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The Dynamics of Short- and Long-Term CDS-spreads of Banks

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Abstract

This paper studies 'Stylised Facts' and 'Determinants' of short-and long-term CDS-spreads of banks. As short-term spreads we choose 6M-, as long-term spreads we choose 5Y-spreads. In the section 'Stylised Facts' we found that the correlation between short- and long-term spreads for the total period is high (97%). However, the correlation in sub-periods varies across all possible correlations. Particularly, spreads can have negative correlation. In contrast to [Covitz and Downing, 2007], we find high positive (Covitz/Downing: high negative) correlation for turbulent market circumstances. In the section 'Deteminants' we confirm the Merton-factors (stock price, stock price volatility, interest rate level) for the 5Y-segment, but not for the 6M-segment. Furthermore, we do not find any empirical support that short-term spreads are particularly sensitive to illiquidity factors. In that sense, we also contrast [Covitz and Downing, 2007].

Keywords: Liquidity, Inslovency, Banks
JEL-Classification: G32

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1 Introduction

Credit risk and credit spreads have been the risk category 'en vogue' during the last decade. The literature about credit spreads can be categorized into (i) Stylised Facts, (ii) Pricing and (iii) Determinants of Spreads. Concerning the instruments, research has been first centred around corporate bond spreads. With the introduction of Credit Default Swaps (CDS) and their increasing market liquidity, research shifted from corporate bonds towards CDS. Credit Spread research reports the following results for long-term maturity spreads (3-10 years):

- Stylised Facts
  [Düllmann et al., 2000] and [Kao, 2000] find that spreads are highly volatile. The volatility is decreasing in credit quality. [Duffie and Singleton, 2003] found that corporate bond spreads are autocorrelated (show persistence). The question whether spreads exhibit mean-reversion (negative relation between change and level) is still pending: studies using corporate bond indices usually report mean-reversion ([v. Landschoot, 2004], [Bhanot, 2005]). However, [Bierens et al., 2003] does not find evidence for mean reversion on a bond portfolio level.

- Pricing
  Concerning the pricing of credit risk, two model families have been developed: structural and reduced-form models. Structural models determine the credit spread based on market- and firm-specific risk factors. Reduced-form models use unobservable, statistic variables to model the default event.
  Although the first structural model ([Merton, 1974]) failed to reproduce market credit spreads[1], advanced structural models incorporating stochastic interest rates, endogenous default boundaries and/ or firm value jumps do replicate CDS-spreads.[2] Reduced-form models are not used to price spreads, but are calibrated against (CDS-)spreads. They are rather used to extract implied spread dynamic parameters.

- Determinants
  The research stream 'Determinants' seeks to corroborate whether credit spreads (changes) are sensitive to the model risk factors (changes).

  - Merton Factors
    The relation (significance, sign) between Merton74-factors and Corporate Credit Spreads has empirically been corroborated:
    spread (- Firm returns, + Firm volatility, - IR-level, - IR-slope, + leverage)
  - Additional Factors
    Merton76-implied factors leave a substantial fraction of corporate bonds credit spread changes unexplained. Factors accounting for credit jump risk,

[1] Basic structural models overpredict in general or overpredict 'low', but underpredict high-quality bond spreads.

[2] [Ericsson et al., 2006] used the [Fan and Sundaresan, 2000]-model and reported a good general matching of model-CDS and market CDS-premia. [Huang and Huang, 2003] report good calibration results for several models.

market liquidity and taxes added substantial explanatory power. These factors have to be incorporated by models as well. However, default risk accounts for the largest part of corporate bond credit spreads and is increasing in both absolute and relative terms the lower the rating.

However, THE 'Credit spread' does not exist. The 'Credit spread' is not an one-dimensional concept that represents a 1:1-link between the credit risk and its compensation. In fact, credit spreads behave differently depending on ...

- Instruments (CDS-premia vs. Corporate Bond Spreads)
- Credit quality (Low vs. high credit quality)
- Maturity (short- vs. long-term spreads)
- Industry (bank vs. non-bank spreads)
- Size (small vs. large debtors)

Our paper studies the dynamic of short- and long-term CDS-spreads of banks. Our study is inspired by [Covitz and Downing, 2007] which studied short-term Commercial Paper and long-term Corporate Bond spreads. According to our literature classification, they report the following findings for a sample of around 2.000 non-financial US-corporates covering CP- and bond spreads from 01/1998 to 12/2001:

Stylised Facts

- Short-term spreads are sizable
  Zero spreads do not exist: even the highest rated firms (AAA-long-term rated) pay on the shortest maturity (Overnight) on average 10 BP. This increases up to 34 BP for BBB (long-term rated) firms.
- Negative Correlation between short-term (Commercial Papers) and long-term spreads (Corporate Bonds)
  Short- and long-term spreads are not perfectly correlated. In some periods, they even evolve in opposite directions. The analysis was performed cross-sectional in order to obtain a distribution of correlations across firms.

Determinants

- Short-term CP spreads are driven by both insolvency and liquidity risk.
- Long-term bond spreads are only sensitive to insolvency risk.
- In times of distressed CP-markets corporates' liquidity risk becomes more important for short-term spreads than for long-term spreads.

Although inspired by [Covitz and Downing, 2007], our paper contributes new aspects to the literature as we choose CDS-spreads instead of CP-/ corporate bond spreads. We choose **CDS-spreads** as they are considered to be pure default risk premia without significant market liquidity biases. Our short-term spreads are of 6M-maturity.

As long-term CDS-spreads we choose 5Y. As our spreads result from the same asset class, we hope to exclude any instrument-induced bias. The disadvantage is that the shortest CDS-spreads are 6M instead of overnight or weekly CP-spreads as studied by [Covitz and Downing, 2007].
[Covitz and Downing, 2007] studied corporate credit spreads. We study CDS-spreads of **banks**. We consider banks an interesting industry as they are usually excluded in default risk studies due to their particular capital structure. Furthermore, we believe that the liquidity-sensitivity of short-term spreads is more pronounced with banks as they have more cash flow risk due to liquidity options and they do not have any freedom to renegotiate the maturity of payment obligations.
According to the literature classification, we study 'Stylised Facts' and 'Determinants' of CDS-spreads. We proceed as follows:

1. Stylised Facts
   We study deltas and correlation between 6M- and 5Y-spreads on the index- and on the bank-level. We particularly analyse the correlation for different time windows and market circumstances.

2. Determinants
   We seek to identify factors that drive short- and/ or long-term CDS-spreads. Particularly, we test whether short-term spreads are more liquidity-sensitive than long-term spreads.

Our paper is structured as follows: section 2 describes our spread data and how we designed our sample. Section 3 discusses the individual and common dynamics of short- and long-term spreads. Section 4 tests for factors that are eligible to drive CDS-spreads. In particular, we follow the idea of [Covitz and Downing, 2007] focussing on insolvency and liquidity factors. Section 5 concludes and gives an outlook for further research.

2 Data and Sample Design

2.1 Data

We obtain daily CDS-quotes of 3068 entities from Markit covering the period from 01.01.2001 to 31.12.2007.

2.1.1 Sample Design

To obtain our final sample, we apply a 4-stage filter:

1. Entities
   As we focus on banks, we filter for 'Financials'. In order to ensure currency homogeneity, we filter for 'EUR'-denominated CDS. This leaves us with 400 entities.

2. CDS-liquidity
   Our paper studies the dynamics of short-term versus long-term CDS-spreads. As short-term maturity we choose 6M as it is the shortest maturity available. Among the long-term available maturities (5Y, 7Y, 10Y), we choose 5Y as it is the most liquid segment by far. While the 5Y-segment has almost daily observations, many entities only have sporadic observations in the 6M-segment. Indeed, the long-term CDS-market is of a much larger size than the short-term one as figure 1 demonstrates: the market segment of up to 1Y is fairly small (about 7% of total market size) compared to the 5Y-segment (about 65% of total market size).[3] Therefore, 6M-CDS-liquidity is our 'bottleneck' and deserves particular attention. In order to identify the entities with the highest trading activities in the 6M-segment, we proceed as follows: first, we select those entities that have 6M-spreads on 14.08.2007 and 11.04.2007. 2007 is a year with a fairly good data coverage in the 6M-segment (our final sample has 65% compared to 25% in 2003). We assume that only entities with 6M-spreads on two random days in 2007, are actively traded entities eligible for our sample. This random filter leaves us with 259 entities. In the next round, we order entities according to the number of brokers that contributed to the 5Y-Markit-average quote. The contributor field seems to be a good liquidity proxy as our first 29 entities have been frequent iTRAXX-financial-members (5Y-index of most liquid CDS of financials) in the last 7 tranches (2004 till first tranche of 2007).[4] From the ordered list, we drop insurances and small entities leaving us with the final sample of 58 entities.

3. Time window
   Our original time series cover the window 01.01.2001 - 31.12.2007. However, not every entity has spreads for all the years. Indeed, figure 2 shows that

[3] Unfortunately, data prior to December 2004 are not available.

[4] This approach suffers from two shortcomings: first, the number of contributors is a liquidity proxy for 5Y, not for 6M. Therefore, the approach assumes that an actively traded 5Y-entity is also an actively traded 6M-entity. Second, the iTRAXX-crosscheck only revealed a high correlation for entities with the highest number of contributors. We do not know whether the field is still reliable for the non-iTRAXX-members. However, this is what we implicitly assume.

