.574(**)	.486(**)		.447(**)	.298(**)	.464(**)	.605(**)	.240(**)	.557(**)	.628(**)	.617(**)	.539(**)	.371(**)	.333(**)	.396(**)	.551(**)	.326(**)	.524(**)	.548(**)	.386(**)
Boeing	.488(**)	.470(**)	.398(**)	.399(**)	.456(**)	.517(**)	.426(**)	.451(**)	.482(**)	.317(**)	.498(**)	.483(**)	.258(**)	.451(**)	.420(**)	.496(**)	.455(**)	.456(**)	.453(**)	.441(**)	.423(**)	.288(**)	.360(**)	.468(**)	.509(**)
Dow Chemical	.695(**)	.545(**)	.431(**)	.440(**)	.458(**)	.599(**)	.413(**)	.509(**)	.521(**)	.299(**)	.570(**)	.565(**)	.336(**)	.519(**)	.484(**)	.561(**)	.466(**)	.441(**)	.499(**)	.496(**)	.486(**)	.365(**)	.403(**)	.569(**)	.399(**)
Goodyear	.492(**)	.527(**)	.418(**)	.394(**)	.443(**)	.499(**)	.351(**)	.397(**)	.506(**)	.248(**)	.523(**)	.487(**)	.204(**)	.405(**)	.417(**)	.492(**)	.406(**)	.470(**)	.382(**)		.383(**)	.261(**)	.339(**)	.452(**)	.377(**)
Procter & Gamble	.381(**)		.312(**)	.365(**)	.321(**)	.421(**)		.363(**)	.404(**)	.268(**)	.440(**)			.360(**)		.376(**)	.339(**)	.289(**)	.440(**)		.303(**)	.284(**)	.312(**)	.348(**)	.428(**)
Transocean	.450(**)		.344(**)	.578(**)	.396(**)	.507(**)	.333(**)		.449(**)	.307(**)	.469(**)		.245(**)			.525(**)	.403(**)	.375(**)	.394(**)		.436(**)	.355(**)	.319(**)	.471(**)	.318(**)
UBS	.473(**)		.418(**)	.388(**)	.756(**)	.635(**)	.434(**)		.446(**)	.278(**)	.478(**)		.262(**)			.590(**)	.559(**)	.398(**)	.348(**)	.338(**)		.309(**)	.488(**)	.578(**)	.381(**)
Unilever	.410(**)		.521(**)	.359(**)	.555(**)	.550(**)	.419(**)		.445(**)	.304(**)	.465(**)		.312(**)			.581(**)	.611(**)	.343(**)	.381(**)		.672(**)	.427(**)	.455(**)	.544(**)	.375(**)
Valeo	.503(**)		.497(**)	.453(**)	.503(**)	.574(**)		.547(**)	.463(**)	.270(**)	.481(**)			.599(**)		.589(**)	.535(**)	.413(**)	.403(**)		.535(**)	.364(**)	.427(**)	.565(**)	.360(**)
Weatherford		.418(**)	.382(**)	.548(**)	.379(**)	.482(**)	.386(**)	.450(**)	.428(**)	.340(**)	.484(**)			.424(**)		.491(**)	.424(**)	.333(**)	.294(**)		.421(**)	.388(**)	.382(**)	.452(**)	.341(**)
WPP 2005	.437(**)	.013(**)	.483(**)	.424(**)	.582(**)	.658(**)	.532(**)	.01/(**)	.491(**)	.315(**)	.509(**)	.0//(**)	.272(**)	.001(**)	./10(**)	.672(**)	.646(**)	.443(**)	.381(**)	.440(**)	.004(**)	.305(**)	.545(**)	.625(**)	.399(**)

```
PPG Ricoh Sabmiller Sanofi Schneider Electr. Scor Sealed Air Siemens Sodex Softbank Solvay Softbank Solvay Softbank Solvay Softbank Solvay Softbank Solvay Starwood Hotels Technip Ericsson Boeing Dow Chemical Goodyear Procter & Gamble Transocean UBS Unilever Valeo Weatherford WPP 2005
     PPG
                 .248(**) 1
    Ricoh
   Sabmiller
                 .320(**) .266(**)
    Sanofi
                 .314(**) .263(**) .484(**)
Schneider Electr. .359(**) .205(**) .383(**) .469(**)
                                                         1
     Scor
                 .274(**) .244(**) .384(**) .489(**)
                                                       .406(**)
                                                                     1
   Sealed Air
                 .412(**) .228(**) .460(**) .449(**)
                                                        .378(**)
                                                                    .389(**) 1
                 .331(**) .284(**) .568(**) .600(**)
                                                                    .491(**) .468(**) 1
   Siemens
                                                        .479(**)
                 .338(**) .252(**) .521(**) .590(**)
                                                                    .529(**) .483(**) .591(**) 1
   Sodexo
                                                        .547(**)
   Softbank
                 .236(**) .343(**) .262(**) .344(**)
                                                        .271(**)
                                                                    .251(**) .280(**) .297(**) .222(**) 1
                 .390(**) .298(**) .509(**) .645(**)
                                                                    .551(**) .502(**) .622(**) .643(**) .320(**) 1
    Solvay
                                                        .544(**)
                 .327(**) .471(**) .326(**) .400(**)
                                                                    .353(**) .288(**) .352(**) .324(**) .471(**) .399(**) 1
                                                       .330(**)
    Sonv
Starwood Hotels .440(**) .267(**) .456(**) .446(**)
