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AN ANALYSIS OF FINANCIAL STABILITY INDICATORS IN EUROPEAN BANKING: THE ROLE OF COMMON FACTORS

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AN ANALYSIS OF FINANCIAL STABILITY INDICATORS IN EUROPEAN BANKING: THE ROLE OF COMMON FACTORS

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Abstract
In this paper, we investigate the information content of three market indicators of financial instability using daily data on subordinated debt spreads (SND), credit default swap spreads (CDS) and implied option volatility (IV) over the period January 2001 – January 2004 for a sample of twenty major European banks. Using common factor analysis, we find for each indicator a significant common factor across banks, which we label the "market" factor. This market factor explains between 61 and 92 percent of total variation. Cointegration analysis shows that the market factor in each case is significantly related to macro financial variables such as the short term nominal interest rate, the yield spread and a European Price earning stock ratio. Hence, market risk is primarily affected by aggregate economic and financial developments which are widely seen to impact financial markets. The driving variables of market risk are different for the bond and equity markets with short-term interest rates and yield curve dominating the bond market (SND) and P/E ratio and short-term interest rate significantly influencing the equity market (IV). The CDS market seems to lie somewhat in between these two classical markets, with closer links, however, to the traditional bond market. Little evidence is found that idiosyncratic bank-specific risks are a major component of SND, CDS and IV developments.

Keywords: Credit Default Swap Spreads, Risk Premium, Financial Integration

JEL classification: G12, G15, G21, C30

1. Introduction

The social benefits of an effective financial system are commonly acknowledged. It is widely accepted that finance contributes to an efficient allocation of real economic resources across time and space, an efficient management of wealth and capital accumulation, both main drivers for development and growth.[1] Modern finance also enables the management of economic and financial risk in a globally integrated economic system by pricing, repackaging and transferring risks. The important role of banks – besides financial markets - as intermediary agent or institution in the process of asset allocation is also widely accepted. Following this line of reasoning, there is also a clear social benefit in *maintaining* this system and its institutions, which hence should be a policy objective.[2] In this respect, "there is clear empirical and theoretical evidence that, at times, public intervention may be required to ensure financial stability. (…)Banking is indeed a business plagued by an inherent instability, which cannot be removed if its economic benefits are to be realised"[3]. At the centre of these problems is the maturity-mismatch between loans and deposits, intrinsic to the banks' business. However, it has to be underlined that "the evil to be avoided is not the failure of just a single bank"[4]. Market entry and exit is a normal process in the banking sector as in any other industry. Nonetheless, the risk of contagion, "recognised as key component in the development of many financial crises"[5], makes supervision necessary, also on a micro level. Yet, supervision on a micro-level is only a means to the end of insuring systemic, macro-stability. The question of how different sources of information interact is precisely what is at the core of the present study.

A practical problem is the fact that situations of distress in the European financial system leading to ultimate bank failures, such as in the case of Bankhaus Herstatt in 1974 or Barings in 1995, lay relatively far behind in history and are rare. Nonetheless, the recent past has shown a number of situations when financial markets seem to have been

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[1] The three roles of modern finance mentioned are presented in "Towards an Understanding of the Meaning of Financial Stability" by Garry Schinasi (2003). The author points out that the capital accumulation might even extend to the accumulation of human capital in modem and highly developed economies.

[2] Whereas the latter view is shared by most academics, the precise definition of "financial stability" and its policy-implications are controversial. In fact, numerous definitions coexist while some central banks, which regularly publish so-called financial stability reports, tend even to avoid the task of defining financial stability or acknowledge the elusiveness of a consistent definition. Tommaso Padoa-Schioppa (2003) presents the following definition: "in general, the core economic functions of the financial system consist in channelling savings into investments and providing for an efficient and safe payment mechanism. Along these lines, I would suggest defining financial stability as a condition where the financial system is able to withstand shocks without giving way to cumulative processes which impairs the allocation of savings to investment opportunities and the processing of payment in the economy."

[3] Padoa-Schioppa, T. (2003)

[4] see above

[5] see above

considerably preoccupied by the financial soundness of several European banks.[6] Situations of substantial financial distress remain a concrete threat.

Generally, financial stability analysis is based on indicators which provide a measure of the stability of individual financial institutions as well as of the entire financial system. Traditionally, this has been accomplished by carrying out on-site inspections of banks in regular intervals and by analysing financial accounting ratios. In recent years, integrating market data into this framework has been an important tendency, supported by the low–cost and high-frequency availability of market data. Commonly used market indicators today are for example subordinated debt spreads, equity prices and equity returns. The current study is an extension of the important research which has been undertaken in this area. It focuses on credit default swaps (CDS) spreads[7], and aims at integrating CDS in the framework of market indicators of financial stability.

CDS are one of the novel credit risk transfer instruments whose use has strongly increased during the recent past. CDS offer protection on default of a credit, comparable to credit insurance, by requiring a regular fee to be paid, the premium or CDS spread, in exchange for protection, a compensation in case of default. The focus in this paper, however, is not on the asset as such but rather on the "price" of it, the CDS spread. The reason is that CDS spreads exhibit two important properties which suggest that, theoretically at least, they are good candidates for financial stability indicators. As will be shown, CDS spreads adequately reflect bank risk and moreover exhibit a high pricing efficiency. In spite of this, CDS have hardly received any attention in the context of financial stability analysis so far.

In order to test how CDS spreads act as stability indicator in practise, their properties will be examined in comparison to two other indicators, subordinated debt spreads and implied volatility[8]. This implies analysing a number of aspects in detail: 1) how do the indicators capture bank-specific and common risk effects? 2) What are the underlying (risk-)dimensions of the indicators? 3) Can a market risk dimension be identified? 4) If so, what are its properties and is market risk related to a number of overall financial indicators?

The paper is set up as follows. In section 2, we will give a brief literature review, while we define the three indicators of financial stability used in this paper in section 3. In section 4 we present data and methodology. Section 5 contains the empirical results and discussion, while we conclude in section 6.

2. Literature review

[6] See for example Financial Times, 14 October 2002, "Bad debts, falling capital, dismal profits"
[7] For more information on CDS and the CDS market, see Annex I.
[8] For an example of the practical use of the mentioned indicators, see for example the most recent "EU banking sector stability" report by the ECB, November 2003, available at www.ecb.int

Testing the properties of CDS spreads as financial stability indicators touches upon two distinct aspects, which have only been separately researched so far[9]. First of all, it concerns the use of market data for financial stability analysis. Research has focussed on various indicators in this context and resulted in a substantial literature on the subject during the last years, which will be presented in the first part of this review. The second important aspect is (practical) CDS pricing - only if CDS spreads adequately reflect risk, they are suitable indicators. Considerably less research has been conducted in this area, mostly because the CDS market has only gained a substantial size during the last three to four years. The existing evidence will be presented in the second part of this literature review.

Market indicators of financial stability

The idea to complement the traditional supervisory approach with market data has received growing attention, both in academic research and practical supervision. The initial research focused on subordinated debt (SND) issued by financial institutions and was later extended to other asset types. In an early theoretical paper Gilbert (1990) analyzes the disciplining effects on a bank's lending behaviour by a (mandatory) subordinated debt issuance policy. He finds that SND issuance can considerably lower risk-taking by banks and the potential costs for deposit insurance. Other research focuses on the practical use of market indicators for supervisory purposes. The widely-shared conclusion is that market indicators are indeed a valuable source of complimentary information for supervision.

In their study of subordinated debt data between 1983 and 1991 Flannery and Sorescu (1996) find that subordinated debt spreads overall reflect bank risk as measured by financial accounting ratios[10]. However, the signalling function by SND spreads can be strongly biased by government guarantees, notably the federal regulators "too big too fail" (TBTF) policy which was announced in 1984[11]. Tests of different subsamples reveal that only in the period after the policy was abandoned in 1988[12], the spreads on

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[9] The only exception to note is the article "Large complex financial institutions: common influence on asset price behaviour?" by Marsh, I.W., Stevens, I. and C. Hawkesby (2003) published in the most recent Financial Stability Review of the Bank of England. However, CDS spreads are the tool, not the object of analysis in this study, which compares large complex financial institutions and common influence on their asset prices. In this respect, the article differs considerably from the scope of analysis to be pursued here. Nevertheless, the methodology used has provided some inspiration for this paper.

[10] The choice of this the proxy is of crucial importance for all studies which try to assess an indicator's viability against a risk benchmark, since it considerably influences the result of the study. Various designs are proposed for such tests, ranging from using financial accounting ratios to implementing event studies based on ratings changes. The drawbacks of the individual methods will be highlighted in the following. For the current paper it can be stated that financial variables are a rather objective risk measure even though they can also be manipulated by capital management and off balance-sheet accounting.

[11] The policy was formally announced by the Comptroller in September 1984 and applied in the case of Continental Illinois Corporation in the same year. However, as Flannery points out, signs that large banks were unlikely to expose creditors to default losses were available earlier.

[12] The retreat of the policy in 1988 implied that bank debenture holders suffered losses when their firm's subsidiary financial institution failed. Examples are First Republic, Bank of New England and Southeast Baking Corp.

subordinated debt spreads clearly convey information on bank risk. Studying the issuance decision of subordinated debt is another option to assess the risk profile of banks. The motivation is that, depending on their (perceived) risk profile, banks issue the junior and risky subordinated debt or refrain from doing so. A study by Federal Reserve System (1999) focuses on this issuance decision by the top-50 US banks between 1986 and 1997. Interestingly, the authors come to the same conclusion as far as the biasing effect of the TBTF policy is concerned. Only with the retreat of the mentioned policy and a general decline in market conditions, there is a significant link between the issuance decision and the banks' risk profile as measured by various accounting ratios.