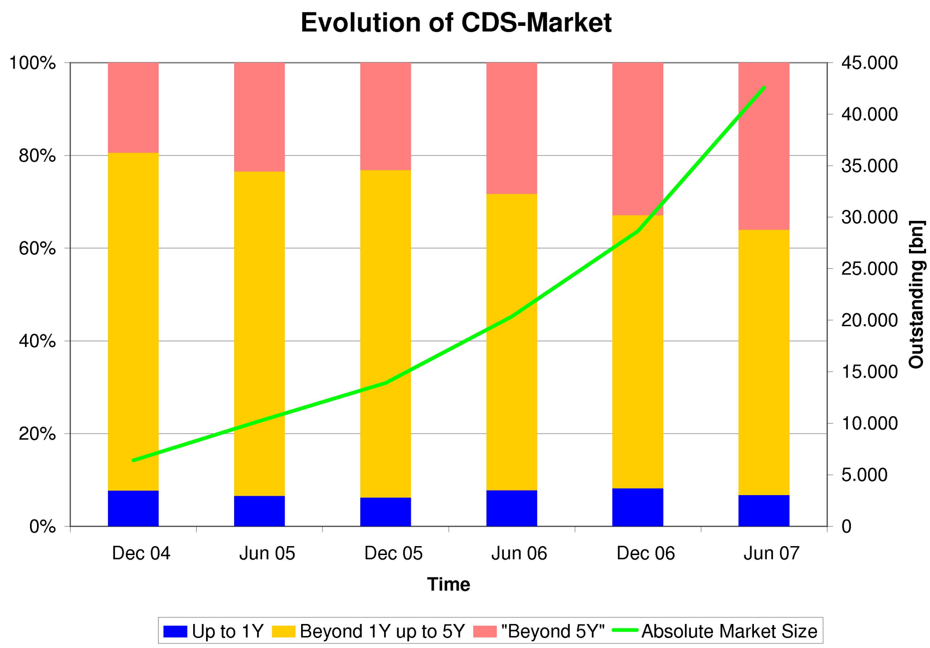

Figure 1: Evolution of CDS-market (Source: Semiannual OTC derivatives statistics, BIS)

only 18% have a (full) history of 7 years. 65% have a history of 6 years or longer. It can be seen that the year 2003 is a 'key year' as it saw the last significant entrance of entities (the percentage of entities increased from 65% (2002-2007) to 90% (2003-2007)). Therefore, we fix the starting year to 2003 and drop the 6 entities with spread histories starting in 2004 or later.[5] Now, 100% of our banks have at least one 6M-spread in 2003. However, we have to ask ourselves how frequent the observations are in 2003? 2003 has a poor data coverage of only 25%. Figure 3 plots the time series of 6M- and 5Y-spreads across 2003: the 6M-segment starts the year with rather sporadic observations suggesting little trading activity. Observations become more frequent towards the end of the year. By contrast, the 5Y-series offers complete data coverage over the whole of 2003. Due to the poor data information in 2003, the impact of outliers is tremendous: if series are averaged, the lack of observations increase the impact of an outlier. This is highlighted in figure 4. 'Cap One Bank' has sporadic extreme spreads in the 6M-segment (up to 500 BP). It has the lowest rating in our sample (BBB in 2003), but this hardly justifies such high 6M-spreads. Together with the series of 'Capital One Bank', figure 4 also plots the average with and without 'Capital One Bank'. It is obvious, that 'Capital One Bank' significantly biases the 6M-average. Favorable to the bias is the low data coverage in 2003 in the 6M-segment. The presumption that 25% data coverage in 2003 is not sufficient, has been confirmed. We therefore drop 2003 and restrict our sample to observations from 01.01.2004 onwards.

[5] We drop HSBC Fin Corp (2004), JPMorgan Chase & Co (2004), Bk of America Corp (2006), CAPITALIA S PER AZIONI (2006), NATIXIS (2006), Intesa Sanpaolo SpA (2007)

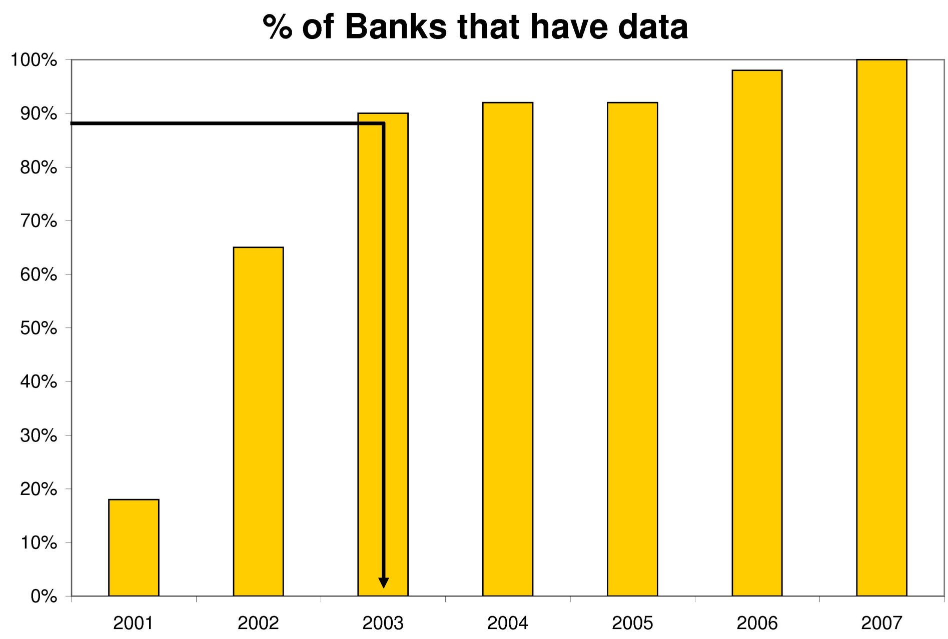

Figure 2: % of banks whose spread series start in ...

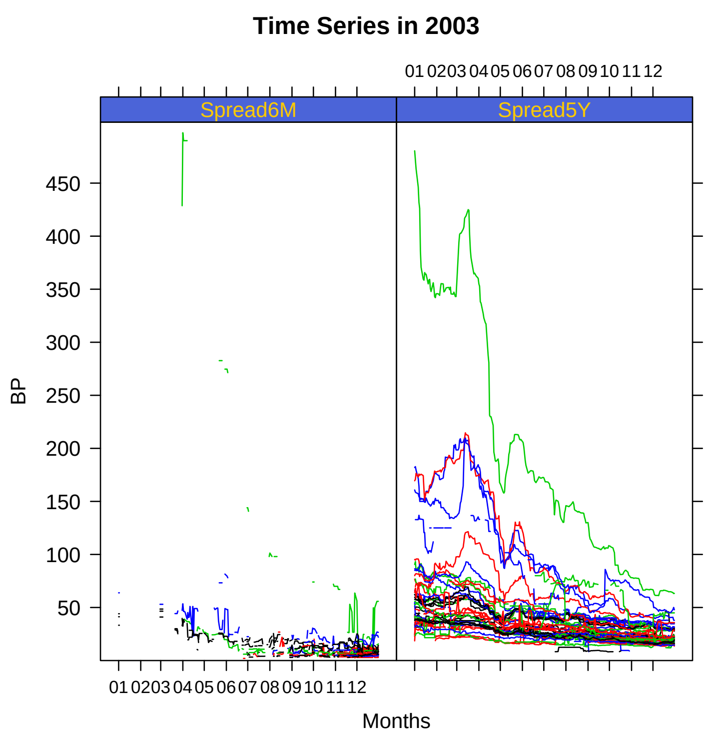

Figure 3: 6M-Times Series in 2003

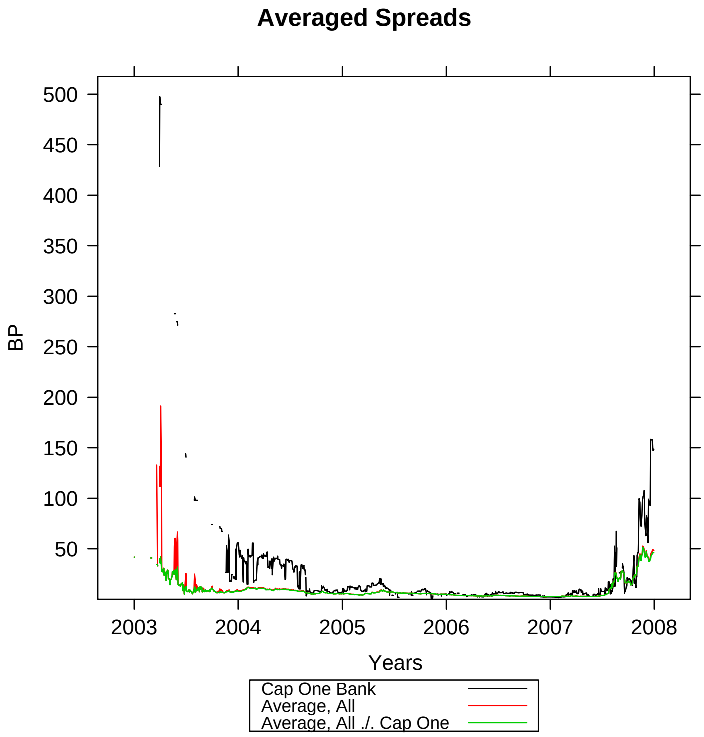

Figure 4: Capital One Bank and Averages

As the data coverage increases, the impact of single time series on the averages are reduced. This is documented in figure 5. While the average in 2003 is dominated by 'Capital One Bank' in the 6M-segment, the impact of the bank vanishes with the years (although, 'Capital One Bank' is still an outlier to some extend due to its low rating). As the 5Y-segment has a better data quality, the impact of 'Capital One Bank' is much smaller. During 2003, there is a small bias that vanishes during the years.

4. Seniority
CDS differ according to their Seniority level. To ensure heterogenity, we restrict the sample to the Seniority with the best data quality. Plotting the absolute number of spread observations per seniority level across time leads to figure 6.[6] We state that 'SNRFOR' has slightly more observations (about 10%) than 'SUBLT2'. However, there is a convergence tendency as the differences in 2007 seem to narrow. The absolute number of observations could be due to large segments. Therefore, we also check the relative data coverage. Figure 7 shows the data quality within the 6M-maturity. Is suggests that 'Senior' (max. 96%) has a better data coverage than 'Subordinated' (max. 82%).
Figure 8 displays the data quality within the 5Y-segment. We do not find significant differences in the relative data coverage between 'Senior' and 'Subordinated': 'Senior' reaches 100% in 2006 and is slightly below 100% in 2007.

