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How to reach the authors

Please direct all correspondence to the first author.

Clemens Kool
Utrecht University
Utrecht School of Economics
Janskerkhof 12
3512 BL Utrecht
The Netherlands.
E-mail: c.kool@econ.uu.nl

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Financial Stability in European Banking:
The Role of Common Factors

Clemens Kool[a]

[a]Utrecht School of Economics
Utrecht University

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Abstract
In this paper, I investigate the development and determinants of CDS spreads for 18 major European banks between December 2001 and January 2004 applying factor analysis to daily data. Two clear-cut conclusions can be drawn. First, the dominating first common factor that explains 88 percent of all variation in the system, impacts on all banks in a similar direction. This suggests a strong market integration. However the size of the response of each bank's CDS spread to the first common factor differs substantially, probably reflecting differences in individual bank's exposure and riskiness. Second, the first common factor appears significantly related to the European P/E ratio and the European-wide 2-year nominal interest rate. This finding suggests that the common factor may be interpreted as a general indicator of market conditions.

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

JEL classification: G12, G15, G21, C30

1. Introduction

An efficient and stable financial system is a crucial ingredient for economic development and growth. A broad consensus exists in the literature that such a system contributes to an efficient allocation of real economic resources across time and space and an efficient management of wealth and capital accumulation. In most developed countries, banks – besides financial markets – play a crucial role as intermediary institutions in the process of asset allocation. Correspondingly, the efficiency and stability of the banking system is a crucial concern for monetary and supervisory authorities.

An important issue in this respect is how and to what extent a trade-off exists between efficiency on the one hand and stability on the other. Focusing on the banking sector, market entry and exit should be a normal phenomenon as in any other industry. That is, competition between banks should be encouraged to allow the market as a whole to become more efficient. In the European context, this was the major goal of the creation of the common market for financial products and services in the early 1990s. As a result, banks from any EU country can now operate throughout the EU with a single banking licence. Financial integration was hypothesized to result in more competition and higher efficiency. Obviously, individual under-performing banks can then default in the process.

However, the occurrence of outright bank failure in the European financial system is a rare event. Nevertheless, the recent past has shown a number of situations when financial markets seem to have been considerably preoccupied by the financial soundness of several European banks.[1] Situations of systemic financial distress remain a concrete threat to both markets and supervisory authorities. Although the default of an individual bank is not the issue here, the risk of contagion makes both markets and supervisory authorities wary of such events. As a result, supervision on a micro-level is used to promote financial stability and to avoid systemic macro-instability.[2]

Given the importance of systemic financial stability and the possible relation between individual bank's fragility to economic shocks and the system's overall vulnerability, appropriate ex ante measurement of individual banks' financial risk is crucial both for investors and other market participants and supervisory authorities. Higher financial integration and stronger (cross-country) competition only serve to increase the importance of

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[1] See for example Financial Times, 14 October 2002, "Bad debts, falling capital, dismal profits"
[2] The precise definition of financial stability is still subject of debate. Padoa-Schioppa (2003) provides a rather broad and general definition of financial stability as "*a condition where the financial system is able to withstand shocks without giving way to cumulative processes which impair the allocation of savings to investment opportunities and the processing of payment in the economy.*"

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financial stability analysis. Traditionally, financial stability analysis of individual financial institutions consisted of regular on-site inspections of banks by regulatory authorities and the analysis of financial accounting ratios. In recent years, however, the use of market-based risk measures has considerably gained popularity. Technological progress in combination with new financial instruments facilitates economic and financial risk management in a globally integrated economic system by pricing repackaging and transferring risks. The corresponding availability of low–cost and high-frequency market data on for instance subordinated debt spreads, equity prices and equity returns have significantly contributed to their use in financial stability analysis. In addition, the reliability and information content of traditional accounting measures is increasingly questioned.

A relatively new financial instrument to transfer and price credit risk is the credit default swap (CDS). CDS offers 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 compensation in case of default. CDS spreads are increasingly accepted as appropriate measures of individual bank's credit risk. In this paper, I investigate the development and determinants of CDS spreads for 18 major European banks between December 2001 and January 2004 using daily data. More particularly, I focus on the question what are the driving forces behind ups and downs in individual banks' CDS. Possibly, they are highly correlated when overall market conditions are the dominant factor behind bank risk. Alternatively, risk premiums on bank debt may mostly reflect idiosyncratic bank risks. In that case, the correlation across banks' spreads can be expected to be much less. Note that the analysis is strictly on ex ante risk premiums and does not go into the analysis of ex post contagion effects.