                                                        .407(**)
                                                                    .395(**) .462(**) .450(**) .441(**) .314(**) .472(**) .342(**)
                                                                                                                                        1
    Technip
                 .305(**) .267(**) .418(**) .488(**)
                                                        .414(**)
                                                                    .424(**) .391(**) .458(**) .483(**) .307(**) .525(**) .364(**)
                                                                                                                                       .390(**)
                 .322(**) .262(**) .520(**) .523(**)
                                                        .385(**)
                                                                    .422(**) .470(**) .629(**) .537(**) .268(**) .575(**) .358(**)
                                                                                                                                       .436(**)
                                                                                                                                                   .420(**) 1
   Ericsson
                .452(**) .262(**) .436(**) .452(**)
                                                        .365(**)
                                                                    .460(**) .498(**) .457(**) .442(**) .238(**) .485(**) .313(**)
                                                                                                                                                   .377(**) .461(**) 1
    Boeing
                                                                                                                                       .464(**)
 Dow Chemical .522(**) .292(**) .496(**) .488(**)
                                                        .403(**)
                                                                    .383(**) .571(**) .495(**) .491(**) .324(**) .521(**) .429(**)
                                                                                                                                       .539(**)
                                                                                                                                                   .448(**) .452(**) .486(**)
                 .430(**) .276(**) .381(**) .433(**)
                                                        .437(**)
                                                                    .376(**) .461(**) .414(**) .423(**) .267(**) .484(**) .344(**)
                                                                                                                                       .483(**)
                                                                                                                                                   .358(**) .391(**) .427(**)
                                                                                                                                                                                .488(**)
   Goodyear
Procter & Gamble .338(**) .239(**) .373(**) .344(**)
                                                       310(**)
                                                                    .283(**) .361(**) .367(**) .334(**) .252(**) .331(**) .307(**)
                                                                                                                                       386(**)
                                                                                                                                                   .353(**) .325(**) .417(**)
                                                                                                                                                                                400(**)
                                                                                                                                                                                           341(**)
              .386(**) .251(**) .432(**) .437(**)
                                                                                                                                                   .473(**) .392(**) .428(**)
  Transocean
                                                        .337(**)