[6]We summarized all other seniorites under 'Others'.

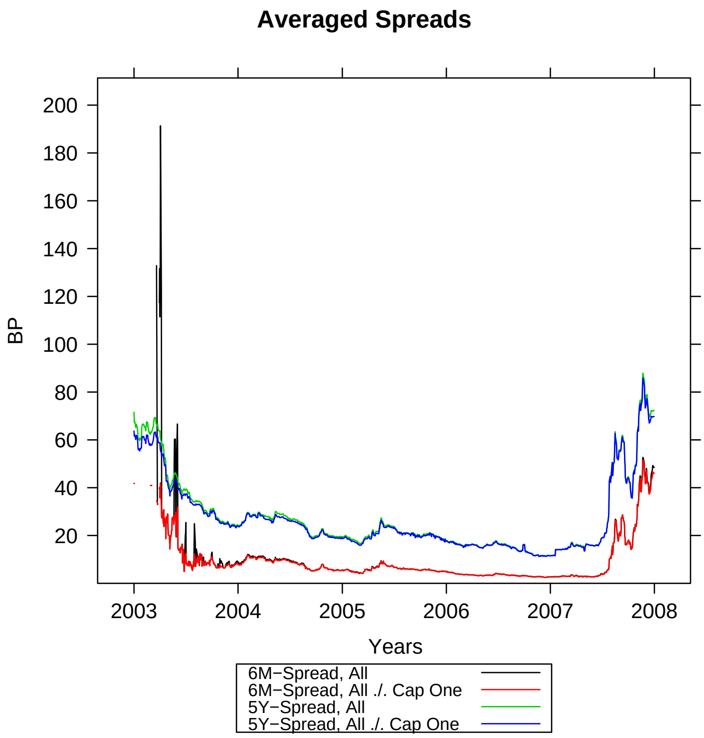

Figure 5: Averaged Spreads with and without Capital One Bank

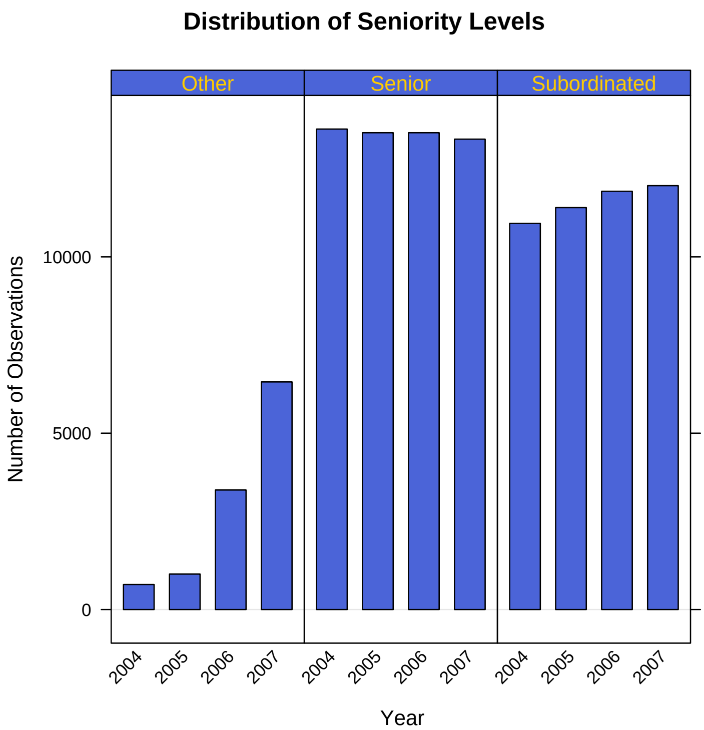

Figure 6: Observations grouped by Seniority

'Subordinated' reaches 100% in 2007 and is slightly below in 2006.
We choose 'Senior' as it has the highest absolute number of observations and the highest relative data coverage in the 6M-segment.

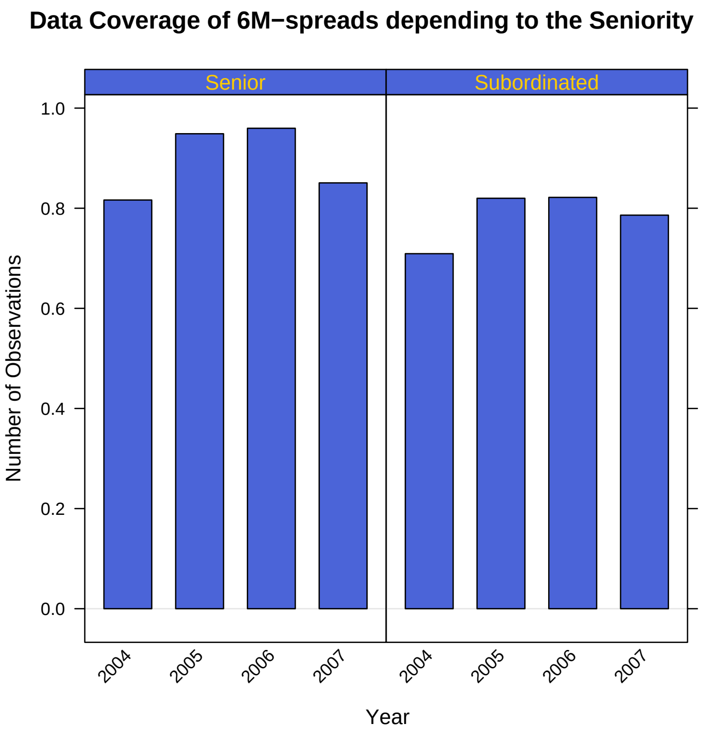

Figure 7: Data Coverage of the 6M-segment per Seniority Level

Our final sample consists of 'senior' spreads of 58 banks, covering the period from 01.01.2004 to 31.12.2007.

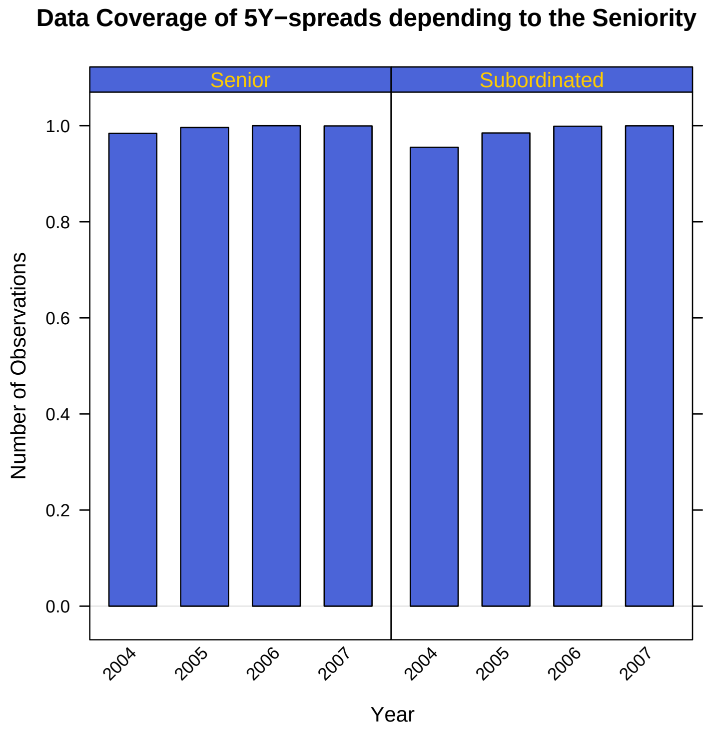

Figure 8: Data Coverage of the 5Y-segment per Seniority Level

3 Stylised Facts

3.1 Time Series of Credit Spreads

We start with an analysis of the averages of 6M- and 5Y-spreads across banks. In the following we call them 'indices'. Indices are defined by (1):

$$\bar{c}_t = \frac{1}{N}\sum_{i=1}^{N} c_t^i, N = 58 \tag{1}$$

The index-time series are plotted in figure 9. Concerning the level, figure 9 documents that the 5Y-index is above the 6M-index. Concerning the evolution, the spread volatility was fairly low from 2004 to mid-2007. From mid-2007 onwards, level and volatility increased sharply during the subprime turmoils. Figure 9 suggests that the spreads of both maturities are mainly driven by a common factor as they move very harmonically. This is confirmed by the correlation that amounts to 97% for the total period. However, we are interested in the question whether the correlation is stable across time.

Plotting the 7-day correlation across time leads to figure 10. Figure 10 confirms that the correlation is not stable and that there are periods of positive and negative correlation. The phenomenon of negative correlations has been reported by [Covitz and Downing, 2007] and [Krishnan et al., 2006][7]. The correlation in our sam-

[7] They obtained a negative correlation of 18% between 7y- and 3y-(Corporate Bond) credit spreads.