Extending the analysis to the equity market, Krainer and Lopez (2002) find that equity data, namely stock returns and estimated distance to default (EDF), are also viable risk indicators for banks. The analysis is conducted by means of an event study on 810 supervisory rating changes (BOPEC) between 1990 and 1999, which are considered to capture decisive changes in the sample banks' risk profile[13]. Swidler and Wilcox (2001) broaden the set of assets to include equity options. Demonstrating that implied volatility is a good predictor of future realized volatility, they deduce that implied volatility also has a signalling function for bank risk. Pointing to the low costs and high-frequency availability of such data, the authors strongly encourage its use for supervisory purposes.

A comparison of an equity-based indicator (distance to default) and a bond-market related indicator (subordinated debt spreads) is presented by Greint, Vesala and Vulpes (2002). The authors carry out the empirical test with European data and by means of an event study which is based on downgrades of FitchIBCA financial stability ratings[14]. They find that the two indicators can have a predictive power up to 18 month in advance of the event, albeit with different magnitude. Whereas distance to default is a weak predictor relatively close to an event, bond spreads react very strongly during that period, and vice versa. In accordance with the previous studies, the authors identify a bias resulting from (implicit) government guarantees which affect the bond-related indicator. All in all, the authors suggest a complimentary use of both equity and bond-indicators, potentially in conjunction with other market or accounting data. Another comparison is carried out by Berger, Davies and Flannery (2000) who focus on the timeliness of the information content of bond and equity indicators as well as (private) supervisory

[13] Supervisory rating changes are the risk proxy implicitly used here. Normally, event studies are based on defaults of financial institutions. However, since the European banking market has not experienced any default in recent history, an alternative set of events is necessary to carry out the analysis. One option is to generate events on the basis of supervisory ratings or ratings changes. Supervisory ratings thus become the absolute measure/proxy of bank risk, despite the danger of an inaccurate or subjective risk assessment. For more details on implementing event studies, see also the later section "Methodology".

[14] These ratings focus on the bank's economic and financial conditions, not taking into account any external support in case of difficulties and hence seem to be rather adequate indicators for this purpose. The authors define an event as a downgrade below category C of these ratings. They motivate this threshold by citing evidence that banks of this rating category experienced considerable financial problems and received public support and/or had to go through major restructuring in the 12 months after such a rating change occurred. Nonetheless, the concerns regarding the subjectivity and accuracy of ratings as ultimate measure of risk profile used in such studies also apply here.

information[15]. The result is that supervisory assessments are much more closely tied to bond ratings than they are to equity market assessments, probably because stock and bond investors have different economic concerns. A further result is that supervisory ratings have a much stronger contemporaneous focus as opposed to the forward-looking market indicators. Also, the time-value of supervisory information declines and considerable private knowledge is only present immediately after an inspection and looses its exclusiveness rather quickly, which is also the finding of DeYoung, Flannery, Lang and Sorescu (2001). Summarizing, Berger et al. note that "supervisors, bond market participants and equity market participants all produce valuable, complimentary information which may contribute to improving the governance of large banking organizations".

Credit default swaps pricing

Since CDS spreads have not yet been tested as stability indicators itself, the following review has to focus on the CDS market in general, with primary interest directed to CDS spreads, the "price" of CDS protection rather than the asset itself. The basic question is if CDS price risk adequately? Besides, the issue of pricing efficiency is discussed and CDS are compared to other assets in this respect. Unfortunately, while there is considerable literature on the theoretical grounds of credit derivative pricing, empirical tests of these theories are rare - only a few studies have investigated this area, which are presented in the following.

The general consensus of the studies examined is that CDS do indeed price risk adequately, i.e. at least as adequately as subordinated debt. However this claim is not universally valid, as Howeling and Vorst (2001) point out. The precision of the pricing procedure depends on the rating of the underlying entity. Spreads for highly-rated institutions are more precise than of lower-rated institutions, which is also the outcome of a study by Hull, Predescu and White (2003). The authors attribute this to counterparty default risk of CDS and a liquidity premium on the issuer's bonds. Longstaff, Mithal and Neis (2003) also find a pricing differential between the CDS and SND market for some entities and demonstrate by means of subsequent tests with different liquidity proxies that liquidity in the bond market is the most likely reason for the observed difference in spreads[16].

The issues of pricing efficiency and price discovery are analysed by Blanco, Brennan and Marsh (2003). In general, when closely-related assets trade in different locations, such as corporate bonds and CDS, the order flow is fragmented and price discovery is split between markets. Price innovation occurs in the market where the best-informed traders

[15] It is important to note that the design of this study differs from the previous one. It does not rely on an event-study framework or on a risk-proxy but directly compares the information content of the three different indicators.

[16] Another possible explanation such as modelling error or the choice of the relevant risk-free rate are rejected. The rejection of the latter is especially surprising since the average spread gap shrinks from 60bp to 4bp when using the swap rate, which is widely viewed as appropriate rate, rather than a government bond yield.

act. Using cointegration analysis and a VECM[17] on daily prices for a sample of 33 entities between January 2001 and June 2002, the authors find that roughly 80% of price discovery happens in the CDS market. The best-informed traders in this context are banks that have superior knowledge on credits and take corresponding positions in the CDS market. The considerable price leadership can be explained by the synthetic nature of this derivative market, whose superior trading efficiency with flexible and costless position-taking translates into superior pricing efficiency. Moreover, the average contract size in the CDS market is also considerably larger than in the bond market resulting in a deeper market[18]. Further support of the price leadership hypothesis is provided in the already mentioned study by Longstaff, Mithal and Neis (2003) who also find substantial price leadership of the CDS market compared to bond and equity markets.

The present study directly builds on the main findings of this literature review. If CDS markets price risk efficiently and moreover have the advantage of superior trading and pricing efficiency, they should be a suitable source of market data for the purpose of financial stability analysis, which will be tested in the following.

3. Indicators of financial stability

Three indicators, CDS spreads, subordinated debt spreads and implied volatility will be examined more closely here. The three indicators are a subset of various potential candidates[19] and represent three major asset markets, the corporate bond market, the CDS market and the equity option market. Besides, data availability is an important factor motivating the choice of the indicators. Due to the relatively short period of time for which CDS prices are available[20], daily data is needed for all indicators to keep the sample size at an acceptable level, which excludes the use of low-frequency variables, such as accounting data. The further reasons for focussing on precisely these three indicators are laid out in detail below.

Subordinated Debt (SND) Spreads

Subordinated debt issued by banks has become a standard indicator for financial stability, as presented in the literature review and thus is included in the set of indicators to be examined. The use of *subordinated* debt is motivated by the higher risk-sensitivity of such more junior debt, since any increase in risk should first translate into higher spreads for the more junior debt tranches. Most importantly, the asymmetric payoff of debt instruments motivates its use for supervisory purposes, as it creates similar interests for bond investors and supervisors. Investors are exposed to all downside risk but do not profit from upside-gains following increased risk-taking and consequently, spreads react

[17] To assess the precise contribution to price discovery two different procedures are used, one by Hasbrouck, the other by Gonzalo and Granger.

[18] The average transaction size in the cash bond market usually amounts to USD 1.5mln, whereas the CDS standard denomination is USD 10mln.

[19] Other potential indicators would be equity prices or returns or financial accounting ratios, for example.

[20] The length of the sample period is about two years for the sample entities with the shortest data availability.

to increases in risk but behave neutrally to upside gains, unlike equity. More formally, Gropp, Vesala and Vulpes (2002) proof the theoretical properties of the SND indicator by showing that it fulfils two basic criteria: an indicator has to be complete, reflecting three major determinants of default risk: the market value of assets, leverage and the volatility of assets. In addition, an indicator has to be unbiased, which implies that it decreases with asset value and increases with leverage and volatility. Using the standard Merton option-pricing formula and explicitly incorporating the SND's specific pay-off (in contrast to senior debt), Gropp et al. derive a pricing formula for subordinated debt, which depends on asset value, leverage and asset volatility, and proof the indicator's completeness and unbiasedness.

Credit Default Swap (CDS)

The positive theoretical properties of CDS as stability indicator have been deduced in the literature review. Also in practise, the structure of a CDS deal gives it a clear advantage over other assets, most importantly corporate bonds, in assessing bank risk profile. Because of the CDS' payoff-scheme, strictly limited to situations of default, CDS spreads are a direct measure of default risk. Inferring default risk from corporate bonds necessitates a number of complicating assumptions and calculation. The issue is to match the corporate bond with an appropriate corresponding risk-free rate in order to obtain a credit spread. Usually, corporate bonds are matched with government bonds of the same currency and comparable maturity. However, such bonds are frequently not available, which implies that a "corresponding yield" has to be interpolated, both increasing complexity and inducing imprecision and errors[21]. Besides, there is considerable controversy on whether government bonds indeed represent the appropriate risk-free rate[22]. Compared to this, CDS provide a rather unambiguous and convenient measure of credit risk. An additional benefit, as indicated by previous studies[23], is the CDS market's superior pricing efficiency compared to ordinary asset markets. As a matter of fact, market participants indicate that the CDS market in practice often leads the bond market in pricing in news on an underlying entity[24]. Taken together, these properties should make CDS a preferred choice for any supervisory approach[25].

[21] Also, many borderline-cases exist in which it is difficult to decide on whether it is preferable to use a government bond of only approximately equal maturity or to interpolate a yield.
[22] This discussion concerns the use of government bonds versus the use of repo curve or swap curve, as risk-free rate.
[23] For example Blanco, Brennan and Marsh (2003).
[24] This was the outcome of a number of interviews conducted with credit analysts of major London-based investment banks at the outset of this study. See also Reuters News, 28 June 2002, World-Bond, "Debt insurance offers early warning for credit". The relation to the equity option market has not been examined so far to my knowledge.
[25] A more formal derivation of the theoretical properties of CDS as financial stability indicator will not be provided at this current point. It can be noted, however, that Cossin et al. (2002) develop a simple structural model for CDS pricing, which at least satisfies the criteria of completeness.