                                                                    .392(**) .467(**) .428(**) .412(**) .292(**) .516(**) .300(**)
                                                                                                                                       .437(**)
                                                                                                                                                                                .464(**)
                                                                                                                                                                                            .394(**)
                                                                                                                                                                                                         .314(**)
     UBS
                 .279(**) .298(**) .486(**) .526(**)
                                                        .460(**)
                                                                    .636(**) .450(**) .550(**) .611(**) .246(**) .575(**) .341(**)
                                                                                                                                       .403(**)
                                                                                                                                                   .454(**) .482(**) .440(**)
                                                                                                                                                                                .503(**)
                                                                                                                                                                                            .436(**)
                                                                                                                                                                                                          .304(**)
                                                                                                                                                                                                                        .419(**)
                                                                                                                                                                                                                                  1
   Unilever
                .329(**) .294(**) .521(**) .553(**)
                                                        .502(**)
                                                                    .458(**) .429(**) .570(**) .633(**) .291(**) .621(**) .366(**)
                                                                                                                                       .398(**)
                                                                                                                                                   .473(**) .508(**) .448(**)
                                                                                                                                                                                .477(**)
                                                                                                                                                                                            .391(**)
                                                                                                                                                                                                         .314(**)
                                                                                                                                                                                                                        .419(**) .509(**) 1
                                                                    .440(**) .457(**) .524(**) .554(**) .259(**) .583(**) .327(**)
                                                                                                                                                   .488(**) .539(**) .422(**)
                                                                                                                                                                                                                        .443(**) .558(**) .536(**) 1