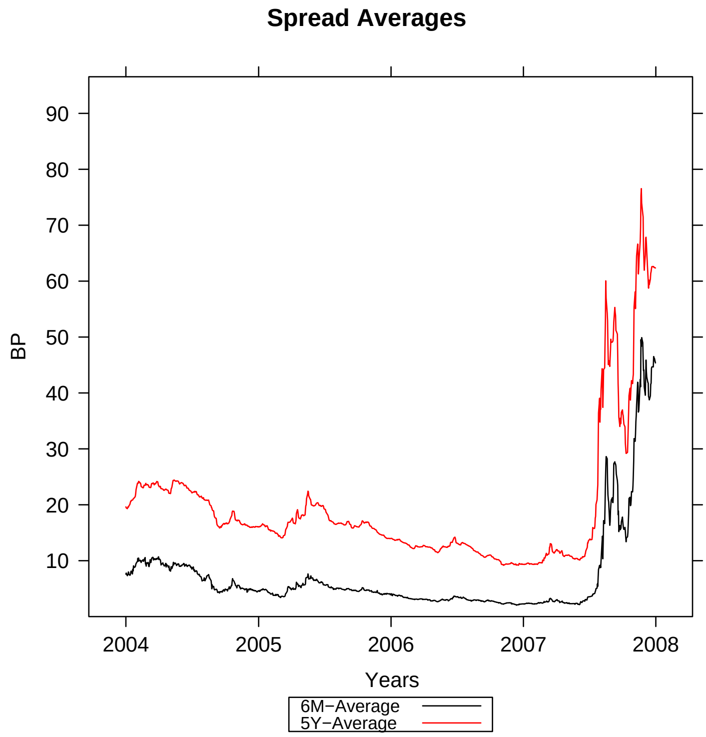

Figure 9: Average Spreads of 6M- and 5Y-maturity

ple varies between -90% up to 99%. [Covitz and Downing, 2007] also report that negative correlation is most pronounced in times of credit market disruptions. Figure 11 plots the correlation against the volatility of the 6M-spread. During the time frame [2004, 2007] we see low and high volatility periods. The low volatility period leads to the point concentration close to the Y-axis. Clearly, in a low volatility period, all correlations are possible. The correlation is between -0.90% and + 99.45%. However, in a high volatility period, only high positive correlation is observable. This suggests that in calm markets, CDS-spreads are rather independent. They might be driven by ideosyncratic shocks. However, in turbulent markets, our result for CDS-spreads is different to that of [Covitz and Downing, 2007]: CDS-spreads are highly correlated if spreads show a high amount of activity. In turbulent markets, they are likely to be driven by one common factor. Negative correlation implies that spreads change into the opposite direction. As we report negative correlation for rather calm markets, we are interested in the question if the spread changes with opposite signs are of significant size or rather 'noise'?

To answer this question, we use a scatter plot of spread deltas. Perfect correlation implies that only the first (+,+) or the third quadrant (-,-) contains observations. Correlation smaller than one results in spread deltas in the second (-,+) and fourth (+,-) quadrant.

Figure 12 documents indeed that all four quadrants contain observations. The (+,+)-quadrant contains the majority of observations (40.3%). Already second (26.7%) is the second quadrant where spread reductions of the 5Y-spread go together with spread

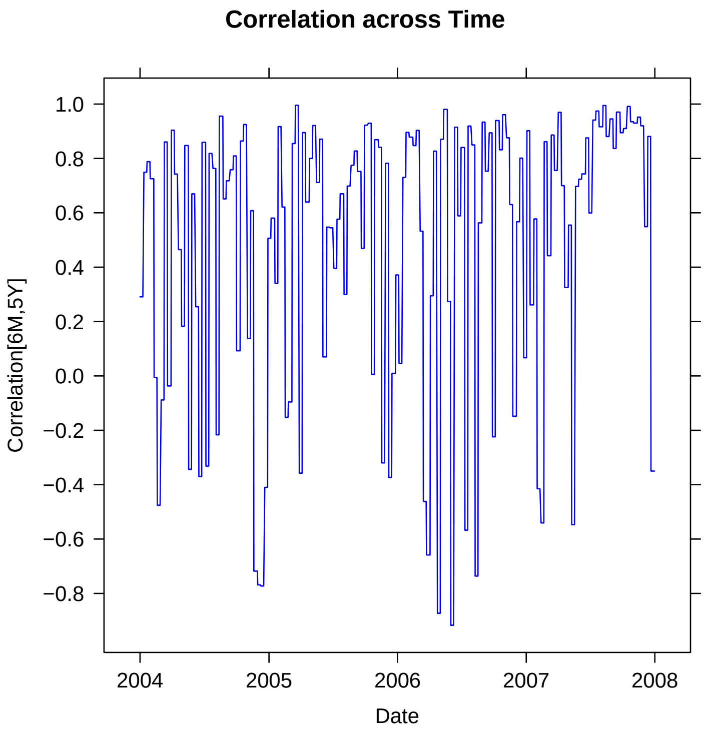

Figure 10: Average Spreads of 6M- and 5Y-maturity

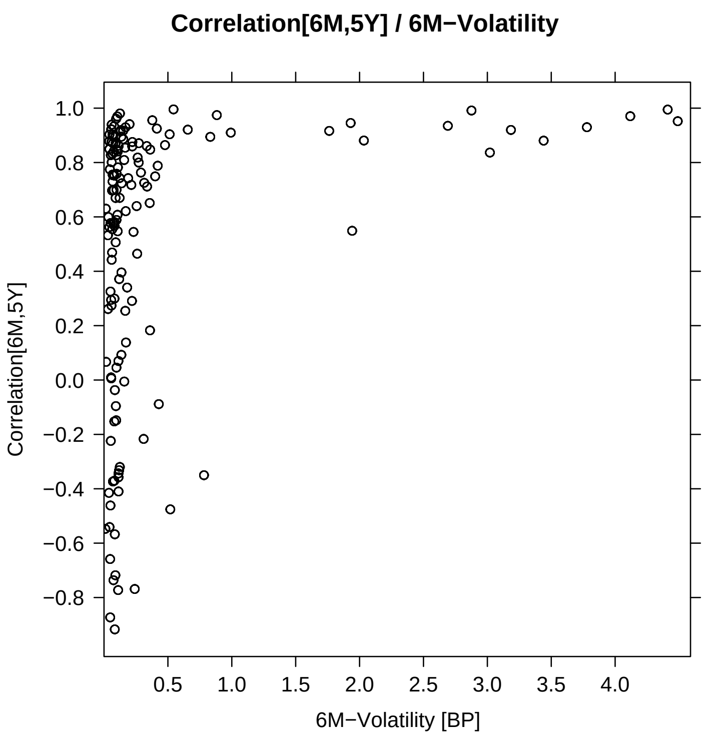

Figure 11: Correlation against Volatility

increases of the 6M-spread. Third comes the (-,-)-quadrant (19.8%). By contrast, in only 13.2% of the observations, the 5Y-spread increases whereas the 6M-spread decreases. We conclude that in 39.9%, spreads move into different directions, whereas it is more pronounced that the 6M-spread increase, but the 5Y-spread does not (26.7%) than the other way round. However, there is a huge bulk of observations close to the

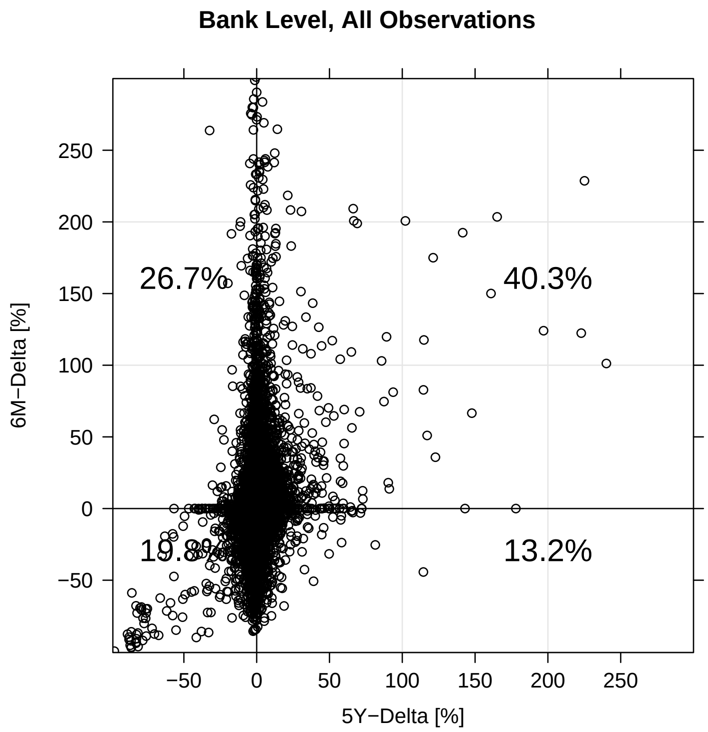

Figure 12: Delta Plot on Bank Level

(0,0)-centre, indicating that both spreads do not move substantially. We believe that these small movements are not due to fundamental changes in the driving factors, but rather due to market liquidity or data error (MarkIt-spreads are averages!). Therefore we eliminate all observations where both deltas are below a relevance boundary of 10%. Our findings are summarized in Figure 13. If we restrict the sample to considerable spread movements, figure 13 shows that only every fifth observation (19.1%) is left. Comparing the relative changes within the quadrants, one observes that first and second quadrant have relatively more small deltas than the third and fourth quadrant, as both quadrants loose observations by the relevance restriction (-7.5% and -5.8%). 6M-spread decreases (3rd and 4th quadrant) are however more likely to be of larger size than the increases (1st and 2nd quadrant). Nevertheless, the large movements are more in the (-,-)-quadrant, i.e. spread falls are relatively large. Are spreads substantially more volatile during subprime (>1.7.2007) than before? Figures 14 and 15 plot the standard deviation of 6M- and 5Y-spreads of each bank before (X-axis) and during the subprime turmoils (Y-axis). If the volatility remains the same, all volatility pairs would be situated on the diagonal. As the majority of observations lie above the diagonal, the volatility during subprime is substantially higher than before.