Implied Volatility (IV)

As Swidler and Wilcox (2001) show, implied volatilities, derived from the price of a call or put option on a firm's equity, are a measure of bank risk. In addition, equity volatility is the main input to another frequently-used measure of financial stability, distance to default (DD). Distance to default combines three key credit issues: the value of a firm's assets, its business and industry risk and its leverage. The measure compares the market net worth of a firm to the size of a one standard deviation move in its asset value. While it is not possible to use standard distance to default measures, as calculated by KMV for example, in this analysis due to their relatively low-frequency availability, implied volatility can be considered an adequate proxy for DD[26]. In fact, implied volatility is not only one of the main inputs to the calculation of DD measures but also the main driver of the latter in the short-run.[27] The use of implied volatilities is thus also motivated by this proxy-function. In line with standard credit risk theory, data on the implied volatility of call options will be used[28].

4. Data description and methodology

Sample period

The time-period examined goes from January 2001 to January 2004. The frequency of observations is daily. However, data availability is not equal for all indicators. While data on the SND and IV indicators is generally available throughout the entire sample period, the data on the CDS indicator starts in May 2001 and its availability increases progressively for the individual entities[29].

Sample banks

The three indicators used here are in fact a set of around 20 time-series each, corresponding to a sample of 20 banks. Thus, each indicator contains data for about 20 banks in its respective market. The following table lists the sample financial institutions. The sample includes the top-10 European banks in terms of total assets. In addition, 17 out of the 20 banks are top-5 banks in their respective national market. It is thus reasonable to claim that the sample provides a fair coverage of the Europe banking market in spite of its small size. Moreover, the largest banks are obviously of particular interest for this kind of analysis due to their relatively higher contagion potential.

Unfortunately, data is not available for all banks and all indicators. The reason for this is most often a lack of available data on the appropriate securities. For some banks such a security does not exist at all, as it is the case for example for Dresdner Bank and Credit Lyonnais whose equity was de-listed after mergers.

[26] The KMV data is only available on a monthly basis.
[27] The other input are the book value of liabilities, which do not change significantly in the short-run. For more details, see "Modelling default risk" by KMV available on www.moodyskmv.com.
[28] Most importantly the credit risk model by Merton (1974).
[29] More information on the data used is presented in Annex II.

Nonetheless, out of the 20 banks in the sample, data on all three indicators is available for 14 banks. The table below displays the data availability for each indicator. The following charts give a first impression of the data used in the study.

Name	Country	European rank (total assets)	National rank (total assets)
UBS AG	Switzerland	1	1
DEUTSCHE BANK AG	Germany	2	1
BNP PARIBAS SA	France	3	1
BAYERISCHE HYPO-UND VEREINSBANK AG	Germany	4	2
BARCLAYS BANK PLC	United Kingdom	5	1
ABN AMRO BANK NV	Netherlands	6	1
SOCIETE GENERALE	France	7	4
ING BANK NV	Netherlands	8	2
COMMERZBANK AG	Germany	9	3
DRESDNER BANK AG	Germany	10	4
LLOYDS TSB BANK PLC	United Kingdom	15	4
BANCO SANTANDER CENTRAL HISPANO SA	Spain	16	1
INTESABCI SPA	Italy	18	1
BANCO BILBAO VIZCAYA ARGENTARIA SA	Spain	21	2
RABOBANK NEDERLAND	Netherlands	23	3
CREDIT LYONNAIS	France	24	8
UNICREDITO ITALIANO SPA	Italy	32	2
SANPAOLO IMI SPA	Italy	35	3
ABBEY NATIONAL PLC	United Kingdom	41	6
BANCA MONTE DEI PASCHI DI SIENA SPA	Italy	52	6

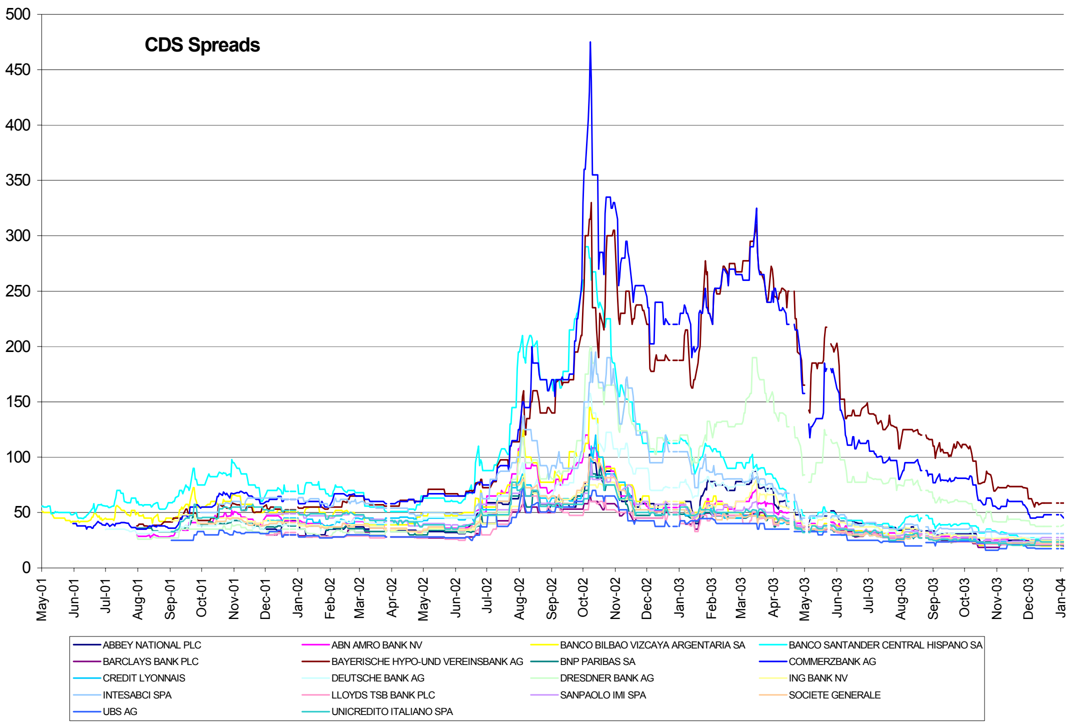
Table 1: Sample banks and relative market position (source: Bankscope)

Subordinated Debt Spreads	CDS Spreads	Implied Volatility
Abbey National PLC	Abbey National PLC	Abbey National PLC
ABN AMRO Bank NV	ABN AMRO Bank NV	ABN AMRO Holding
Banco Bilbao Vizcaya Argentaria SA	Banco Bilbao Vizcaya Argentaria SA	Banco Bilbao Vizcaya Argentaria SA
Banco Santander Central Hispano SA	Banco Santander Central Hispano SA	Banco Santander Central Hispano SA
		Banca Monte dei Paschi
Barclays Bank PLC	Barclays Bank PLC	Barclays PLC
Bayerische Hypo- und Vereinsbanks AG	Bayerische Hypo- und Vereinsbanks AG	Bayerische Hypo- und Vereinsbanks AG
BNP Paribas SA	BNP Paribas SA	BNP Paribas SA
Commerzbank AG	Commerzbank AG	Commerzbank AG
Credit Lyonnais	Credit Lyonnais	
	Deutsche Bank AG	Deutsche Bank AG
Dresdner Bank AG	Dresdner Bank AG	
ING Bank NV	ING Bank NV	ING Groep
	Intesa BCI SPA	Intesa BCI Spa
Lloyds TSB Bank PLC	Lloyds TSB BANK PLC	Lloyds TSB Group PLC
San Paolo IMI Spa	San Paolo IMI Spa	San Paolo IMI Spa
Societe Generale	Societe Generale	Societe Generale
Standard Chartered		Standard Chartered
UBS London	UBS AG	UBS AG
Unicredito Italiano Spa	Unicredito Italiano Spa	Unicredito Italiano Spa

Table 2: Data availability for each indicator

CDS data

The graph displays the CDS data used, taken from CreditTrade. The most remarkable feature in the data is certainly the enormous hike in CDS spreads for some entities during the latter half of 2002 and the first half of 2003[30]. All in all, the data for most banks moves relatively closely together over large sections of the sample period.



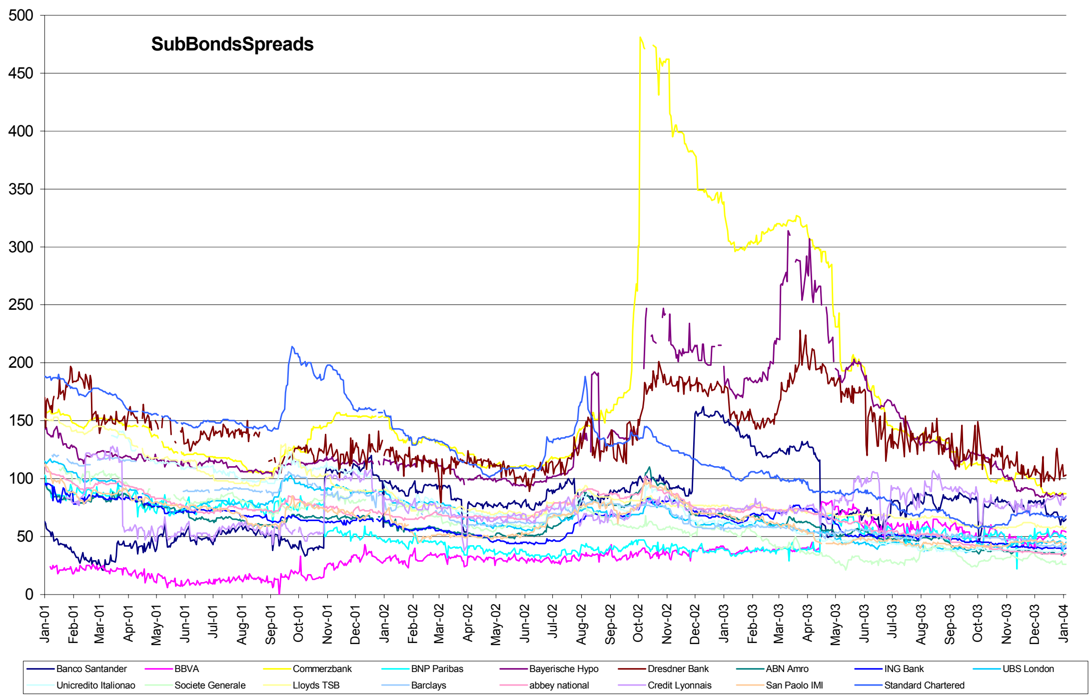
Graph 1: CDS data (source: CreditTrade)

A test of the time-series properties reveals that all CDS spread series have a unit root. The augmented Dickey-Fuller test can not rejects the hypothesis of non-stationarity at a confidence level of 5% for the series.