The empirical evidence convincingly demonstrates that two (significant) common factors can be extracted from the data. Two conclusions arise. First, the dominating first common factor explains about 90 percent of total CDS spread variation across time and across banks. Moreover, it impacts on all banks in a similar direction though with different magnitude. It suggests, that it is not changes in individual banks' characteristics that change its perceived riskiness, but overall market conditions. Second, the first common factor appears to be significantly related to the European P/E ratio and the European- wide 2-year nominal interest rate. This provides additional support for the interpretation of the first common factor as an indicator of the overall market conditions.

The paper is set up as follows. In section 2, I briefly discuss the literature with respect to the use of market indicators of financial risk. In section 3, I present CDS spread data and

the proposed research methodology, while empirical results are presented and discussed in section 4. In section 5 I elaborate on the link between the observed common factor in CDS spreads and two aggregate financial variables, the European P/E ratio and the European 2-year interest rate. Section 6 concludes.

2. 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. Market indicators of financial stability should 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. That is, in principle, any market-based indicator of an individual bank's riskiness should include both the riskiness associated with direct shocks in its own operations and with indirect shocks to market conditions that subsequently impact on the bank's operations and position.

Initially, research with respect to market indicators of credit risk focused on subordinated debt (SND) issued by financial institutions, see Gilbert (1990) for an early analysis. The use of subordinated debt is motivated by the higher risk-sensitivity of such junior debt. 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 to increases in risk but behave neutrally to upside gains, unlike equity.[3] By now, bank subordinated debt has become a standard indicator in financial stability analysis. Flannery and Sorescu (1996) find that subordinated debt spreads overall reflect bank risk as measured by financial accounting ratios. However, this only holds in the absence of government guarantees to bail out banks.[4]

Extending the analysis to the equity market, Krainer and Lopez (2002) find that equity data, in particular stock returns and estimated distance to default (EDF), are also viable risk indicators for banks. Swidler and Wilcox (2002) broaden the set of assets to include equity options. They demonstrate that implied volatility is a good predictor of future realized volatility and conclude that it also has a signalling function for bank risk. Note that implied

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[3] See Gropp, Vesala and Vulpes (2002) for a theoretical foundation.
[4] For a discussion of potential problems associated with the use of subordinated debt spreads as risk indicators, I refer to Birchler and Hancock (2004), Elton, Gruber, Agrawal and Mann (2001) and Hancock and Kwast (2001).

equity volatility is the main input to another frequently used measure of financial stability, distance to default, and is its main driver in the short-run.

Gropp, Vesala and Vulpes (2002) compare an equity-based indicator (distance to default) to a bond-market related indicator (subordinated debt spreads). They suggest a complimentary use of both equity and bond-indicators, potentially in conjunction with other market or accounting data. Berger, Davies and Flannery (2000) provide a similar comparison. They conclude that supervisory assessments are much more closely tied to bond ratings than to equity market assessments. However, supervisory ratings have a much stronger contemporaneous focus than forward-looking market indicators. Also, the time-value of supervisory information declines and considerable private knowledge is only present immediately after an inspection.[5] Berger et al. (2000), therefore, conclude: "*supervisors, bond market participants and equity market participants all produce valuable, complimentary information which may contribute to improving the governance of large banking organizations*".

Recently, CDS spreads have become increasingly popular as direct and easy indicators of firm credit risk. Theoretically, the structure of a CDS deal gives it a clear advantage over other assets, most importantly corporate bonds, in assessing a firm's credit risk profile. Because the CDS payoff-scheme is strictly limited to situations of default, CDS spreads are a direct measure of default risk. Research on CDS spreads is still limited, mostly because the CDS market has only gained substantial size since the early 2000s. All studies are subject to the criticism of relatively short time-series and/or small cross-section dimensions.