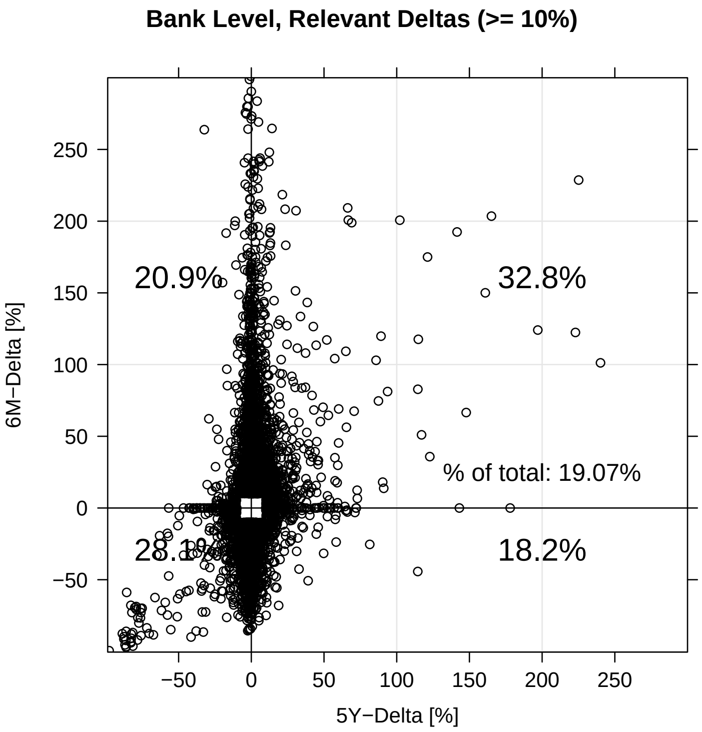

Figure 13: Delta Plot on Bank Level

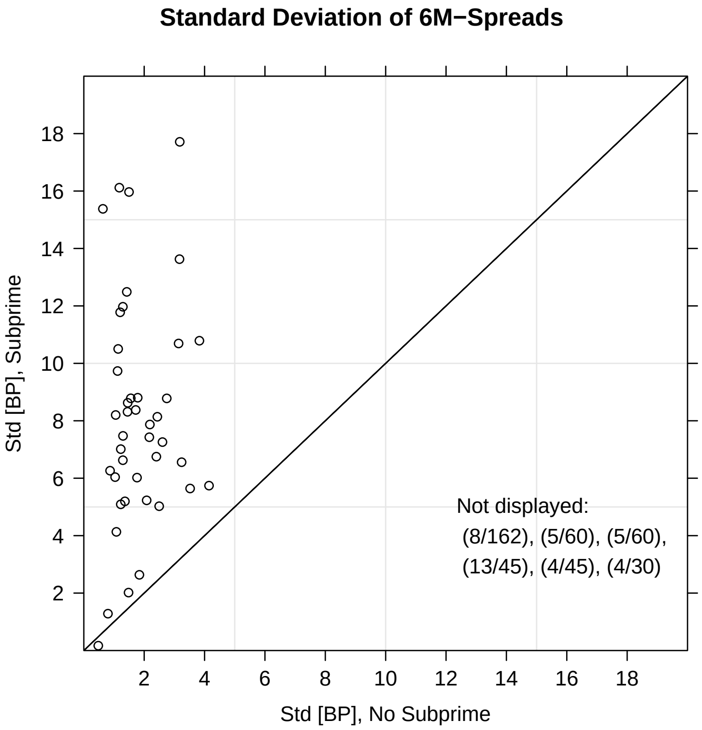

Figure 14: Standard Deviation of 6M-Spreads Before (X) and During (Y) Subprime

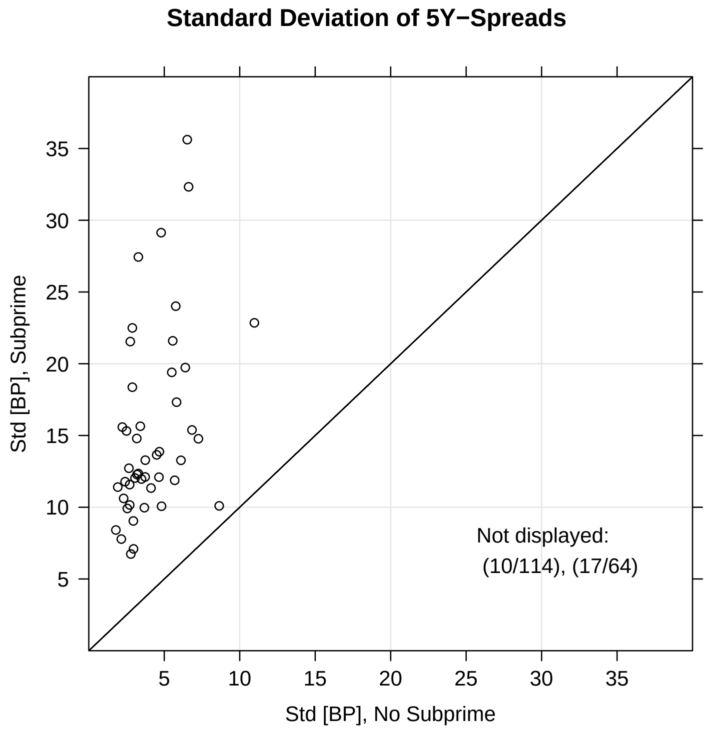

Figure 15: Standard Deviation of 5Y-Spreads Before (X) and During (Y) Subprime

This holds for 6M-and 5Y-spreads. In order to facilitate the reading, we restrict the graphics to 20 (6M) and 40 (5Y). Thus, we exclude 6 observations in the 6M- and 2 observations in the 5 year-plot.
Based on the higher volatility, it is worth to have a look at whether or not subprime spread deltas behave differently to spread deltas before suprime. For that reason, we split up the sample into 'before' and 'during' subprime and redo the delta plots. Figure 16 displays the delta plot of subprime-observations. The quadrant distribution states that there are minor changes compared to the overall delta plot. Within subprime, there are less observations of an increasing 6M-spread that is accompanied with a decrease in 5Y-spreads (2nd quadrant: -5.4%). Does the delta size change compared to the overall delta plot? For this purpose, we eliminate observations where both deltas are smaller than 10%. Thus, we obtain figure 17. Figure 17 displays the relevant deltas ($\geq$ 10%) for each quadrant. For comparison, the figures of relevant deltas on the total sample are given in parantheses. The first observation is that during subprime, the proportion of relevant observations (36.35%) is higher than on the total sample (19.07%). During subprime, the relevant deltas in (+,+) have increased. This is in line with a general increase of spreads during subprime. All other quadrants of the subprime subset exhibit less relevant deltas than the overall sample, whereas the reduction in the (-5Y,+6M)-quadrant and (-,-)-quadrant is substantial. This particularly implies that the negative correlation of the (-5Y,+6M)-quadrant results rather from the period 'before subprime' than 'during subprime'.
To summarize, we can report the following 'Stylised Facts':

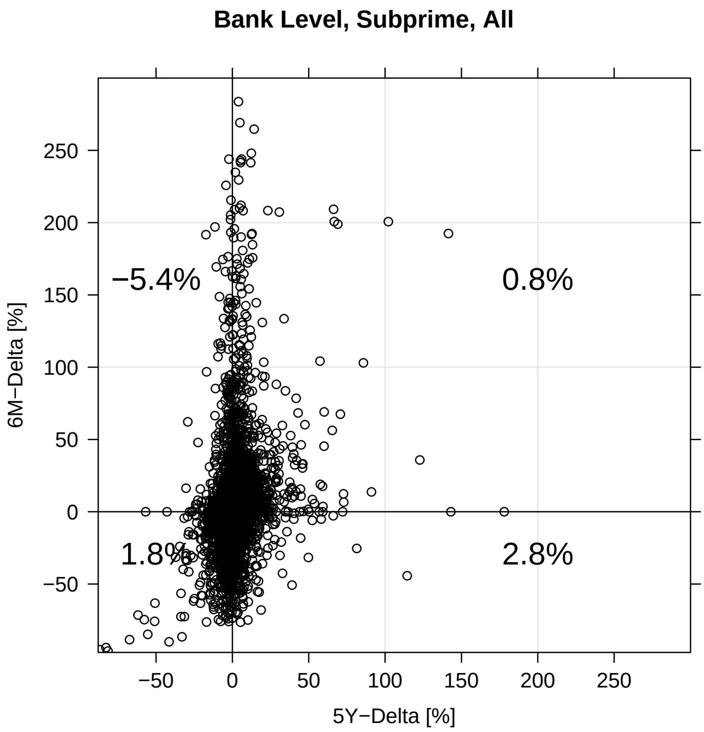

Figure 16: Delta Plot on Bank Level

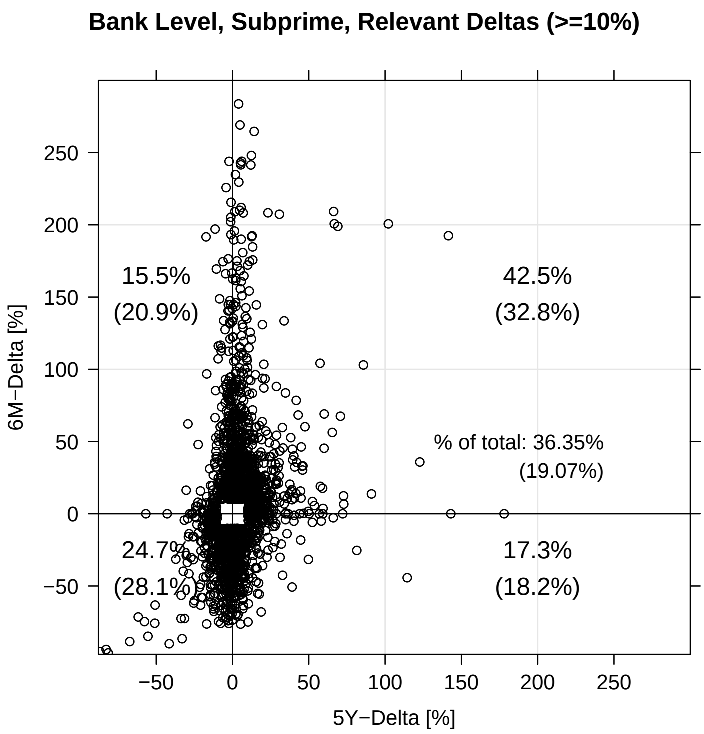

Figure 17: Delta Plot on Bank Level, Subsample: Subprime

On the index-level, we make the following observations:

- 5Y-spreads are higher than 6M-spreads.
- The correlation for the total period is 0.97.
- The 7-day correlation varies between -90% and 99%.
- High volatiltiy goes together with high correlation.