[30] This hike affected mostly German banks and will be examined in detail in a later section of the paper.

Subordinated Debt data

The subordinated debt data is taken from Bloomberg. Corporate bond data for the sample banks is matched with comparable government bonds in order to calculate a credit spread. The SND data also exhibits a strong hike in spreads for some entities in the period mentioned before. In addition, a significant rise in spreads can be seen during September 2001.



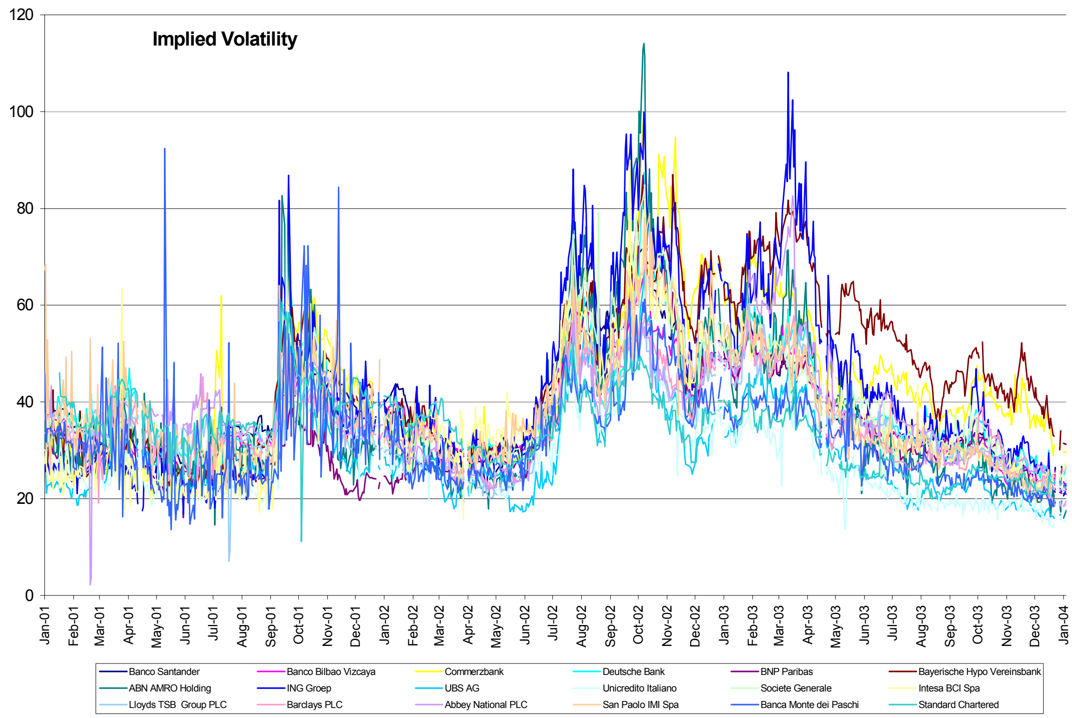
Graph 2: Subordinated Debt data (source: Bloomberg and own calculations)

Testing the time-series properties of the data yields that the SND spread time series are non-stationary[31]. The augmented Dickey-Fuller test can not reject non-stationarity at a 5% confidence interval.

[31] An exception is the data for Credit Lyonnais, for which the Dickey-Fuller tests rejects the hypothesis of non-stationarity at the 5% confidence interval. In light of the overwhelming evidence of unit roots for all other time-series, Credit Lyonnais is nonetheless kept inside the sample.

Implied Volatility data

The data on implied volatility is directly taken from Bloomberg. In spite of the high volatility of the individual time series, the data moves together in a relatively close band over most of the period examined. Extreme peaks in volatility are reached in June and September 2001 and around October 2002.



Graph 3: Implied Volatility data (source: Bloomberg)

Also for the implied volatility data, a test for stationarity reveals that all time-series are I(1). The augmented Dickey-Fuller test rejects non-stationarity at a 5% confidence level for all series.

Methodology

As the literature review has revealed, testing the properties and comparing market indicators of financial stability is often accomplished by means of event studies, which juxtapose the asset price development (as explanatory variable) to a set of (credit) events for each entity in order to test if the indicator can predict these events. In the classical sense of the term, a "credit event" represents default of a financial institution. Thus, theoretically this type of direct comparison can provide insights into the timing and magnitude of reaction (thus the easiness of observation) of individual indicators and also show if an indicator is superior to another. Implementing this approach in practise, however, poses a major problem, as has been pointed out - no bank defaulted in Europe in recent history. Thus, strictly speaking, an event study based on "credit events" in the classical sense of the term is not possible. Consequently, events are defined as substantial declines in the risk profile of banks, situations of substantial financial distress, which are filtered from the data of various risk-proxies. As has been highlighted, the use of such risk proxies, however, is not without any problems[32]. Nonetheless, there is little doubt that situations of financial distress have affected a number of banks, or at least, in a number of cases financial markets have perceived such situations, also in the recent past. Thus, the "perceived financial healthiness" of banks changed over time, which is what an indicator based on market variables can potentially track.[33]

The alternative is to focus on the information content of individual indicators and compare them to each other[34]. This is the approach which is pursued in this paper. The advantage is that it is not necessary to define clear-cut but obviously artificial credit events in light of their absence in recent history. However, clear qualitative statements on the performance of individual indicators are not possible with this kind of analysis. The comparison is carried out with correlation and common factor analysis. The latter method is able to detect the underlying structure in the relationships between a set of variables. It is able to analyse the unknown or latent dimensions (factors) in the data, common trends which drive different variables over time. By applying common factor analysis, it is thus possible to identify the dimensions which lie beneath the risk captured by the indicators. In light of the nonstationary nature of the sample data for the three indicators, the implemented statistical procedure follows Stock and Watson (1988). The estimation is carried out in STATA and Eviews.

[32] Concerns can be raised as to the precision and objectivity of risk proxies, such as supervisory ratings, if used as ultimate risk measure. These concerns may be even larger in the case of private ratings, which are used in the European context, as no supervisory ratings exist for the entire European market. Finally, the definition of events is normally based on some threshold level, which is also due to subjectivity.

[33] This still leaves the problem of defining a set of events. For the time period under examination here it was practically not possible to define a sufficient number of events - based on ratings for example – in order to carry out a sensible event study due to the short period for which CDS data is only available. As a consequence, this type of analysis is not pursued any further.

[34] This kind of analysis is more in line with the studies by Berger, Davies and Flannery (2000) or DeYoung, Flannery, Lang and Sorescu (2001)

5. Comparing financial stability indicators

Distinguishing different risk dimensions

Market indicators of financial stability should clearly react to any change in the underlying risk profile which they measure, be it risk *specific* to one bank (idiosyncratic risk), or *common* to all banks in the market (systemic risk). As has been highlighted in the introductory section on the subject of financial stability, idiosyncratic risk per se should not pose a threat to system stability. Theoretically at least, the banking industry is not different from other industries in this respect and market entry and exit are normal processes in a functioning market. In practice, however, this strict distinction between individual risks and systemic risks is more difficult to maintain in the modern banking system. Banks operate more and more on an international basis, the traditional boundaries between activities such as commercial banking, insurance and investment banking are disappearing and interaction, hence mutual exposure between individual institutions, national markets and different types of financial institutions is rising. The increase of mutual exposure provides an ideal structure for the propulsion of contagion effects, "the strong propagation of failures from one institution or market to another, through the financial system"[35]. The propagation of such effects is further facilitated by the interlinkage of banks via large value payment and security settlement systems and the exposure to volatile asset markets.

The problem from a supervisory perspective is that contagion itself is neither directly visible nor can it be directly measured. What is visible and can be measured is its outcome, *ex post*, i.e. situations of distress having spread through the system and affecting a considerable number of banks. Of course, such situations of distress could also stem from market-wide forces, which simultaneously but separately affect banks. A precise distinction therefore is not possible. The consequence is that effective supervision, with the aim of assuring systemic stability and minimizing the danger of contagion, has to focus on systemic risks as well as on idiosyncratic risks. This is especially true for large financial entities with the highest contagion-risk. Hence, banking supervision must encompass the common, market (macro) level as well as the bank (micro) level. Accordingly, the set of indicators used in practise for this exercise also has to capture both micro and macro risks.

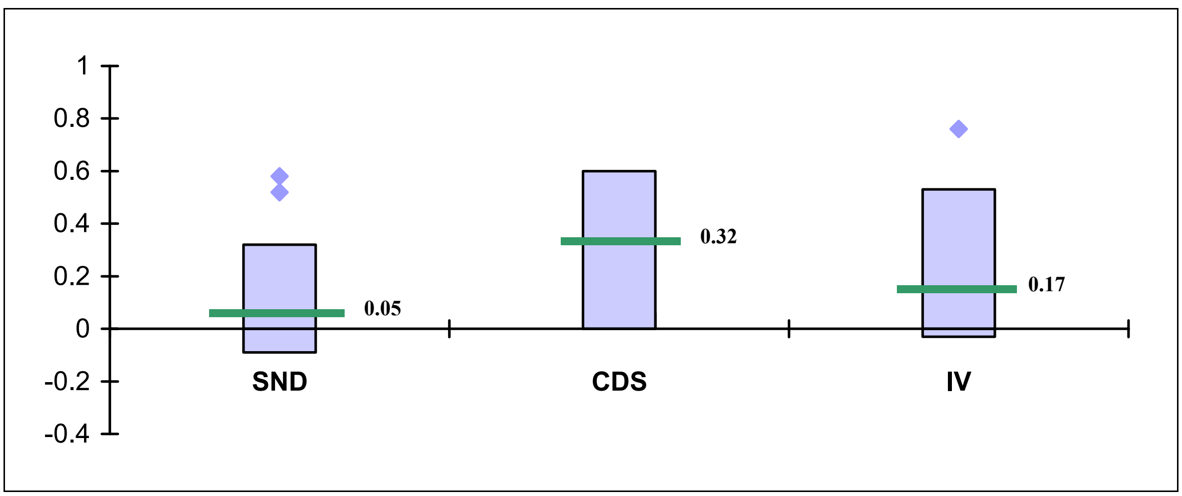
Sensitivity to common and bank-specific risk

Applying this insight to the data, it turns out that the three indicators capture banks-specific and common risk effects to a different degree. Simple correlation analysis can provide a first indication: the correlations between the individual time series for each indicator reveal to which extent the time-series of the individual sample entities move

[35] See Hartmann and de Brandt (2000).

together or diverge[36]. Considerable homogeneity in those movements would suggest that the indicator is driven by common risk factors which impact most or all banks. Conversely, considerable heterogeneity of the individual time-series would suggest that the indicator captures more bank-specific risk.