Most empirical studies so far focus on the pricing characteristics of CDS spreads. Examples are Norden and Weber (2004), Zhu (2004), Longstaff, Mithal and Neis (2004), Cossin and Lu (2004), and Blanco, Brennan and Marsh (2004). The general consensus in these studies is that CDS spreads do indeed price credit risk efficiently.[6] Both Blanco et al. (2004) and Norden and Weber (2004) conclude that for most firms in their sample an equilibrium parity condition holds between CDS spreads and bond spreads, where the CDS market leads the bond market with respect to price discovery. Deviations from parity do exist for some firms, however. Both Longstaff, Mithal and Neis (2004), Cossin and Lu (2004) and Zhu (2004) document similar (transitory) price differences.

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[5] DeYoung, Flannery, Lang and Sorescu (2001) arrive at a similar conclusion.
[6] Houweling and Vorst (2001) point out that the precision of the pricing procedure depends on the rating of the underlying entity. Spreads for high-rated firms are more precise than those for lower-rated firms. Hull, Predescu and White (2004) support this finding and explain it by counter party default risk of CDS and a liquidity premium on the issuer's bonds.

Few studies exist that investigate the determinants of CDS spreads. Exceptions are Aunon-Nerin et al. (2002) and Ericsson et al. (2005). Aunon-Nerin et al. (2002) use both firm-specific information and market information to explain CDS spreads. Significant firm-specific drivers of CDS spreads are its rating, asset volatility, stock price change, leverage and market capitalization. In addition, a higher money market interest rate – supposedly capturing a positive macro-economic outlook – reduces CDS spreads significantly. Ericsson et al. (2005) provide similar evidence that firm leverage, volatility and the risk free interest rate explain a significant amount of variation in the data. This paper is related to Aunon-Nerin et al. (2002) and Ericsson et al. (2005) in that it investigates determinants of CDS spreads. However, both the focus and the approach taken are somewhat different. With respect to the focus of the paper, I only consider banks, while most other studies have a mix of industrial and financial firms. Concerning the approach taken, first the overall variation in spreads is decomposed into common factors and residual (idiosyncratic) noise. Subsequently, each bank's sensitivity to changes in these common factors is investigated. The results strongly suggest that the first common factor that explains the majority of CDS variation can be interpreted as an overall indicator of market conditions.

3. Data description and methodology

Sample banks
The sample consists of 18 major European banks and includes all top-10 European banks. In addition, 16 out of the 18 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 European banking market in spite of its small size.

Sample period
The time-period examined runs from December 2001 to January 2004. Data are averages of bid and ask quotes taken from CreditTrade. These CDS spreads offer protection against junior (subordinated debt). For two banks – notably the Spanish banks BBVA and BSCH CDS daily data start in May 2001. Only from December 2001 onward, CDS spreads are available for all 18 banks. Occasionally, data are missing for specific days and banks. Throughout the analysis, I use a balanced panel of daily data consisting of 532 observations. In addition to the short time span of the data, a number of other caveats apply, mainly due to limited availability of appropriate data. First, quotes rather than transactions data and average quotes rather than separate bids or ask quotes are used. Second, market liquidity may vary across time and

across banks. Especially in the early period, markets may have been thin and liquidity low. Third, the maturities of the bonds underlying the CDS spreads used differ substantially across banks. Admittedly, this could affect some of the results. Caution should be applied in the interpretation, therefore.

Table 1 reports stylised statistics for the CDS spreads per bank. Spreads are reported in basis points. Most banks experienced a mean spread of 40 to 50 basis points over the period. Exceptions are Bayerische Hypo and Commerz Bank with a mean spread of about 136 basis points and BSCH, Intesa and Dresdner with a spread of about 70 to 80 basis points. Standard deviations for most banks are around 10-20 basis points. Commerz has the highest standard deviation equal to 88 basis points. Generally, mean spreads and standard deviations appear positively correlated.[7]

Figure 1 graphically shows the development of the CDS spreads over the sample period, split out per country. Spreads are relatively stable over 2001 and the first half of 2002. From the middle of 2002 till around October/November there is a run-up in spreads for most banks, though in different degrees. Subsequently, spreads gradually decline with a new hike in early 2003 for a subset of banks. By the end of the sample, spreads typically have declined to levels similar to or even lower than the levels prevailing in 2001. Note that there seems to be considerable variation in spreads both within countries and across countries.