On the bank-level, we report the following findings:

- 39.9% of 5Y- and 6M-spread deltas have opposite signs which is inconsistent with standard credit risk models. Restricting the deltas to 'significant' deltas ($\leq$ 10%) only leaves 19%. However, among these deltas there are 39.1% delta pairs with opposite signs.
- Restricting the sample to the 'subprime observations', there are slightly less pairs with opposite signs (-2,6%). Taking into account the size of spread deltas, we report that the deltas in the subprime window are higher. However, the proportion of pairs with opposite signs is lower than for the total period.

The analysis suggests that during turbulent markets, spreads move more systematically than in calm markets. This result sharply contrasts [Covitz and Downing, 2007] who found negative correlation most pronounced in turbulent markets. However, we do not find perfect correlation either. That is why we study potential factors that determine CDS-spreads in the next section. As there is no perfect correlation between short- and long-term spreads, we hypothesize that short- and long-term spreads might be driven by different factors. According to [Covitz and Downing, 2007], we test for liquidity and insolvency factors.

4 Determinants of CDS-Spreads

4.1 Factor Classification and Approaches

Factors can be grouped economically into systematic/ unsystematic and insolvency/ illiquidity factors. Systematic factors are factors that are the same for every bank. In general, these are market prices. Bank-specific factors vary across banks.
Apart from an economic classification, we technically distinguish high- and low frequency factors. We call factors with daily observations 'high frequency' and factors with any other frequencies (monthly, quarterly and annual data) 'low frequency' factors. According to this classification scheme, figure 18 summarizes our factors. Using

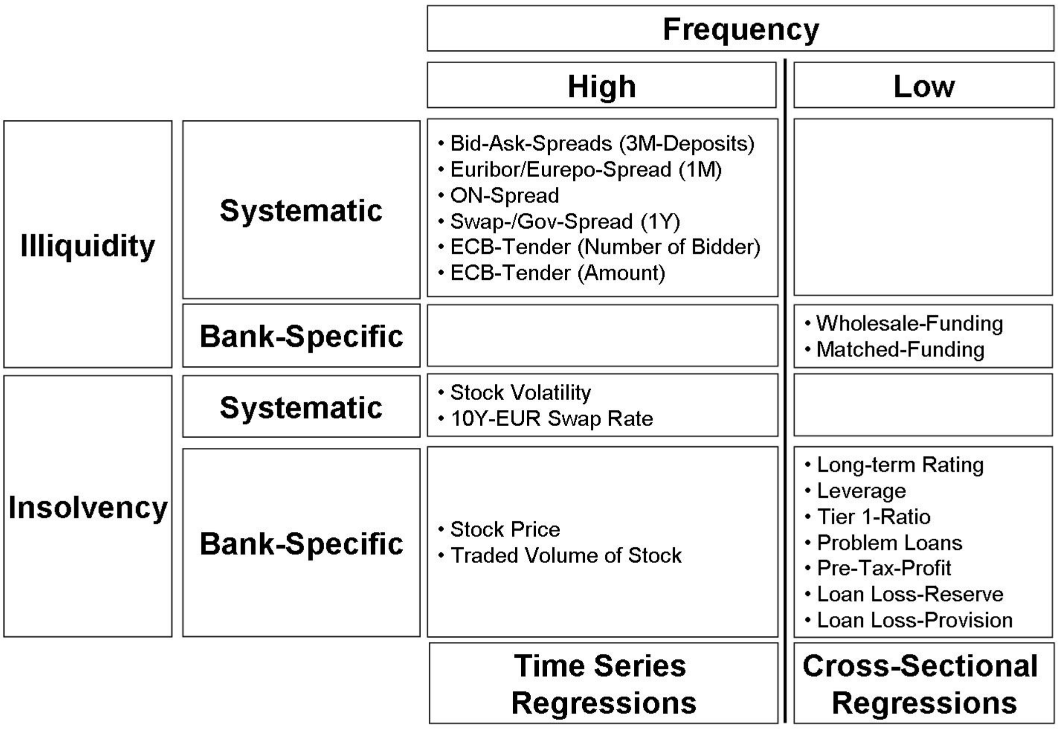

Figure 18: Factor Classification

factors of different frequencies pose the problem, of how to harmonize the frequency: use only selected time points of the high-frequency factors (and ignore many observations) or to extrapolate low-frequency data to unobserved time points? Or combine both approaches using a 'middle' frequency?
Our factor set does not allow for a natural distinction such as: all systematic factors are of a low, all bank-specific factors are of a high frequency. Also the distinction between illiquidity and insolvency factors is not helpful: they are of low and high-frequency.
As the frequency itself is at the origin of those problems, we decide to make a cut between low- and high-frequency factors: high-frequency factors are used in time series regressions whereas low frequency factors are used in cross-sectional regressions. A panel approach would be technically possible, but involves the above mentioned

'compromise' frequency.
Using cross-sectional regressions, we are in line with [Covitz and Downing, 2007]. However, instead of quarterly regressions, we perform annual regressions due to data constraints. By contrast, [Covitz and Downing, 2007] did ot perform time series regressions. The next section is dedicated to the time series approach.

4.2 Time Series Regressions

4.2.1 Factor Description

Figure 19 summarizes factors, sources and expected signs for Time Series Regressions. In the following, we describe the factors and substantiate their impact on CDS-spreads.

		Factor	Source	Expected Sign
Illiquidity	Systematic	• Bid-Ask-Spreads (3M-Deposits)	Reuters	+
		• Euribor/Eurepo-Spread (1M)		+
		• ON-Spread		+
		• Swap-/Gov-Spread (1Y)		+
		• ECB-Tender (Number of Bidder)	ECB	-
		• ECB-Tender (Amount)		-
Insolvency	Systematic	• EUROSTOXX-Volatility	Reuters	+
		• 10Y-EUR Swap Rate		-
	Bank-Specific	• Stock Price	Reuters	-
		• Traded Volume of Stock		+
		Time Series Regressions		

Figure 19: Factors used in Time Series Regressions

Illiquidity Factors As systematic proxies for liquidity we use variables of the European Money and Central Bank Market. Money Market data are obtained from Reuters. Central Bank data are obtained from the European Central Bank. High frequency bank-specific liquidity proxies would be information based on banks' internal liquidity models. We did not have access to such information. Therefore, we cannot test for bank-specific high-frequency illiquidity factors.
In the following, we explain the expected signs of the factors.

- Bid-Ask Spreads of 3M-Deposits
  The bid-ask spread is a measure for market liquidity. Its size is related to the mismatch of supply and demand. As maturity we choose 3M, as 3M is considered to be 'middle term' in the Money Market. In fact, ECB-tenders with 3M-term are already considered 'long-term'. We hypothesize that a higher spread reflects that banks find it more difficult to borrow 3M. Accordingly, a higher bid-ask

spread would increase the illiquidity risk and lead to higher short-term spreads (expected sign: +).

- Euribor-Eurepo-Spread (1M)
  Euribor is a Money Market index for unsecured, Eurepo for secured funding. Euribor/Eurepo-Spread is also used by the ECB to monitor the conditions on the Money Market and to decide about interventions.[8] We hypothesize that less confidence in the Money Market leads to significantly higher premia for unsecured, but only moderately higher premia for secured funding. Therefore, tightened Money Market conditions should lead to a higher Euribor-/Eurepo-spread and higher short-term CDS-spreads (expected sign: +).

- ON-spread
  The ON-spread is the bid-ask spread for the shortest maturity available. The same arguments as for the 3M-spread apply. However, 'overnight' is the short-term maturity of the Money Market segment. We expect a positive sign.

- Swap-/Government Spread
  The Swap-/Government spread measures the difference between funded and unfunded interest rates. We hypothesize that swaps are less sensitive to money market conditions, as no liquidity is needed for their origination. By contrast, the yield for Government securities is derived from bonds that involve liquidity at the origination. We calculate the spread as 1Y-swap rate minus 1Y-government yield. We hypothesize that a worsening of liquidity conditions lead to higher bond prices, implying lower yields. Raising this argument, swap rates reflect pure interest rate, government yields interest and liquidity conditions. Therefore, a worsening of liquidity conditions leads to a higher Swap-/Government spread. The expected sign is positive.

- ECB-Tender (Amount)
  Our starting point is the official tender file of the ECB that contains all tenders, i.e. of all types (Liquidity Absorbing/ Providing, Regular/ Quick-Tenders) and all maturities (ON-, 1W, 3M).[9] In order to eliminate any expected elements, we exclude regular tenders but only keep quick tenders that are unexpected by banks. Absorbing tenders are flagged '-', providing tenders are flagged '+'. We hypothesize that large providing quick tenders improve market conditions and should lead to lower CDS-spreads. Hence, we expect a negative sign.

- ECB-Tender (Number of Bidders)
  We use the number of bidders as a proxy for the need of liquidity. For fixed volume tenders, only the tender rate can proxy the need for liquidity. We hypothesize that the number of bidders is an indication for the need to access central bank money. Analogously to the amount, we flag the number of bidders of providing tenders by '+', of absorbing tenders by '-'. We expect a negative sign.