The results of the correlation analysis are summarized in the graph below. The mean correlation of the individual constituents, a measure of the overall level of homogeneity, differs substantially between the three indicators. The CDS indicator has a very high average correlation of 0.32, pointing to high homogeneity, considering that it is based on changes in daily data. At the other extreme, the mean correlation of the SND indicator is close to zero, suggesting very heterogeneous time series underlying the SND indicator. Considering the distribution of the correlations clearly confirms these findings. The distribution for the SND data points at a very high degree of heterogeneity with correlations ranging from–0.09 to 0.52 This implies that the SND data for some sample banks diverges considerably from the rest of the entities - moving in opposite directions - which translates into negative correlations for 30 pairs of banks. As opposed to this, the correlations for the other two indicators are positive with one exception for the IV indicator. Accordingly, the individual constituents of the CDS and IV indicator move mostly together. This suggests that the indicators capture more common risk in contrast to the SND which captures more specific risk.



Graph 4: Correlations between the constituents of each indicator; mean (green) and distribution (blue) of correlations (with extreme outliers graphed as dots) per indicator (common sample, first differences)

Recalculating the correlations for different sample periods further backs these findings. As data is not available for exactly the same period for the three indicators, the common and individual samples are examined, as well as a third sample starting in September 2001 in order to check for any particularity when including this month. The increase of the correlations for the IV indicator when the two longer samples are considered reflects

[36] More precisely, the correlations for all possible pairs of time-series (entities) are calculated for each indicator. In order to aggregate this information, the mean of the correlations is calculated for each indicator. The analysis has to be based on first differences as all the time series are I(1).

the fact that most time series move smoothly together at the beginning of the sample, in particular during September 2001[37]. The result for the SND indicator is more puzzling and is probably linked to selection bias which results from the exclusion of 6 banks for this sample. Nonetheless, the clear divergence as regards the co-movement in the CDS and IV indicator on the one hand and the SND indicator on the other is independent from different samples[38].

	SND indicator	CDS indicator	IV indicator
Common sample Sample	**0.05** *03/12/2001-05/01/2004*	**0.32** *03/12/2001-05/01/2004*	**0.17** *03/12/2001-05/01/2004*
Individual sample Sample	**0.06** *15/03/2001-05/01/2004*	**0.32** *03/12/2001-05/01/2004*	**0.26** *18/01/2001-05/01/2004*
Common sample incl. Sept '01 Sample *(excluding 6 banks)*	**0.03** *30/08/2001-05/01/2004*	**0.32** *30/08/2001-05/01/2004*	**0.21** *30/08/2001-05/01/2004*

Table 3 : Mean correlations between the indicators' individual constituents

Regarding the low correlations found for the subordinated debt data, it could be argued that this heterogeneity in the data could stem from the hike in spreads several banks exhibited during a part of the sample period[39]. Two arguments oppose this hypothesis: firstly, this hike in spreads is also present in the CDS market for the same institutions but does not translate into the results of the correlation analysis. Secondly, when repeating the calculation for the SND spreads without the institutions involved, the correlation is only slightly higher, with about 0.07 but still far below the correlations found for the other two indicators. Hence, it is not possible to reduce these findings to sample-specific features.

All in all, the correlation analysis shows that there is a considerable difference in the indicators' overall "sensitivity" to common and bank-specific risk. One possible explanation could be that the CDS and implied volatility markets are more driven by forces or factors that have a common influence on all banks, whereas individual, bank-specific forces drive the main movements in the SND market. One way to investigate these underlying factors is by means of common factor analysis, which is presented in the next section.

Analysing the underlying risk dimensions

As has been noted, the sensitivity to common and bank-specific risk indicates that market-wide and bank-specific risk factors impact the indicators, and hence the banks' risk profile. In the context of market indicators, this means that these risk factors influence the financial markets that deliver the (pricing) information which the market

[37] There is a strong common reaction to the events of this months.
[38] This statement is of course only valid in the narrow boundaries of the three sample periods tested.
[39] In fact, this hike affects three German banks and will be examined more closely in a later section of this paper.

indicators are based on. The emerging questions are what exactly lies beneath these factors and to which extent their influence on markets is reflected in the data of individual or all entities? This amounts to identifying the data's underlying or latent risk dimensions or factors, both common and specific ones, and can be accomplished with common factor analysis.

Identifying a market risk level

Following Stock and Watson (1988), a set of I(1) series can be expressed as a combination of one or several common factors that are I(1) and an I(0) component. More formally, each element of X_t, a (n x 1) vector containing the indicators' data can be rewritten as a linear combination of ($k \leq n$) independent common trends which are I(1) and (n-k) stationary components.
Hence, the nonstationary time series are decomposed into (a) nonstationary common trend(s) and a remaining residual, which is stationary, according to this procedure[40]. The common trends reflect the latent dimension(s), which is/are of predominant interest at this current stage. It captures all movements in the time-series, which are common to all series. In this way, a decomposition can be achieved into a common (risk) level and a specific (risk) level. Moreover, the analysis allows examining the nonstationary time series without differencing, which would imply the loss of information on the data's level-dynamics.

Applying this insight to the data at hand, common trends can be extracted for all three indicators. For the SND data, three common trends emerge, which are I(1). Two common trends can be extracted from the CDS data and one from the implied volatility data[41].

Restricting the analysis to the first common trend of each indicator, it can be noted that it accounts for a majority of the variance for each of the indicators' data.[42] Moreover, the factor loadings show that the first common factors are closely linked to most or all of the respective time series of each indicator.

This pattern of relationships strongly suggests the presence of a risk dimension common to all variables, a market risk dimension for each indicator[43]. This market risk dimension accounts for a major share of variation in the movements of the time series[44]. Along the

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[40] The analysis relies on a factor analysis and a subsequent test of the extracted factors for non-stationarity. As Holmes (2001) notes, the first (k) common factors, accounting for the largest share of common variance, are most likely to be nonstationary and thus correspond to the common factors. Thus, the test for nonstatinarity, starting with the first common factor, is carried out until the $(k+1)^{th}$ factor is found to be stationary.
[41] The detailed output of the factor analyses and the tests for unit roots in the common factors can be found at the end of this chapter.
[42] The common variance captured by the first common factors is 61%, 88% and 92% (SND, CDS, IV) respectively.
[43] Obviously, in light of the small size of our sample, the term "market risk factor" has to be used with caution. However, with 20 large European banks in the sample, it nonetheless captures a reasonable share of the European market. The term "market risk factor" will thus continue to be used.
[44] The interpretation of this common risk dimension may warrant some caution. After all, it is not possible to determine if a truly common (systemic) risk dimension is present or if markets are just not able to distinguish different (idiosyncratic) risks and thus perceive a common risk dimension where none exists.

terminology of Stock and Watson, a common trend underlies the time-series of each indicator. These common trends are able to explain a large part of the individual time series' movements and could probably be characterised as "market trends", reflecting a common market risk level.

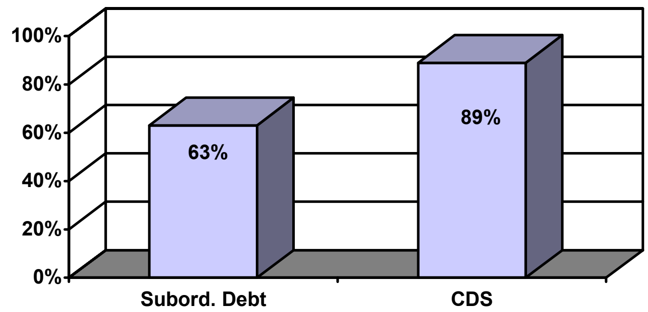
This identification and interpretation of the common trends gains further support when the common trends are graphed together with the individual time series. It appears that the common trends indeed explain the movements of the time series over large parts of the sample period. Even though there are substantial differences in the extent to which the market data on the individual entities follows the market risk factors, overall the banks' time series move closely together with the market factors for most of the time, as could be expected. After all, the nature of market risk is that it captures the common risk dimension, which largely explains the movements of the individual time series.

Since the market risk factors capture the common risk dimension, any deviation from them can be attributed to bank-specific factors. Hence, whenever there is a substantial gap between the market risk factors and the market data, this hints at firm-specific effects influencing a bank's risk profile[45].

The degree to which the market risk factors can explain the common movements of the individual time series is reflected in the variance captured by the common factors. The individual magnitude of variance reflects the outcome of the previous correlation analysis: while the market risk factors account for a very large part of the movements in the CDS and IV data, the amount of variance explained in the SND data is smaller, albeit still higher than 50%. All in all, between 61% and 92% of the common movement in the data, which forms the input to the individual risk indicators, can be attributed to this market risk factor.