Methodology

It is the purpose of the exploratory analysis to decompose CDS spreads across banks into one or more common factors – to which banks can respond differently – and idiosyncratic factors, attributable to one bank or possibly a small group of banks. Standard multivariate factor analysis presupposes stationarity of the data. While a case can be made that risk premia theoretically follow a stationary process – though confounded perhaps with permanent jumps – unreported unit root tests show that the existence of a unit root cannot be rejected for any of the CDS spreads in our sample.[8] The first difference series are all stationary. However, first-differencing the data would result in a loss of information with respect to the data's level-dynamics.

Due to the non-stationary properties of the actual input data, I have therefore decided to use the method proposed by Stock and Watson (1988) and Gonzalo and Granger (1995) to extract common factors or trends corresponding to the latent risk dimensions in the data.

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[7] Unreported results show that CDS spreads had no significant trend over the sample. Mean changes are all quite close to zero, especially when compared to their standard deviations.
[8] Results are based on ADF tests and are available from the author on request.

However, I also applied conventional factor analysis for the 18 CDS series as a check on the robustness of the results. Extracted common factors were virtually identical in both approaches. Consequently, the following results are insensitive to the assumption of (non) stationarity. Stock and Watson (1988) show that if a vector X_t is cointegrated, a common factor representation exists of the form

(1) $\quad X_t = A_1 f_t + \widetilde{X}_t$

Thus, if X_t is a (px1) vector of I(1) series with cointegration rank r, then the elements of X_t can be explained in terms of a smaller number of (p - r) I(1) variables, f_t, called common factors plus some I(0) components, $\widetilde{X}_t$. Gonzalo and Granger (1995) present a procedure for extracting the common factors, by imposing two identifying assumptions:

1) f_t are linear combinations of X_t, allowing to associate the common factors with the observable variables,

2) $A_1 f_t$ and $\widetilde{X}_t$ form a P-T (permanent-transitory) decomposition, implying that the common factors summarise the long-run behaviour of the original variables.

On the basis of this, the factor model $X_t = A_1 f_t + \widetilde{X}_t$ can be rewritten as $X_t = A_1 f_t + A_2 z_t$, where $f_t = \gamma_\perp X_t$, $z_t = \alpha' X_t$ and $\widetilde{X}_t = A_2 \alpha' X_t = A_2 z_t$. The routine to extract the factors f_t is largely based on the cointegration test proposed by Johansen and Juselius (1990). Estimates for $\gamma_\perp$ and α' are obtained by regressing ΔX_t and X_{t-1} on ($\Delta X_{t-1}, \dots, \Delta X_{t-q+1}$), providing residuals R_{0t} and R_{1t}. From the residuals, the product moment matrix $S_{ij} = T^{-1} \sum_{t=1}^{T} R_{it} R'_{jt}$ i,j = 0,1 is formed. Subsequently, solving the equations $\left| \lambda S_{11} - S_{10} S_{00}^{-1} S_{01} \right| = 0$ and

$\left| \lambda S_{00} - S_{01} S_{11}^{-1} S_{10} \right| = 0$ yields eigenvalues and their corresponding eigenvectors V and M, from which estimates of α' and $\gamma_\perp$ are obtained.

In practice, the analysis by Gonzalo and Granger consists of a cointegration test in order to determine the number of underlying common trends/factors in the data. The common trends are then extracted from the data in a second step. This routine becomes problematic, however, when high dimensionality datasets have to be examined, for which standard tests of cointegration cannot be implemented.[9] This is also the case at hand.

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[9] Critical values for the cointegration rank, r, are not available for r >10 in standard tests.

In order to circumvent this problem, Gonzalo and Granger show that it is possible to analyse a set of variables in (logical) smaller subsystems. They demonstrate that combining the analysis of two separate subsystems yields results identical to an analysis of the entire system[10]. In the present case, in order to handle the dimension of 18 CDS spreads (banks), the data are split into two subsystems, each containing the data of 9 banks. Subsequently, a factor analysis is carried out for the two subsystems separately in a first step, resulting in a set of I(1) common factors for each subsystem. In the second step, a cointegration test on these common factors (extracted from the two subsystems) then determines the number of common trends/factors for the entire system. Combining the common factors from the two subsystems in a second common factor analysis merges all available information and yields a new set of common factors that capture the underlying dimension of the entire dataset.[11]

By means of this procedure, a decomposition of the data into a common (non-stationary) and a specific (stationary) dimension can be achieved - reflecting the common and specific risk level. The extracted common trends capture the common long-run characteristics of the banks' time series and reflect the latent dimension(s) that underlie the data. It is expected to yield a decomposition of the risk captured by the indicators into a common and a bank-specific dimension and should thus permit a more in-depth analysis of the forces driving CDS spreads.