                 .388(**) .271(**) .494(**) .508(**)
    Valeo
                                                        .461(**)
                                                                                                                                       .471(**)
                                                                                                                                                                                .590(**)
                                                                                                                                                                                            .482(**)
                                                                                                                                                                                                         .300(**)
  Weatherford .336(**) .309(**) .368(**) .424(**)
                                                        .424(**)
                                                                    .417(**) .450(**) .450(**) .394(**) .313(**) .511(**) .357(**)
                                                                                                                                       .399(**)
                                                                                                                                                   .488(**) .394(**) .372(**)
                                                                                                                                                                                .445(**)
                                                                                                                                                                                            .412(**)
                                                                                                                                                                                                         .280(**)
                                                                                                                                                                                                                        .619(**) .402(**) .412(**) .400(**)
  WPP 2005
                .356(**) .323(**) .588(**) .614(**)
                                                        .484(**)
                                                                    .528(**) .468(**) .687(**) .618(**) .241(**) .644(**) .363(**)
                                                                                                                                       .477(**)
                                                                                                                                                   .517(**) .654(**) .509(**)
                                                                                                                                                                                .540(**)
                                                                                                                                                                                           .442(**)
                                                                                                                                                                                                         .338(**)
                                                                                                                                                                                                                        .453(**) .600(**) .578(**) .589(**) .458(**)
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Appendix F: PCA total variance explained

Results from Principal Component Analysis for the 75 firms sample. Source Stata

		Lateral Eli		F.A.	i C C.		Rotation Sums of Squared Loadings					
Component		Initial Eligen										
	Total		Cumulative %			Cumulative %			Cumulative %			
1	31.722		42.296	31.722		42.296	13.704		18.272			
2	3.140	4.186	46.482	3.140	4.186	46.482	6.288	8.384	26.656			
3	2.773	3.698	50.180	2.773	3.698	50.180	4.567	6.090	32.746			
4	2.230	2.974	53.154	2.230	2.974	53.154	4.337	5.782	38.529			
5	1.901	2.535	55.689	1.901	2.535	55.689	4.154	5.539	44.067			