The latter would imply that the market has an exaggerated contagionary view on individual banks. While it is difficult to test this here, Flannery (1998) gives an overview of the empirical evidence in equity markets and comes to the conclusion that "the literature provides broad, though not unanimous, support for the hypothesis that bank equity holders respond rationally to announced news. (…) These results seem to reject the possibility that bank investors (and, by extension, sophisticated depositors) routinely engage in "pure contagion" inferences about all banks, which augurs well for the efficiency of market discipline." Yet, it is the mere nature of market data that it reflects a perception of reality rather than reality itself and hence is due to erroneousness. In this context, Flannery cautiously adds that "perhaps these studies have only identified the misinformation on which investors base their mistaken inferences!".

[45] A detailed analysis of the bank-specific risk dimension will be presented in a later section.



Graph 5: Variance captured by market risk factor (first common factor); (source: own calculation)

A further option for analysing the relationship between the market risk factors is to exploit the nonstationary property of the common trends by means of cointegration analysis. Intuitively, if market risk is comparable in the SND and CDS market, this should be reflected in a common long-run cointegration relationship between the two market risk factors. The result of the cointegration tests are summarized below[46]:

Unrestricted Cointegration Rank Test				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 Percent Critical Value	1 Percent Critical Value
None	0.032233	13.35456	15.41	20.04
At most 1	4.87E-05	0.019821	3.76	6.65
*(**) denotes rejection of the hypothesis at the 5%(1%) level				

Table 4: Johansen Cointegration Test for SND and CDS market risk factor; (source: own calculations)

Unrestricted Cointegration Rank Test				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 Percent Critical Value	1 Percent Critical Value
None	0.002726	1.393420	15.41	20.04
At most 1	0.000518	0.222290	3.76	6.65
*(**) denotes rejection of the hypothesis at the 5%(1%) level				

Table 5: Johansen Cointegration Test for SND and IV market risk factor; (source: own calculations)

Unrestricted Cointegration Rank Test				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 Percent Critical Value	1 Percent Critical Value
None	0.018200	8.828490	15.41	20.04
At most 1	0.001560	0.691574	3.76	6.65
*(**) denotes rejection of the hypothesis at the 5%(1%) level				

Table 6: Johansen Cointegration Test for CDS and IV market risk factor; (source: own calculations)

[46] The Johansen cointegration test is performed. The optimal leg-length for the cointegration test is determined beforehand by an unrestricted VAR based on the Schwartz-criterion.

None of the test can reject the hypothesis of zero cointegration relationships in favour of the presence of one cointegration relationship at standard confidence levels. However, there are substantial differences as to the magnitude of rejection of the hypotheses. Especially regarding the SND and CDS indicator, the trace statistic is relatively close to the 5% critical value - which makes the suspected link not entirely unlikely.

Graphing the common trends together further supports the hypothesis of a close link between market risk in the CDS and SND as opposed to the IV market. The two series move surprisingly closely together. By contrast, the IV market risk factor follows a different path during most of the sample period.

Graph 6: Market factors for SND, CDS and IV indicator; (source: own calculations).

Practically, the outcome of the analysis suggests that alternative and maybe complementary information on market risk is provided by the different market indicators, namely the bond-related as opposed to the equity-market related indicators[47]. This is not implausible since markets are generally driven by various factors, which on intuitive grounds can be assumed not to be identical in such different markets as the equity and bond market. The same should hold for market risk, which should also be driven by different factors in different markets. The relationship between markets and market risk, as well as the forces driving the latter is analysed in the following section.

[47] This issue as well as its consequences for the use of indicators will be analysed in more detail in a later section.

What drives market risk?

After the simple extraction of the market risk factors the options for more in-depth analysis are rather limited with common factor analysis. A clear drawback of this procedure is that the exact nature of the factor remains opaque and can only be hypothesized. To overcome this deficiency, it is possible to compare the extracted factors to a number of exogenous variables. This allows a closer analysis of the market risk factors and to identify the forces driving market risk. Due to the relatively short sample-period, the variables used for this purpose have to be observable at high frequency. Essentially, daily data is needed to keep the sample size at an adequate level for subsequent analysis, which leaves only financial variables as potential candidates[48]. The resulting selection of variables represents a set of key economic and financial variables[49]:

- the Euro-Area three-month interbank rate
- a yield-curve indicator (subtracting the short-term interest rate from the long-term bond yield)
- the P/E ratio of the DataStream European Equity market index

Analysing the relation between the market risk factor and the selected exogenous variables should allow a closer identification of the market factors' characteristics. In this context, the link to each of the macro variables as well as the comparison between these links should provide further insights. Moreover, a close link between a financial variable and market risk – either positive or negative – allows an assumption on the driving forces of market risk in the respective market. On the basis of the nonstationarity nature of the market factors and the financial variables, cointegration tests will be conducted in order to test for the long-run and short-run dynamics between market risk and the selected variables.

The output of the Johansen test for cointegration is presented below[50].

Unrestricted Cointegration Rank Test				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**5 Percent Critical Value**	**1 Percent Critical Value**
None *	0.050113	51.23971	47.21	54.46
At most 1	0.031707	23.16875	29.68	35.65
At most 2	0.009280	5.576075	15.41	20.04
At most 3	0.000889	0.485733	3.76	6.65
*(**) denotes rejection of the hypothesis at the 5%(1%) level				
Trace test indicates 1 cointegrating equation(s) at the 5% level				

Table 7: Cointegration test for SND market factor and exogenous variables

[48] The market risk factors are based on a sample of daily data for about two years (excluding missing observations).

[49] All variables are taken from Datastream.

[50] Optimal lag length for the test is determined beforehand in an unrestricted VAR with the Schwartz-Criterion.

Unrestricted Cointegration Rank Test				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**5 Percent Critical Value**	**1 Percent Critical Value**
None **	0.052637	54.89936	47.21	54.46
At most 1	0.032254	27.43007	29.68	35.65
At most 2	0.019333	10.77504	15.41	20.04
At most 3	0.001687	0.857812	3.76	6.65
*(**) denotes rejection of the hypothesis at the 5%(1%) level				
Trace test indicates 1 cointegrating equation(s) at both 5% and 1% levels				

Table 8: Cointegration test for CDS market factor and exogenous variables

Unrestricted Cointegration Rank Test				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 Percent Critical Value	1 Percent Critical Value
None *	0.051443	49.82055	47.21	54.46
At most 1	0.015158	16.91802	29.68	35.65
At most 2	0.009657	7.402126	15.41	20.04
At most 3	0.002175	1.356374	3.76	6.65
*(**) denotes rejection of the hypothesis at the 5%(1%) level				
Trace test indicates 1 cointegrating equation(s) at the 5% level				

Table 9: Cointegration test for IV market factor and exogenous variables

The cointegration tests yield one cointegration equation for all three indicators at the 5% confidence level. Consequently, a VECM including the above variables is estimated. The detailed output can be found at the end of this chapter.

Considering the long-term relationship, it can be noted that all market risk factors are significantly and positively linked to the short-term interest rate. A higher interest rate thus goes together with a worsened risk outlook as measured by the market risk factors. The effect is significantly stronger for SND than for CDS and IV. A potential explanation is that an increase in interest rates raises the refinance costs for companies economy-wide and for the banks in particular. This weakens the economic outlook and also the business outlook for banks. Moreover, in economies with floating-rate credit agreements, hikes in interest rates can cause an increase of uncollectible debt.

In the SND regression, the restriction that the P/E ratio does not enter the cointegrating regression cannot be rejected. For CDS and IV, the exclusion of the yield spreads cannot be rejected. The positive effect of the yield curve on the SND market factor is counterintuitive. Generally, a positive yield spread points to a better business cycle outlook and improving interest margins for banks. The result for the CDS market factor may also be considered surprising since the coefficient for the P/E ratio, an equity-market variable, turns out significant. If anything, we would have expected the yield curve to play a role in the CDS regression. Note though that the yield curve and the P/E ratio are related to some extent and may partly capture the same effect. The IV market factor is most strongly linked to the P/E ratio. The corresponding coefficient is highly significant and implies a negative effect. The underlying economic or financial link may be the following: a higher risk outlook for banks is compatible with a lower relative valuation of its equity, thus a lower P/E ratio.

To summarize, we have shown that the three indicators capture common and specific risks to considerably different degrees. Market-risk dimensions can be extracted from the data of all indicators[51]. Regarding the market risk captured by the indicators, it appears that closely related markets, such as the CDS and SND market share very similar market risk. In contrast to this, market risk in the equity market seems to be different.
All market risk factors are closely linked to various financial variables, such as interest rates or the P/E ratio. Hence, market risk is affected by main economic and financial parameters which are widely seen to impact financial markets. Finally, the driving variables of market risk are different for the bond and equity markets with short-term interest rates and yield curve dominating the bond market and P/E ratio and short-term interest rate significantly influencing the equity market. The CDS market seems to lie somewhat in between these two classical markets, with closer links, however, to the traditional bond market.

6. Conclusions

The current analysis has focused on the market risk level so far and yielded a number of interesting findings about market risk in the three different asset markets and the indicators' ability to capture this market risk. However, the link between market risk and asset categories can still give rise to questions: Even if differences in risk measures exist on a market level, shouldn't there be (a) common risk (factor) which impacts all markets, and thus the banks' risk profile, irrespective of the asset category of the indicator used? This would presuppose the existence some common risk level next to or above the market risk in the individual markets, an issue certainly worth to investigate further.

Besides, the result of the common factor analysis has only been partially exploited. The remaining common factors or trends leave ample space for interpretation. As already mentioned, a particular development in the market data for a number of German banks can be observed in the CDS and SND market. This should also translate into the factor analysis, potentially giving rise to a "German factor".

Finally, the analysis has completely ignored the specific (idiosyncratic) risk level until now. Of course, the comparison of the three indicators can also be carried out on this level. In this context, it is very insightful to examine if the relationships between indicators which have emerged from the analysis so far can also be found on this level. Finally, by focusing on a limited number of institutions, a set of bank-specific risk events could be generated, which could provide the basis for an event-study. This would allow a clear qualitative test of the indicators in their ability to predict such risk events.