4. Results

Using the procedure described above yields two non-stationary common factors for the CDS spreads.[12] In figure 2, both factors – standardized at a mean of zero and a standard deviation of one – are presented. The first factor captures the general pattern that is present in all CDS spreads across banks. It accounts for 88 percent of total variation in the system. Factor loadings (correlations) for individual banks are invariably very high. Apart from three German banks – Bayerische Hypo, Commerz and Dresdner – they are all above 0.90. One might interpret this as the overall market factor.[13] The second factor that only explains about 7

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[10] Granger and Haldrup (1997) point out some theoretical limitations of this procedure.

[11] Repeating the procedure for different combinations of banks in the subsystems does not affect the results. Since a standard factor analysis covering all 18 banks simultaneously also leads to the same outcome, I feel confident that the procedure proposed by Gonzalo and Granger is valid here.

[12] Unreported unit ADF root tests do not reject the unit root in these series.

[13] Obviously, in light of the small size of the 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. Possibly, it may even be a global factor. The lack of non-European banks in the sample precludes any definite conclusions on this issue.

percent of total variation has quite different characteristics. It has a trough in 2002 and a peak in the first half of 2003. Especially the German banks but also the UK banks plus the Dutch ING load positively on this factor, while all French, Spanish, Italian and Swiss banks plus the Dutch ABN AMRO load negatively. Not all loadings are significant. A more structural and economic explanation of this result is left for future research.

Table 2 reports more detailed evidence on the dynamics of changes in credit spreads. For each bank the change in the spread has been regressed on the contemporaneous changes in the first factors and the (unrestricted) lagged levels. The regression has the following form:

(2) $\Delta cds = \alpha_0 + \alpha_1 \Delta factor1 + \alpha_2 \Delta factor2 + \alpha_3(cds_{-1} - \alpha_4 factor1_{-1} - \alpha_5 factor2_{-1})$

where Δ represents the first difference operator, cds is the spread for an individual bank and factor1 and factor 2 are the two extracted common factors. This allows the estimation of the speed of mean reversion (α_3) in credit spreads to their long-run level. In the table, White's heteroskedasticity-consistent standard errors are in parentheses.[14]

Focusing first on the level part of the regression (cds$_{-1}$ – α_4 factor1$_{-1}$ – α_5 factor2$_{-1}$), a few important observations stand out. First, for most banks the coefficient on the first factor (α_4) is between 10 and 20. For six banks, a considerably higher sensitivity is estimated. This is the case for all four German banks – though to a different degree – plus the Italian Intesa bank and the Spanish BSCH. Note that the German banks, together with Intesa and BSCH also have the highest average spreads over the sample period. Second, coefficients on the second factor (α_5) are especially large and positive for all German banks apart from Deutsche Bank, and relatively large and negative for the two Spanish banks BBVA and BSCH. Note that the German banks, together with Intesa and BSCH also have the highest average spread over the sample period.

Overall, the results suggest that the market as a whole largely moves together. That is, overall market conditions appear to be the main driver of the required credit risk premium for each bank. On the other hand, it is true that banks differ in the level and volatility of the required risk premium. Especially the German banks and some Spanish and Italian banks have a substantially higher average CDS spread and a substantially higher sensitivity of the required spread with respect to changes in market conditions than the other banks in the sample.

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[14] Unreported Johansen-Juselius cointegration tests indicate cointegration between the two common factors and each individual bank's CDS spread. Given the construction of the factors, this is not surprising. The last part of eqution (2) in parentheses therefore may also be interpreted as the cointegration vector.