[8] See [European Central Bank, 2007a, p. 30]. Unfortunately, we could not access other variables monitored by ECB as EONIA-volume and ON-rates ([European Central Bank, 2007b, p. 25ff.]). EONIA-Swap rates were accessible but only had a history of 18 months.

[9] For tender information and definitions, see [European Central Bank, 2006, p.8]

Insolvency Factors Our insolvency factors are inspired by the traditional 'Merton'-model.[10]:

- Firm Value
  We proxy the firm value by the stock price. It is a bank-specific insolvency factor. Higher stock prices go along with lower CDS-spreads, implying an expected negative sign.

- Volatility of Firm Value
  We proxy the volatility of firm value by the implied stock price volatility. As we do not have access to time series of implied volatilities for individual stocks, we use EUROSTOXX-implied volatilities instead. Our factor is a systematic one. The expected sign is positive.

- Interest Rate-level
  The Merton model predicts that higher interest rates lead to lower credit spreads. We use the 10y-EUR swap rate as proxy for the interest rate level. The expected sign is negative.

The Merton model also evokes the 'leverage'. Our sample contains the leverage, but as a low frequency factor. Hence, it is included in cross-sectional regressions.
We also apply the traded stock volume as proxy for investor's nervosity.
The factor 'Stock Price' is a bottleneck in our analysis as some banks do not have publicly traded stocks. For other banks, we do not have complete data between 1.1.2004-31.12.2007. Table B in the appendix documents the stock price availability.
We exclude the following 7 banks as they do not have publicly traded stocks:

- WestLB
- Rabobank
- BayernLB
- Helaba
- HSBC Holdings
- Dresdner Bank
- Banca Nazionale del Lavoro SpA

Due to the exclusion, we can only perform 41 time series-regressions.

4.3 Stationarity

In order to avoid spurious regressions, we have to check whether spread and factors series are stationary. We first discuss the stationarity of CDS-spreads.

[10] See [Merton, 1974].

4.3.1 CDS-Spreads

Figure 20 shows the distribution of the Augmented-Dickey-Fuller statistic for several setups (original series, Diff(), Log(), DiffLog(), Original/NoSubprime, Original/Subprime). Diff() stands for the delta-, log() for the log- and difflog() for the log-return transformation of the original series. NoSubprime and Subprime split up the sample into spreads before (NoSubprime) and after 01.07.2007 (Subprime).
The critical value for the ADF-statistic is -3.96[11]. It is given as red cut-off-line in figure 20. Series with an absolute ADF-value of more than 3.96 can be considered to

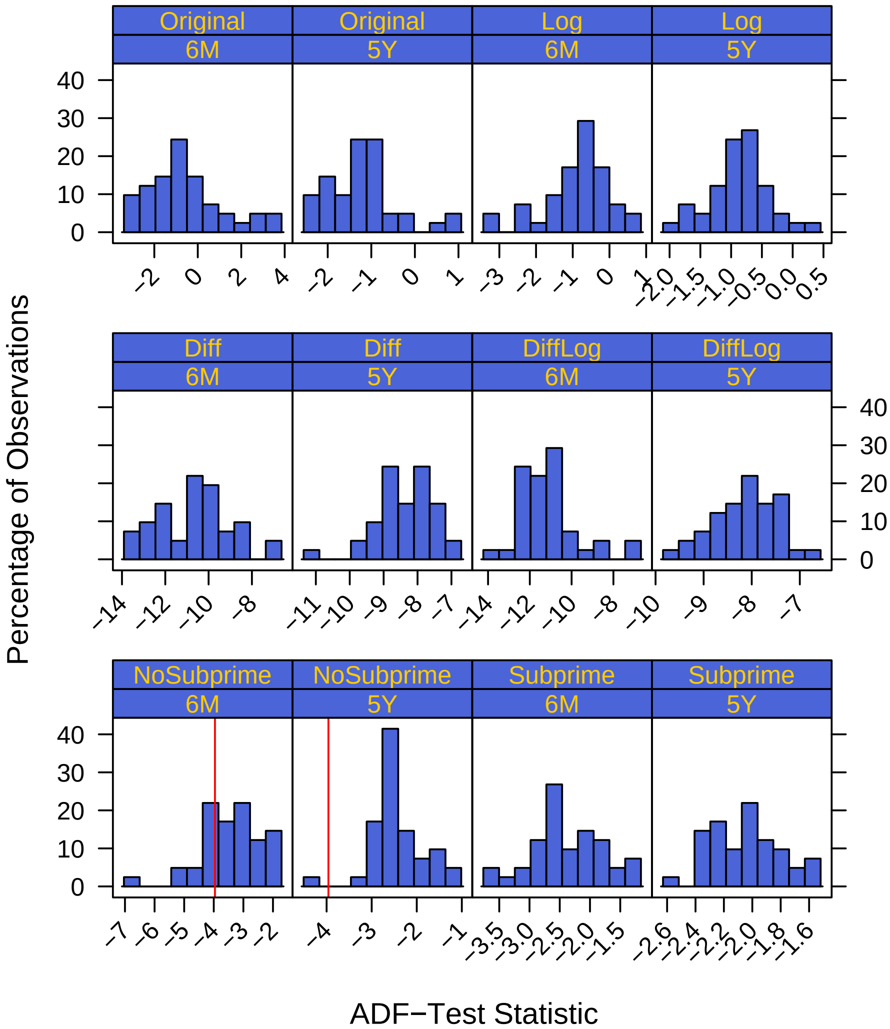

Figure 20: Results of Augmented-Dickey-Fuller Test for several setups

be stationary at the 1%-error level.
Figure 20 clearly shows that the original spread series are non-stationary. Also, taking the logs does not de-trend them. However, taking differences or log-returns leads to

[11]See [Gujarati, 2003, p.975].

stationary series.[12] The split up into 'No subprime' and 'Subprime' does not lead to stationary series either. Especially the distribution of the subprime-observations are far from being stationary.[13]
We conclude that we have to use diff() or log-returns to operate with stationary spread series.

4.3.2 Factors

The same stationarity analyses as for spreads have to be performed for the factors as well. We start with the stationarity of systematic factors.

Systematic Factors The stationarity results for systematic factors are summarized in figure 21. Figure 21 is grouped by factors. For each factor, the stationarity of six setups (orginal, diff-, logreturn- and NoSubprime/Subprime-series) is analysed. The cut-off-value is plotted as line. However, as the ECB-series (Amount, Bidder) contain 'zeros', we cannot use log()- nor difflog()-transformation. Their adf-result is set to zero. For the IMF-series (GDP, UMP, CPI) and BIS-Housing Prices, the sample split up into NoSubprime/ Subprime failed as there are no value updates during the 'Subprime'-window and the adf-test does not work on a constant. These respective adf-results are also set to zero.
Figure 21 suggests that only the orginal series of ON-Spread and ECB-Tender (Bidders) are likely to be stationary (at a 1%-level). Somewhat surprising is the non-stationarity of 10Y-swap rates, as interest rates are largely assumed to be mean-reverting, i.e. to have a constant long-term mean. One possible explanation for that observation might be our rather short-term time series of 4 years.
Figure 21 also proposes ways to make series stationary: diff()- and difflog()-transformations always lead to stationary series. The split up into NoSubprime/ Subprime-window results in a stationary NoSubprime-series, but often the subprime-part is still non-stationary.
We conclude that we can use the original series of 'ON-spread' and 'ECB-Tender (Bidders)'. All other series have to be made stationary by taking diff().

Bank-specific Factors The stationarity of bank-specific factors has to be checked for every bank. We use 'Stock Price' and 'Traded Volume' as bank-specific factors in our time series regressions. Figure 22[14] confirms that stock price series are not stationary: the red cut-off line for the critical value (-3.96) is not even plotted for the 'Original' series as the ADF-values for all banks are lower. Taking 'logs ' or splitting up the models into 'NoSubprime'/'Subprime' does not make the series stationary either. However, by taking diff() or diff(log()) we obtain stationary series.
In contrast to stock prices, the 'Traded Stock Volume' is already stationary as figure 23 suggests. We conclude that the 'Stock Price'-series have to be 'delta'-ed. 'Traded Stock Volume' can be used in its original form.

[12] Taking differences does not lead to a stationary serie for one bank.
[13] The sample split up reduces the number of observations. As the critical value depends on this quantity, a higher critical value applies to the sub-sample. This underlines that the sub-sample 'Subprime' is not stationary.
[14] Due to lacking data, no ADF-test could be performed for 'Barclays Bk plc'.