[51] Obviously, this also supposes the presence of a bank-specific risk dimension, which has been neglected so far and will be analysed in a later section.

Detailed output of the vector error correction models:

Vector Error Correction Estimates – SND indicator

Included observations: 546
Excluded observations: 185 after adjusting endpoints
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
B(1,1)=1 B(1,4)=0
Maximum iterations (500) reached.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(1)	1.116598
Probability	0.290652

Cointegrating Eq:	CointEq1
F1(-1) *(market factor)*	1.000000
EUR3M(-1) *(3 month rate)*	-17.83120 (4.31634) [-4.13109]
EURYC(-1) *(Yield curve variable)*	-32.92194 (6.43111) [-5.11917]
EUPE(-1) *(P/E ratio)*	0.000000
C	101.9607

Error Correction:	D(F1)	D(EUR3M)	D(EURYC)	D(EUPE)
CointEq1	-0.000260	-0.000305	0.000455	0.001126
	(0.00040)	(6.6E-05)	(0.00019)	(0.00091)
	[-0.64704]	[-4.65383]	[2.40213]	[1.24143]
D(F1(-1))	-0.297408	0.014438	0.026942	0.182711
	(0.04152)	(0.00678)	(0.01959)	(0.09377)
	[-7.16346]	[2.12930]	[1.37495]	[1.94843]
D(EUR3M(-1))	-0.252355	0.111056	-0.118282	-1.109546
	(0.26315)	(0.04298)	(0.12420)	(0.59436)
	[-0.95898]	[2.58404]	[-0.95236]	[-1.86677]
D(EURYC(-1))	0.114920	0.022970	-0.095649	0.020469
	(0.09287)	(0.01517)	(0.04383)	(0.20977)
	[1.23737]	[1.51435]	[-2.18209]	[0.09758]
D(EUPE(-1))	-0.012583	0.003549	0.040841	0.059244
	(0.01951)	(0.00319)	(0.00921)	(0.04406)
	[-0.64500]	[1.11398]	[4.43572]	[1.34455]
C	-0.006438	-0.002458	0.000511	-0.005877
	(0.00395)	(0.00065)	(0.00187)	(0.00893)
	[-1.62870]	[-3.80755]	[0.27409]	[-0.65831]
R-squared	0.091426	0.078075	0.052774	0.021851
Adj. R-squared	0.083013	0.069538	0.044003	0.012794
Sum sq. resids	4.389388	0.117080	0.977747	22.39244
S.E. equation	0.090158	0.014725	0.042552	0.203636
F-statistic	10.86757	9.146167	6.017130	2.412640
Log likelihood	542.0558	1531.431	952.0183	97.19303
Akaike AIC	-1.963574	-5.587659	-3.465268	-0.334040
Schwarz SC	-1.916293	-5.540378	-3.417987	-0.286759
Mean dependent	-0.004159	-0.002899	0.000385	-0.003663
S.D. dependent	0.094151	0.015265	0.043520	0.204951

Determinant Residual Covariance	1.21E-10
Log Likelihood	3146.627
Log Likelihood (d.f. adjusted)	3134.561
Akaike Information Criteria	-11.37934
Schwarz Criteria	-11.15870

Vector Error Correction Estimates – CDS indicator

Included observations: 508
Excluded observations: 33 after adjusting endpoints
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
B(1,1)=1 B(1,3)=0
Convergence achieved after 19 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(1)	1.047158
Probability	0.306163

Cointegrating Eq:	CointEq1
F5(-1) *(market factor)*	1.000000
EUR3M(-1) *(3 month rate)*	-2.015248 (0.27817) [-7.24468]
EURYC(-1) *(Yield curve variable)*	0.000000
EUPE(-1) *(P/E ratio)*	0.594260 (0.08158) [7.28418]
C	-3.078973

Error Correction:	D(F5)	D(EUR3M)	D(EURYC)	D(EUPE)
CointEq1	-0.011287	0.003624	0.000510	-0.002913
	(0.00663)	(0.00077)	(0.00271)	(0.01291)
	[-1.70138]	[4.73628]	[0.18838]	[-0.22568]
D(F5(-1))	0.045992	0.006682	0.015782	0.014150
	(0.04446)	(0.00513)	(0.01815)	(0.08649)
	[1.03443]	[1.30291]	[0.86974]	[0.16360]
D(EUR3M(-1))	-0.174308	0.039572	-0.217875	0.475469
	(0.37563)	(0.04333)	(0.15330)	(0.73076)
	[-0.46404]	[0.91332]	[-1.42121]	[0.65065]
D(EURYC(-1))	-0.019476	-0.000126	-0.097052	0.044942
	(0.11041)	(0.01274)	(0.04506)	(0.21479)
	[-0.17639]	[-0.00986]	[-2.15382]	[0.20923]
D(EUPE(-1))	-0.026611	0.003611	0.053152	0.018722
	(0.02484)	(0.00287)	(0.01014)	(0.04833)
	[-1.07118]	[1.26007]	[5.24242]	[0.38737]
C	-0.002979	-0.001860	0.000907	-0.004664
	(0.00483)	(0.00056)	(0.00197)	(0.00939)
	[-0.61703]	[-3.33923]	[0.46007]	[-0.49653]
R-squared	0.014155	0.061026	0.054452	0.001494
Adj. R-squared	0.004336	0.051674	0.045034	-0.008451
Sum sq. resids	5.755151	0.076570	0.958583	21.78086
S.E. equation	0.107072	0.012350	0.043698	0.208298
F-statistic	1.441577	6.525244	5.781825	0.150204
Log likelihood	417.1973	1514.386	872.4656	79.13951
Akaike AIC	-1.618887	-5.938528	-3.411282	-0.287951
Schwarz SC	-1.568921	-5.888562	-3.361316	-0.237985
Mean dependent	-0.002662	-0.001982	0.000837	-0.005709
S.D. dependent	0.107305	0.012682	0.044717	0.207424

Determinant Residual Covariance	1.24E-10
Log Likelihood	2923.420
Log Likelihood (d.f. adjusted)	2911.349
Akaike Information Criteria	-11.35177
Schwarz Criteria	-11.11859

Vector Error Correction Estimates – IV indicator

Included observations: 623
Excluded observations: 139 after adjusting endpoints
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
B(1,1)=1
B(1,3)=0
Convergence achieved after 12 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(1)	1.017502
Probability	0.313112

Cointegrating Eq:	CointEq1
F7(-1) *(market factor)*	1.000000
EUR3M(-1) *(3 month rate)*	-1.646564 (0.19600) [-8.40099]
EURYC(-1) *(Yield curve variable)*	0.000000
EUPE(-1) *(P/E ratio)*	0.843076 (0.07376) [11.4305]
C	-7.857622

Error Correction:	D(F7)	D(EUR3M)	D(EURYC)	D(EUPE)
CointEq1	-0.033538	0.005823	-0.000221	0.014455
	(0.00999)	(0.00141)	(0.00270)	(0.01329)
	[-3.35631]	[4.13723]	[-0.08194]	[1.08744]
D(F7(-1))	-0.242770	-0.020251	0.024040	-0.035998
	(0.05078)	(0.00715)	(0.01373)	(0.06755)
	[-4.78080]	[-2.83137]	[1.75117]	[-0.53289]
D(EUR3M(-1))	-0.169409	0.098927	-0.314543	0.288458
	(0.31747)	(0.04472)	(0.08582)	(0.42232)
	[-0.53362]	[2.21233]	[-3.66501]	[0.68302]
D(EURYC(-1))	-0.202357	0.028328	-0.047181	0.259025
	(0.16060)	(0.02262)	(0.04342)	(0.21364)
	[-1.26001]	[1.25231]	[-1.08671]	[1.21241]
D(EUPE(-1))	-0.052448	-0.012051	0.046846	-0.014697
	(0.04089)	(0.00576)	(0.01105)	(0.05439)
	[-1.28274]	[-2.09261]	[4.23820]	[-0.27021]
C	-0.000906	-0.003125	0.001015	-0.010323
	(0.00672)	(0.00095)	(0.00182)	(0.00894)
	[-0.13492]	[-3.30204]	[0.55876]	[-1.15502]
R-squared	0.061369	0.050169	0.047105	0.005756
Adj. R-squared	0.053763	0.042472	0.039383	-0.002301
Sum sq. resids	16.90541	0.335394	1.235479	29.91688
S.E. equation	0.165528	0.023315	0.044748	0.220199
F-statistic	8.068100	6.517851	6.100166	0.714400
Log likelihood	239.5547	1460.661	1054.493	61.75381
Akaike AIC	-0.749774	-4.669858	-3.365949	-0.178985
Schwarz SC	-0.707066	-4.627150	-3.323241	-0.136277
Mean dependent	-0.000343	-0.003292	0.001554	-0.010594
S.D. dependent	0.170165	0.023826	0.045656	0.219946

Determinant Residual Covariance	6.45E-10
Log Likelihood	3067.903
Log Likelihood (d.f. adjusted)	3055.845
Akaike Information Criteria	-9.720207
Schwarz Criteria	-9.520902

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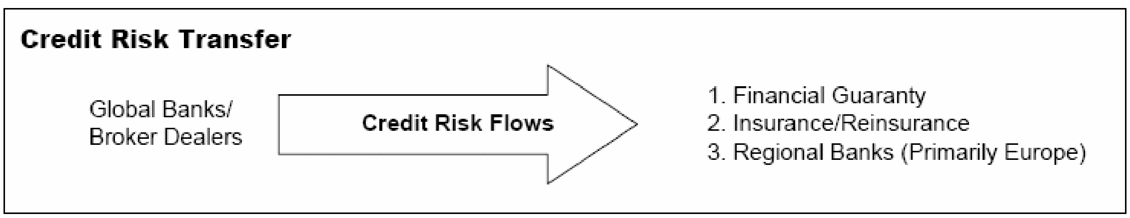
Annex I : CDS and the market for credit derivatives

It is important to note that CDS are just one instrument of the broad market for credit risk transfer (CRT), which is expected to reach a size of 4 $ trillion notional during this year according to the British Bankers' Association[52]. The market has grown massively over the last couple of years, largely because of the introduction of various novel risk-transfer instruments.