The error correction coefficient (α_3) is around -0.10 for most banks, suggesting that about 10 percent of a deviation from the long-run equilibrium relation is corrected in one day. In most cases, the effect of a contemporaneous change in one of the factors (α_1; α_2) on the spread is of the same order of magnitude as the corresponding long-run effect. It suggests that the gap between the long run credit spread level as determined by the nonstationary common factors and the actual spread may be primarily driven by stationary firm-specific factors.

5. What's behind the first common factor?

In the discussion so far, the maintained assumption has been that the first common factor essentially captures overall market conditions. This was primarily based on the consistently high positive loading of each and every individual bank's CDS spread on the factor. It is hard to imagine how a series of independent idiosyncratic risk determinants originating from different banks could lead to such synchronized behaviour of all spreads in the market.

In this section, I explicitly investigate whether it is possible to link the first common factor to a number of exogenous aggregate economic variables. This allows a closer analysis of the market risk factors and potential identification of the forces driving market risk. Due to the relatively short sample-period, the variables used for this purpose need to have a daily frequency, corresponding to the CDS spread data. This leaves only financial variables as potential candidates. In the subsequent analysis, I use two key aggregate financial variables[15]:

- the Euro-Area 2 year nominal interest rate
- the P/E ratio of the DataStream European Equity market index

In a first pass through these data, I perform unit root tests on the two individual series. For neither of these series the unit root is rejected. Note that the same caveats apply as with respect to the estimated nonstationarity of the CDS spreads. Subsequently, I perform a Johansen-Juselius cointegration test between the first common factor and the above two aggegrate financial series. The Max-eigenvalue test indicates 1 cointegrating equation at both the 5% and 1% levels with normalized cointegrating coefficients of 0.83 (standard error 0.07) for the P/E ratio and –1.80 (standard error 0.20) for the nominal 2-year interest rate. That is, high European price earning ratios reduce the CDS spreads, while a high nominal interest rate increases the CDS spread for all banks. Note that the direction of the interest rate effect is opposite to the one found by Aunon-Nerin et al. (2002). Overall, the evidence supports the interpretation of the first common factor as an indicator of overall market conditions.

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[15] The variables are taken from Datastream.

A corresponding cointegration test between the second common factor and the P/E ratio and the nominal 2-year interest rate fails to indicate a cointegrating relation between these three variables. It suggests that more research is required to determine the drivers behind the second common factor.

6. Conclusion

Financial stability is a major concern for market participants and supervisory authorities alike. Banks play a major role in the global financial system and have become more interconnected over the last decades, due to deregulation, liberalization and technological progress. The creation of the internal European market for the purpose of higher competition and efficiency has added to these developments. However, it has also raised new questions on the system's stability. Increased freedom of operation due to liberalization and deregulation has therefore also resulted in increasing attention for monitoring and supervision. Market indicators of financial risk play an increasingly important role in this respect, due to their real-time availability and their efficient reflection of all available information.

The market for credit default swaps has started to take a central place as it provides an efficient way to transfer and price credit risk. Moreover, CDS spreads provide a direct and easy measure of an individual bank's credit risk. Assuming that the CDS market appropriately prices each bank's riskiness into the CDS spreads, differences between banks may arise from two sources. On the one hand, a bank's risk level may be affected by common (market) conditions, which of course can impact on a bank's riskiness to different degrees depending on the bank's exposure and vulnerability. On the other hand a bank's risk level may be a function of its own characteristics, unrelated to market conditions.

In this paper, I have focused on the development and determinants of CDS spreads for 18 major European banks between December 2001 and January 2004 using daily data. More particularly, spreads are decomposed into common factors and a remaining group of (stationary) idiosyncratic determinants. I have demonstrated that two (nonstationary) common factors can be extracted from the data that together explain most CDS spread variation across time and across banks. The dominating first common factor impacts on all banks in a similar direction, suggesting strong market integration. The group of German banks plus a few Southern-European banks appear to systematically have high CDS spreads and to be relatively sensitive to changes in this factor. The quantitatively less important second factor has opposite effects on credit spreads. Finally, I show that the first common factor may

indeed be interpreted as a measure of market conditions as it is cointegrated with the European P/E ratio and the 2-year nominal interest rate.