6	1.668	2.224	57.913	1.668	2.224	57.913	4.093	5.457	49.524			
7	1.433	1.910	59.823	1.433	1.910	59.823	3.899	5.199	54.723			
8	1.262	1.683	61.506	1.262	1.683	61.506	3.642	4.856	59.580			
9	1.201	1.601	63.107	1.201	1.601	63.107	1.798	2.398	61.978			
10	1.108	1.477	64.584	1.108	1.477	64.584	1.637	2.183	64.160			
11	1.040	1.387	65.971	1.040	1.387	65.971	1.212	1.616	65.777			
12	1.016	1.354	67.326	1.016	1.354	67.326	1.162	1.549	67.326			
13	0.974	1.299	68.624									
14	0.938	1.250	69.874									
15	0.912	1.216	71.090									
16	0.828	1.105	72.195									
17	0.809	1.078	73.273									
18	0.750	1.000	74.272									
19	0.740	0.987	75.259									
20	0.722	0.962	76.221									
21	0.697	0.929	77.150									
22	0.677	0.902	78.052									
23	0.656	0.874	78.926									
24	0.651	0.868	79.794									
25	0.615	0.820	80.614									
26	0.590	0.786	81.400									
27	0.570	0.760	82.161									
28	0.542	0.722	82.883									
29	0.530	0.706	83.589									
30	0.525	0.700	84.289									
31	0.515	0.687	84.976									
32	0.480	0.640	85.616									
33	0.455	0.606	86.222									
34	0.451	0.601	86.823									
35	0.432	0.576	87.399									
36	0.412	0.550	87.949									
37	0.408	0.544	88.493									
38	0.396	0.528	89.020									
39	0.386	0.515	89.535									
40	0.376	0.502	90.037									
41	0.362	0.482	90.519									
42	0.353	0.471	90.991									
43	0.337	0.450	91.440									
44	0.335	0.447	91.887									
45	0.332	0.443	92.330									
46	0.327	0.436	92.766									
47	0.307	0.409	93.174									
48	0.302	0.402	93.577									
49	0.294	0.392	93.969									
50	0.278	0.370	94.339									

Component		Initial Eligen	values	Extract	tion Sums of Sq	uared Loadings	Rotati	on Sums of Squ	ared Loadings
·	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
51	0.272	0.362	94.701						
52	0.265	0.353	95.054						
53	0.248	0.330	95.384						
54	0.240	0.320	95.704						
55	0.234	0.313	96.017						
56	0.225	0.300	96.317						
57	0.213	0.283	96.600						
58	0.206	0.274	96.874						
59	0.197	0.263	97.137						
60	0.192	0.256	97.394						
61	0.185	0.246	97.640						
62	0.183	0.243	97.884						
63	0.178	0.237	98.120						
64	0.173	0.230	98.351						
65	0.161	0.215	98.566						
66	0.151	0.202	98.767						
67	0.144	0.193	98.960						
68	0.141	0.188	99.148						
69	0.130	0.173	99.321						
70	0.123	0.165	99.485						
71	0.110	0.146	99.632						
72	0.099	0.132	99.764						
73	0.075	0.100	99.864						
74	0.067	0.090	99.954						
75	0.035	0.046	100.000						

Appendix G: Factor loadings matrix in PCA.

Varimax rotation constrained to factors with eigenvalues >1. Source Stata

						Comp	onent					
	1	2	3	4	5	6	7	8	9	10	11	12
Linde	0.784	0.108	0.106	0.123	0.110	0.197	0.216	0.176	0.045	0.042	-0.003	0.096
Henkel	0.740	0.128	0.140	0.124	0.119	0.198	0.208	0.184	0.023	0.010	0.024	0.010
Bayer	0.734	0.154	0.107	0.171	0.119	0.207	0.171	0.124	-0.038	0.087	-0.032	0.029
Akzo Nobel	0.734	0.167	0.120	0.199	0.092	0.208	0.260	0.192	0.031	0.042	-0.104	0.031
Unilever	0.718	0.216	0.122	0.220	0.148	0.142	-0.010	0.133	0.148	-0.031	0.125	-0.029
DSM	0.714	0.135	0.128	0.174	0.127	0.124	0.253	0.299	0.019	0.108	0.074	0.040
Solvay	0.678	0.238	0.177	0.010	0.107	0.242	0.248	0.170	-0.040	0.077	-0.026	0.016
Astrazeneca	0.671	0.132	0.120	0.008	0.159	0.091	0.146	0.006	0.040	0.034	-0.007	0.011
Bae Systems	0.662	0.234	0.182	0.183	0.109	0.163	0.238	0.126	0.145	0.086	0.046	0.069
Nestle	0.661	0.271	0.158	0.178	0.108	0.052	-0.054	0.199	0.123	0.017	0.149	0.103
Sanofi	0.661	0.187	0.113	0.143	0.238	0.146	0.152	0.122	0.072	0.056	0.006	0.041
Diageo	0.610	0.359	0.157	0.234	0.051	0.082	-0.154	0.225	0.014	0.040	0.074	0.011
Sodexo	0.608	0.385	0.111	0.249	0.100	0.053	0.063	0.216	0.164	-0.111	0.171	0.019
WPP 2005	0.605	0.315	0.151	0.213	0.098	0.028	0.238	0.181	0.036	0.256	-0.040	0.011
Philips	0.597	0.193	0.205	0.197	0.120	0.046	0.226	0.228	0.177	0.216	0.031	-0.078
Kering	0.582	0.526	0.224	0.168	0.138	0.121	0.092	0.135	0.074	0.040	-0.100	-0.066
Glaxosmithkline	0.571	0.028	0.057	0.099	0.184	0.106	0.173	0.201	0.097	0.005	0.357	-0.082
Pernod Ricard	0.554	0.432	0.194	0.200	0.161	0.157	0.088	0.098	0.052	0.138	-0.167	-0.078
Technip	0.539	0.144	0.397	0.027	0.235	0.211	-0.071	0.051	0.012	0.001	0.029	-0.004
Lafargeholcim	0.522	0.309	0.203	0.130	0.046	0.292	0.238	0.181	0.074	0.067	-0.174	0.090
Schneider Electric	0.518	0.186	0.106	0.073	0.357	0.113	0.009	0.104	0.058	0.193	0.188	-0.100
Siemens	0.515	0.242	0.289	0.175	0.166	0.031	0.136	0.214	0.093	0.411	0.066	-0.008