The CRT market

Regarding the exact size, participants and functioning of this market, exact figures are very difficult to obtain, as surveys can only reach a fraction of the players in the market. The most comprehensive information is presented, to my knowledge, in a survey conducted by FitchRatings, published in March and September 2003[53]. Additional information is taken from a report on Credit Risk Transfer by the BIS Committee on the Global Financial System[54].

The Fitch survey targets about 200 financial institutions and identifies 1.7 $ trillion protection sold via credit derivatives, out of which 40% is reported by European institutions. Major credit risks have been transferred from the banking sector, mostly to the insurance sector. Fitch quantifies the risk shedding by the banking sector to 229 $ billion. On the other side, the insurance sector holds a net position (protection sold) of 137 $ billion[55] according to FitchRatings.



Source: Fitch

However, aggregate data for the banking industry can be misleading, as individual participation differs enormously between countries and individual institutions.

Regarding the counterparties in the market, these are highly concentrated with the main global investment banks acting as the major players.

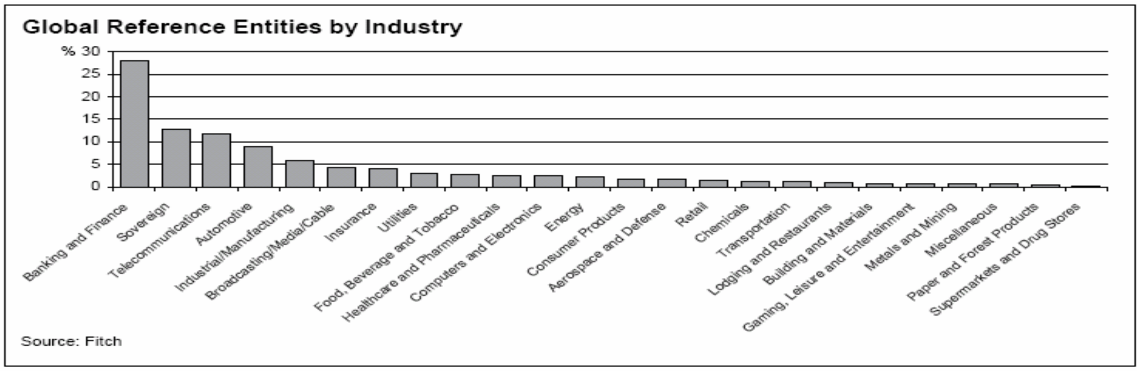
Top 25 Counterparties*

	Counterparty	Rating	Outlook
1	JP Morgan Chase	A+	Stable
2	Merrill Lynch	AA-	Negative
3	Deutsche Bank	AA-	Stable
4	Morgan Stanley	AA-	Stable
5	Credit Suisse First Boston	AA-	Negative
6	Goldman Sachs	AA-	Stable
7	UBS	AA+	Stable
8	Lehman Brothers	A+	Stable
9	Citigroup	AA+	Stable
10	Commerzbank	A-	Stable
11	Toronto Dominion	AA-	Negative
12	BNP Paribas	AA	Stable
13	Bank of America	AA-	Positive
14	Bear Stearns	A+	Stable
15	Societe Generale	AA-	Stable
16	Royal Bank of Canada	AA	Stable
17	Barclays	AA+	Stable
18	Dresdner	A-	Stable
19	Royal Bank of Scotland	AA	Stable
20	ABN AMRO	AA-	Stable
21	CIBC	AA-	Stable
22	Rabobank	AA+	Stable
23	WestLB	AAA	Stable
24	HVB	A	Stable
25	AIG	AAA	Negative

* Commonly quoted counterparties, based on frequency of occurrence.
Source: Fitch

[52] This figure is also taken from the survey by FitchRating, presented below.
[53] The September publication updates the previous findings. The study is available at www.fitchratings.com. One considerable drawback of the survey is that Hedge funds, an ever more important player in the CRT market, are not included in the survey.
[54] The report is available at www.bis.org/publ/cgfs20.pdf
[55] Excluding financial guarantors

In terms of reference entities, the banking and financial industry is the most actively traded sector.



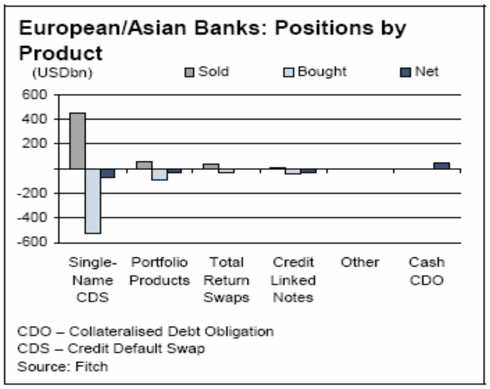
Regarding the products, the market is characterised by a variety of instruments, still strong innovation and ongoing expansion.

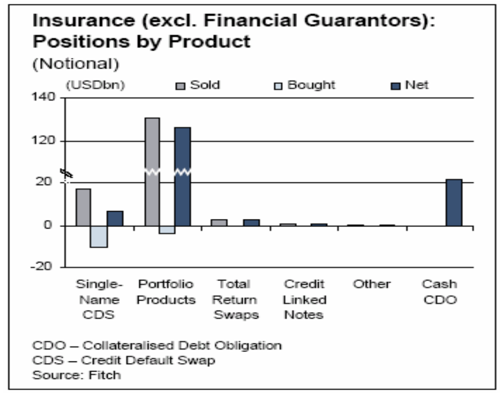
A typology of the various instruments is presented in the matrix below[56]:

Instruments		Funded	Unfunded
Single Name	*Direct risk transfer*	Loan trading	Guarantees, Credit Insurance
			Credit Default Swaps, Total Return Swaps
Portfolio	*Direct risk transfer*	Credit Linked Notes	Portfolio Credit Default Swaps
	SPV	Asset Backed Securities, Cash CDOs	Synthetic CDOs

The majority of these instruments is highly customised and individually structured to a client's needs. However, in terms of market share, the most standardized product[57], single-name CDS, are clearly the most important instrument for banks. CDS represent the largest market segment, corresponding to about 80% of the derivative activity of European banks, according to FitchRatings.

[56] As presented in a comparable way in the BIS report on credit risk transfer.
[57] Standardization implies that a standard legal documentation has emerged for CDS, published by ISDA, the International Swaps and Derivatives Association, in 1999 which is at the basis of nearly all credit default swap contracts.



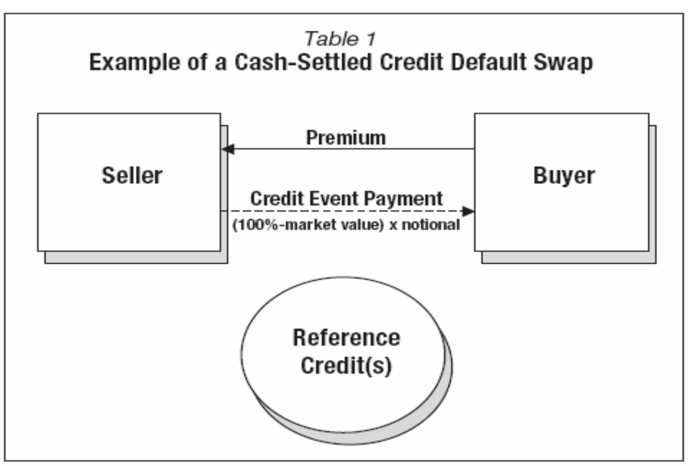


For the insurance sector, the primary participation is via portfolio products such as synthetic CDOs, representing 92% of the total net exposure for these players.

Credit Default Swaps

A CDS contract provides protection against the losses caused by the occurrence of a "credit event" affecting the underlying asset(s) issued by a specified reference credit, which is called the reference entity. The basic difference to credit insurance is that the payoff of CDS is not bound to the actual materialization of a loss, as it is the case of insurance. Stated differently, an investor can obtain or hedge exposure to a credit, *synthetically,* by means of a CDS, i.e. without actually owning the asset of the underlying credit the CDS is written on.

As far as the CDS structure is concerned, the buyer of protection pays either a regular sum or an upfront-amount for the protection while the protection seller compensates for the potential loss in case of default[58]. The regular payment or upfront-amount, normally a certain percentage of the notional amount of protection, is referred to as premium or spread. This is the pricing information, which is used as market data for the CDS indicator in this study. The structure of a typical CDS is displayed in the graph below.



Source: Moodys Structured Finance: Understanding the Risks in Credit Default Swaps (2001)

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[58] This exchange of different cash flows is probably also what motivates the name credit default *swap.*

Compensation in case of default can follow two modalities: one option is physical delivery of a reference asset at par by the protection buyer, "physical delivery". In this case, the protection buyer sells the underlying asset at par value to the protection seller. If he does not own the asset, he has to acquire it. The precise set of bonds, which are deliverable, is defined by the legal documentation and normally encompasses all bonds with the same seniority as the reference obligation. Physical delivery is the primary form of settlement. The alternative is "cash settlement", a payment of the notional minus the post-default market value of the reference asset by the protection seller to the protection buyer[59].

The set of "credit events", which trigger the pay out of the CDS, encompasses bankruptcy, failure to pay (principal or interest payments), default, acceleration, repudiation or moratorium (for sovereigns) and restructuring[60].

To summarize, the main parameters defining a CDS contract are

- reference entity
- maturity
- currency
- modality of settlement
- denomination / contract size
- definition of relevant credit events

[59] The residual value after default is defined by a dealer poll.

[60] This point together with the conditions of settlement are the most controversial features of a CDS contract. A number of judicial disputes have led to changes regarding the modalities of settlement and the definition of credit event. For example, since last year, the ISDA documentation includes the restructuring option of "modified modified restructuring" and allows a broader set of deliverable assets in terms of settlement. For more details, see www.isda.org