In my view, the results of this first exploratory analysis of the data yield interesting and promising results. Some questions remain for future research, however. Most importantly, I have paid no attention as yet to individual bank characteristics, such as ratings, leverage, stock return volatility etc that have been shown to play a role in the pricing of credit risk in related research. Possibly, differences in these characteristics across banks may explain their differential sensitivity to the common market indicator. Also, further analysis in this direction may shed additional light on the determinants of the second common factor. Finally, extending and improving the dataset both with respect to the number of banks and the number of observations, and accounting in a better way for differences in liquidity and maturity is important to determine the robustness of the current results.

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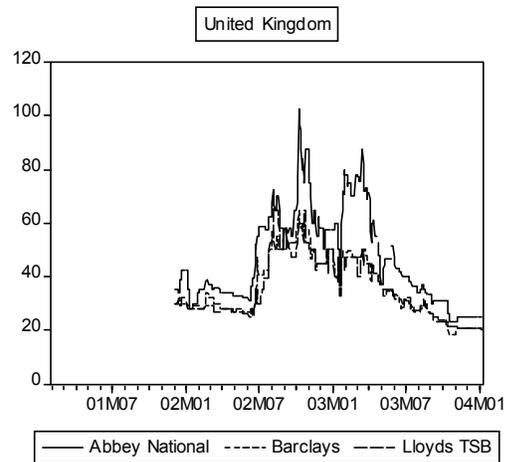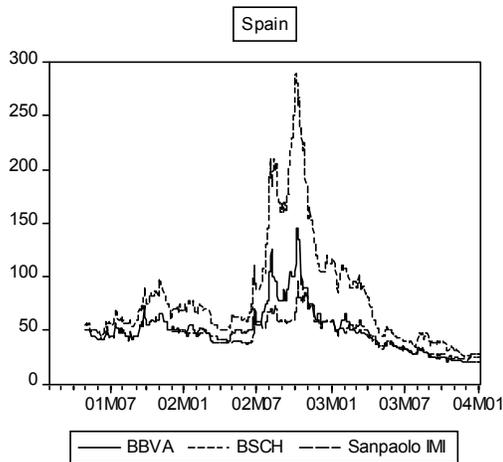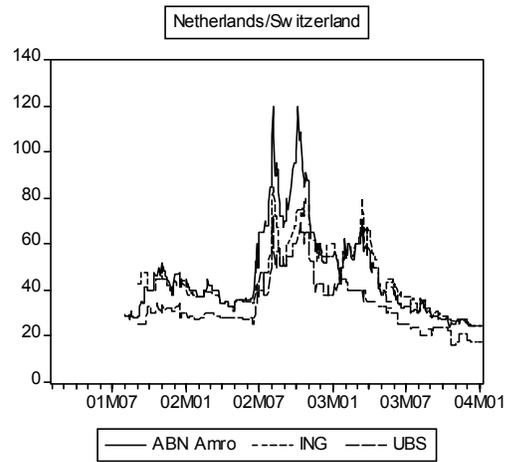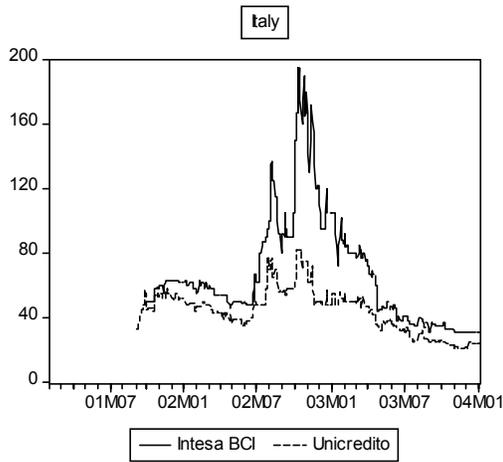
Table 1: Stylised Statistics on CDS Spreads *(levels, in basis points)*