Electrolux	0.506	0.355	0.080	0.179	0.119	0.083	0.066	0.101	0.010	-0.145	-0.032	-0.097
British American Tobacc	0.503	0.324	0.172	0.230	0.142	0.050	0.189	0.145	0.176	0.132	0.074	0.075
SabMiller	0.470	0.213	0.209	0.321	0.183	0.067	0.045	-0.004	0.316	0.266	-0.163	0.093
Heidelbergcement	0.453	0.371	0.258	0.149	0.167	0.195	0.373	0.128	0.174	0.066	-0.171	0.100
Ericsson	0.378	0.319	0.176	0.177	0.001	0.024	0.246	0.015	0.063	0.347	-0.015	-0.090
Nokia	0.370	0.070	0.159	-0.025	0.049	-0.014	0.336	0.218	0.081	0.273	-0.177	-0.145
BMW	0.330	0.730	0.197	0.149	0.188	0.078	0.125	0.096	0.137	0.130	0.050	0.052
Daimler	0.334	0.720	0.178	0.144	0.183	0.092	0.158	0.103	0.121	0.145	0.045	0.039
Valeo	0.332	0.694	0.124	0.067	0.150	0.129	0.206	0.159	-0.035	0.080	0.070	-0.038
Continental	0.349	0.664	0.133	0.063	0.228	0.148	0.166	0.198	0.026	0.136	-0.017	0.015
GKN	0.342	0.662	0.098	0.043	0.161	0.099	0.201	0.206	-0.004	0.043	0.036	-0.047
Volvo	0.510	0.575	0.226	0.111	0.158	0.058	0.162	0.084	0.097	0.002	-0.052	-0.049
Transocean	0.164	0.156	0.753	0.113	0.219	0.151	0.060	0.002	0.027	0.108	0.005	0.041
BP	0.248	0.107	0.687	0.012	-0.034	-0.004	-0.007	0.217	0.018	0.006	-0.137	-0.025
Halliburton	0.128	0.174	0.628	0.135	-0.021	0.095	0.219	0.016	0.015	0.106	0.300	0.009
Apache	0.199	0.105	0.620	0.101	0.074	0.081	0.158	0.175	0.044	0.106	0.055	0.032
Weatherford	0.168	0.108	0.596	0.040	0.162	0.176	0.111	0.064	0.063	-0.035	-0.131	-0.030
Baker Hughes	0.153	0.138	0.584	0.165	0.347	0.048	0.171	0.060	0.019	0.140	0.144	-0.002
Bristol-Myers Squibb	0.172	0.130	0.073	0.734	0.069	0.096	0.161	0.189	0.020	0.157	-0.014	-0.031
Pfizer	0.160	0.135	0.020	0.714	0.165	0.130	0.105	0.214	-0.017	0.083	-0.091	-0.049
Baxter	0.291	0.044	0.112	0.712	0.122	0.054	0.092	0.178	0.043	0.058	0.015	0.005
Procter & Gamble											0.013	
Mcdonald's	0.295	0.086	0.179	0.482	0.251	0.042	0.161	0.078	0.139	-0.120	0.308	0.000
Mondelez											0.283	-0.040
Boeing	0.315	0.131	0.159	0.360	0.335	0.170	0.261	0.294	-0.109	0.244	0.199	0.104

						Comp	onent					
	1	2	3	4	5	6	7	8	9	10	11	12
Johnson Controls	0.263	0.204	0.168	0.185	0.702	0.127	0.168	0.063	0.081	0.091	-0.133	-0.003
Borgwarner	0.293	0.180	0.173	0.091	0.686	0.249	0.107	0.125	0.174	0.159	0.106	-0.157
Goodyear	0.188	0.405	0.116	0.067	0.558	0.120	0.185	0.164	0.125	0.052	0.122	0.042
Starwood	0.150	0.168	0.079	0.270	0.524	0.014	0.078	0.039	0.073	0.049	-0.041	0.028
Caterpillar	0.344	0.085	0.310	0.305	0.452	0.278	0.277	0.168	0.019	0.032	-0.047	0.115
PPG	0.236	0.185	0.261	0.239	0.440	0.158	0.279	0.065	0.118	-0.069	0.319	0.081
Nissan	0.239	0.199	0.130	0.082	0.095	0.837	0.088	-0.019	0.049	0.013	0.039	-0.005
Honda	0.215	0.127	0.100	0.021	0.069	0.828	0.110	0.058	0.052	0.077	0.108	0.018
Sony	0.201	0.063	0.082	0.165	0.119	0.741	0.026	0.095	0.252	0.127	0.052	0.021
Komatsu	0.311	-0.062	0.113	0.093	0.105	0.545	0.221	0.073	0.405	-0.026	-0.066	-0.072
Softbank	0.120	0.072	0.197	0.144	0.118	0.514	0.042	0.047	-0.029	-0.143	-0.346	-0.053
Avnet	0.310	0.262	0.145	0.247	0.149	0.138	0.672	0.093	0.121	0.124	0.053	-0.035
Arrow Electr.	0.322	0.281	0.161	0.274	0.139	0.084	0.642	0.046	0.206	0.024	0.113	-0.019
Sealed Air	0.288	0.196	0.147	0.093	0.305	0.087	0.553	0.133	-0.112	0.054	-0.028	-0.022
Hewlett-Packard	0.266	0.263	0.169	0.171	0.145	0.136	0.485	0.198	0.101	0.208	0.069	0.013
Eastman Chemical	0.198	0.339	0.263	0.253	0.311	0.224	0.463	0.118	-0.009	-0.136	0.105	0.148
E. I. Du Pont	0.301	0.126	0.266	0.356	0.347	0.174	0.406	0.046	0.117	-0.067	0.057	0.107
Dow Chemical	0.293	0.316	0.211	0.245	0.377	0.237	0.393	0.136	0.062	-0.139	-0.061	0.140
UBS	0.351	0.203	0.112	0.145	0.042	0.045	0.126	0.778	0.105	0.076	0.063	0.009
Credit Suisse Group ag	0.376	0.287	0.114	0.209	0.090	0.028	0.115	0.721	0.054	0.034	0.061	-0.029
Scor	0.334	0.049	0.154	0.185	0.162	0.159	0.063	0.696	0.045	0.099	-0.016	-0.019
Hannover Ru.	0.417	0.243	0.159	0.205	0.104	0.039	0.069	0.620	0.029	0.008	-0.074	-0.003
Citigroup	0.221	0.276	0.192	0.217	0.090	0.083	0.201	0.443	0.338	-0.150	0.018	0.183
Ricoh	0.124	0.149	0.044	0.085	0.161	0.369	0.115	0.115	0.653	0.014	-0.018	-0.014
Canon	0.217	0.087	0.043	-0.067	0.185	0.469	0.034	0.151	0.575	0.067	0.123	-0.101
Heineken	0.208	0.297	0.316	0.151	0.240	0.105	0.040	0.069	0.041	0.570	-0.030	0.142
Marsh & Mclennan	0.110	0.297	0.141	0.242	0.301	0.145	0.188	0.135	-0.161	0.371	0.204	0.040
Arcelormittal	0.045	-0.021	0.016	-0.030	0.008	-0.037	0.009	0.005	-0.032	0.038	0.002	0.902