Bank	Country	Mean	Std. Dev.	Min.	Max.
Abbey Nat'l	UK	46.71	17.69	23.50	102.50
ABN AMRO	Netherlands	47.76	20.76	23.50	120.00
Barclays	UK	35.85	11.31	18.50	65.00
Bayer Hypo	Germany	136.02	75.90	50.50	330.00
BBVA	Spain	49.97	23.59	20.00	145.00
BNP Paribas	France	39.70	14.64	20.50	95.00
BSCH	Spain	84.72	56.49	24.50	290.00
Commerz	Germany	135.99	88.12	45.00	475.00
Credit Lyonn	France	44.40	17.00	20.00	120.00
Deutsche	Germany	54.81	25.42	25.50	15750
Dresdner	Germany	78.00	43.64	28.00	200.00
ING	Netherlands	44.55	14.35	24.50	85.00
Intesa	Italy	68.14	35.49	30.50	195.00
Lloyds TSB	UK	35.31	11.36	21.00	72.50
San Paolo	Italy	45.15	14.46	22.50	95.00
Soc Gen	France	42.24	16.55	22.50	100.00
UBS	Switzerland	33.98	12.38	16.00	72.50
Unicredito	Italy	43.43	14.25	20.00	82.50

Table 2: First Difference (ECM) Regressions (common sample)

Bank	Intercept	D(F1)	D(F2)	ECM	F1(-1)	F2(-1)	Adj R2
Abbey Nat'l	4.39 (1.52)	17.71 (2.72)	3.21 (1.61)	-0.094 (0.03)	17.14 (1.56)	4.72 (1.18)	0.389
ABN AMRO	4.98 (1.78)	20.74 (3.69)	-7.62 (1.84)	-0.104 (0.04)	18.26 (1.53)	-4.74 (1.03)	0.511
Barclays	3.60 (0.96)	11.70 (1.39	-2.44 (0.96)	-0.100 (0.03)	11.25 (0.70)	1.00 (0.48)	0.481
Bayer Hypo	11.88 (3.66)	71.09 (7.45)	41.25 (6.20)	-0.087 (0.03)	62.28 (5.29)	51.04 (3.49)	0.631
BBVA	8.56 (3.08)	24.65 (3.86)	-10.99 (2.23)	-0.171 (0.06)	19.94 (1.21)	-8.49 (0.79)	0.530
BNP Paribas	9.35 (2.52)	13.35 (1.92)	-4.24 (1.68)	-0.236 (0.06)	13.85 (0.55)	-2.57 (0.35)	0.433
BSCH	3.43 (2.31)	27.26 (5.02)	-10.54 (3.18)	-0.041 (0.03)	42.48 (7.22)	-28.67 (10.20)	0.287
Commerz	14.36 (7.92)	66.42 (8.29)	43.21 (5.88)	-0.106 (0.06)	80.75 (4.79)	40.37 (4.57)	0.534
Credit Lyonn	6.10 (1.74)	14.26 (1.75)	-3.21 (2.08)	-0.137 (0.04)	14.99 (1.66)	-5.17 (0.63)	0.337
Deutsche	4.85 (1.31)	23.39 (2.93)	5.22 (1.67)	-0.088 (0.02)	23.67 (1.96)	1.88 (1.67)	0.458
Dresdner	4.27 (1.17)	40.53 (3.02)	14.96 (3.16)	-0.054 (0.01)	39.82 (3.84)	27.17 (3.14)	0.653
ING	5.49 (1.88)	15.77 (3.26)	-0.35 (1.17)	-0.123 (0.04)	14.42 (0.98)	1.78 (0.95)	0.428
Intesa	3.96 (1.71)	33.62 (3.37)	9.95 (2.17)	-0.059 (0.03)	33.72 (5.11)	-2.06 (2.87)	0.479
Lloyds TSB	4.47 (0.94)	9.98 (1.27)	-0.49 (1.09)	-0.126 (0.03)	11.04 (0.84)	0.25 (0.84)	0.259
San Paolo	2.78 (0.99)	13.84 (1.54)	2.43 (1.24)	-0.062 (0.02)	13.08 (2.06)	-1.98 (1.10)	0.451
Soc Gen	7.33 (1.72)	14.64 (2.21)	-3.83 (1.01)	-0.173 (0.04)	15.30 (0.56)	-3.81 (0.47)	0.507
UBS	5.24 (1.38)	9.51 (1.93)	-2.05 (1.31)	-0.154 (0.04)	11.58 (0.60)	-2.25 (0.68)	0.293
Unicredito	2.983 (0.89)	15.91 (2.22)	-1.47 (1.14)	-0.069 (0.02)	12.83 (1.64)	-2.81 (1.34)	0.434

Figure 1 CDS Spreads per Country

Figure 2 Common Factors