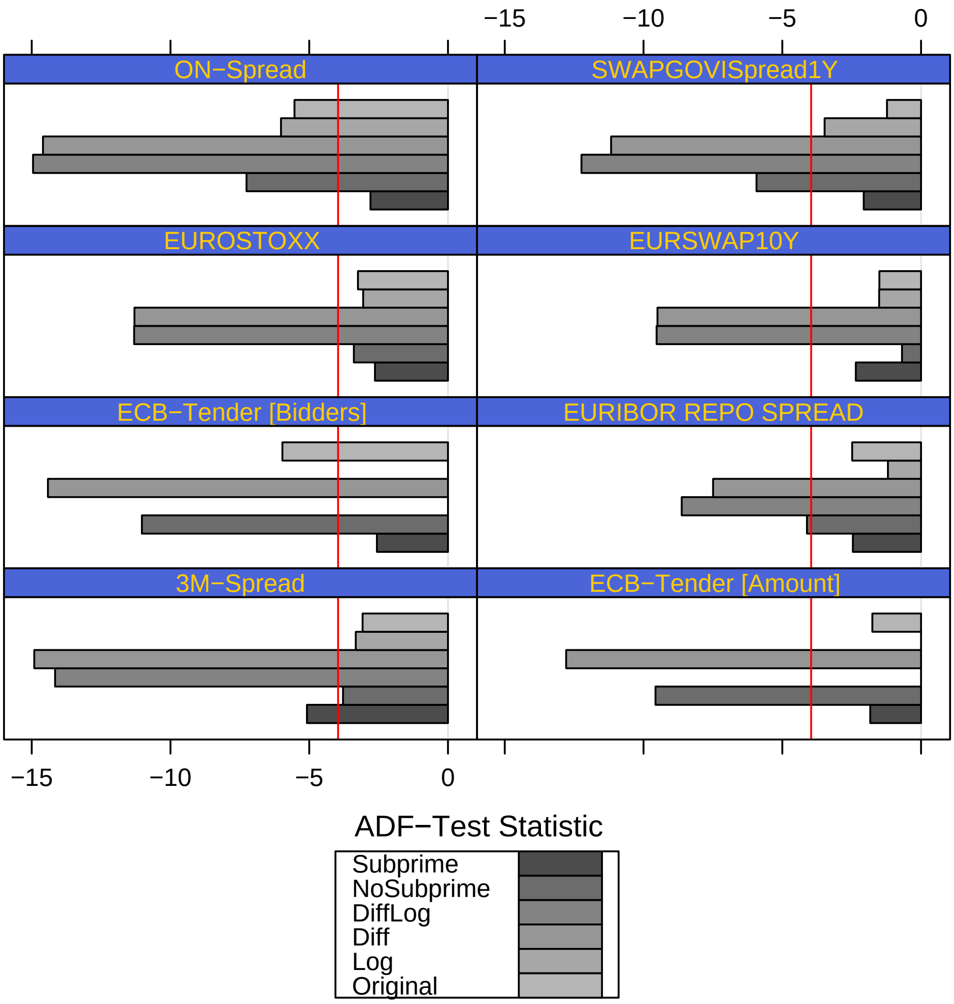

Figure 21: Results of Augmented-Dickey-Fuller Test for Systematic Factors

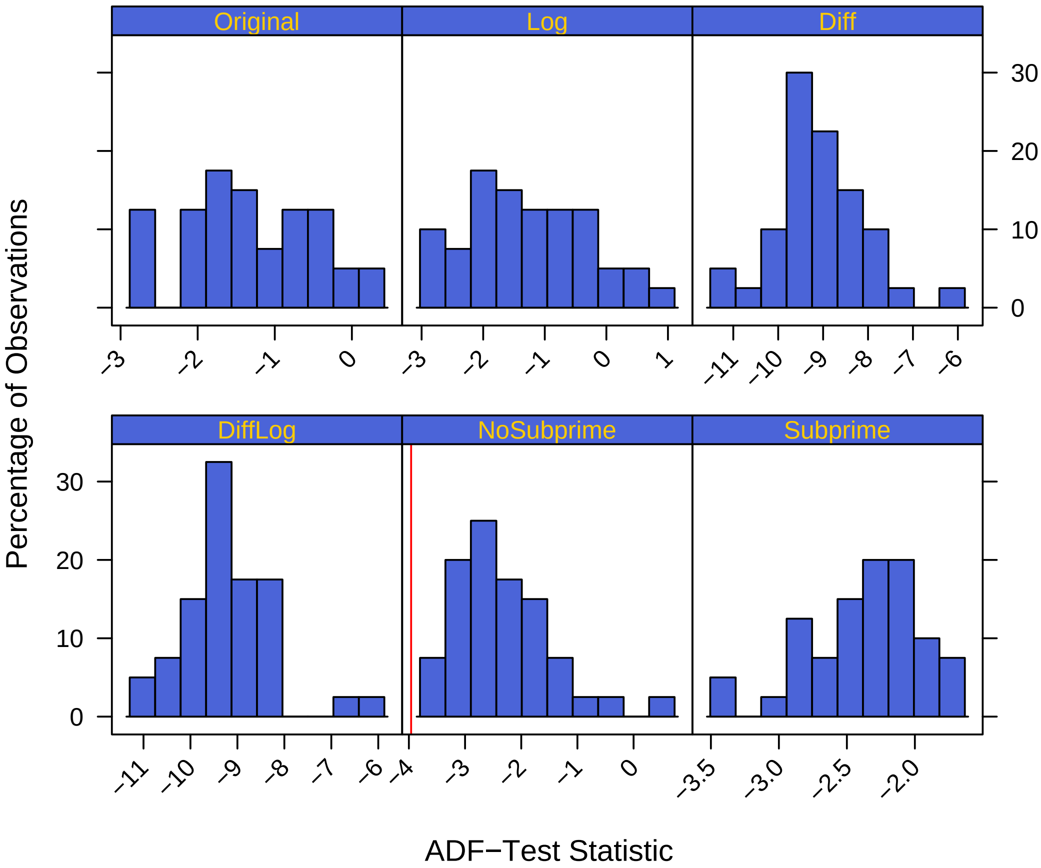

Figure 22: Results of Augmented-Dickey-Fuller Test for Factor 'Stock Price (N=40')

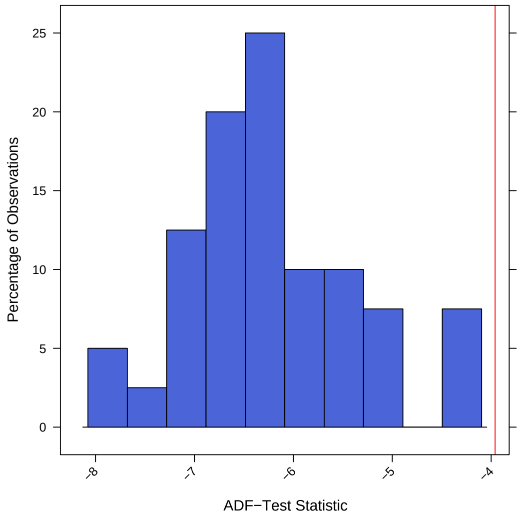

Figure 23: Results of Augmented-Dickey-Fuller Test for Factor 'Traded Stock Volume'

4.3.3 Results

The time series regressions estimate the following econometric model for 6M and 5Y respectively:

$$\begin{aligned}\Delta c_t^i &= \beta_0 + \beta_1 \cdot \Delta(\text{Euribor-/Eurepo-Spread})_t^i \\ &+ \beta_1 \cdot \text{Stock-Volume}_t^i + \beta_2 \cdot \text{ECB-Tender (Bidders)}_t^i \\ &+ \beta_3 \cdot \text{ON-Spread}^i + \beta_4 \cdot \Delta\text{3M-Spread}_t^i \\ &+ \beta_5 \cdot \text{ECB-Tender (Amount)}_t^i + \beta_6 \cdot 1_{t \in T_{\text{Subprime}}} \\ &+ \beta_7 \cdot \Delta(\text{Stock Price})_t^i + \beta_8 \cdot \Delta(\text{1Y-Swap-/Gov-Spread})_t^i \\ &+ \beta_9 \cdot \Delta(\text{EUROSTOXX})_t^i + \beta_8 \cdot \Delta(\text{EUR-Swap 10Y})_t^i \\ &+ \epsilon_t^i, \forall \text{i=1,...,41, t = 1.1.2004, ..., 31.12.2007}\end{aligned}$$

For the 41 regressions, we obtain a distribution of R^2 that is displayed in figure 24. The R^2s of the 5Y-segment are higher than of the 6M-segment: in the 6M-segment, there are only a few regressions beyond 10% R^2. By contrast, the 5Y-segment sees many regressions beyond 10%. The maximal R^2 in the 5Y-segment is 61%. For the 6M-segment, the best regression hardly reaches 30%. However, we can document that the R^2s are fairly small, indicating that our factor set is unlikely to contain all factors. Drilling down on the factor level, we obtain the t-value distribution as shown in figure 25. In general we can state that we do not observe significant factors in the 6M-segment: the t-values oscillate around zero indicating that 6M-spreads are almost insensitive to our factors. This statement holds for both insolvency and illiquidity factors. By contrast, we find the four Merton-factors significant and with a consistent sign for 5Y-spreads:

- EUROSTOXX-Volatility
  The positive relation between the volatility and the spread is significant for

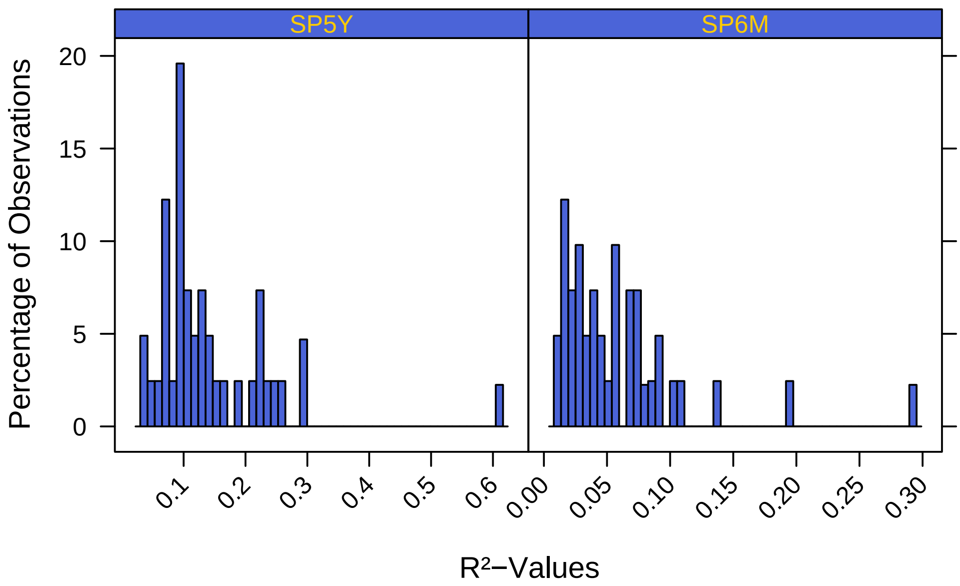

Figure 24: R^2-Values

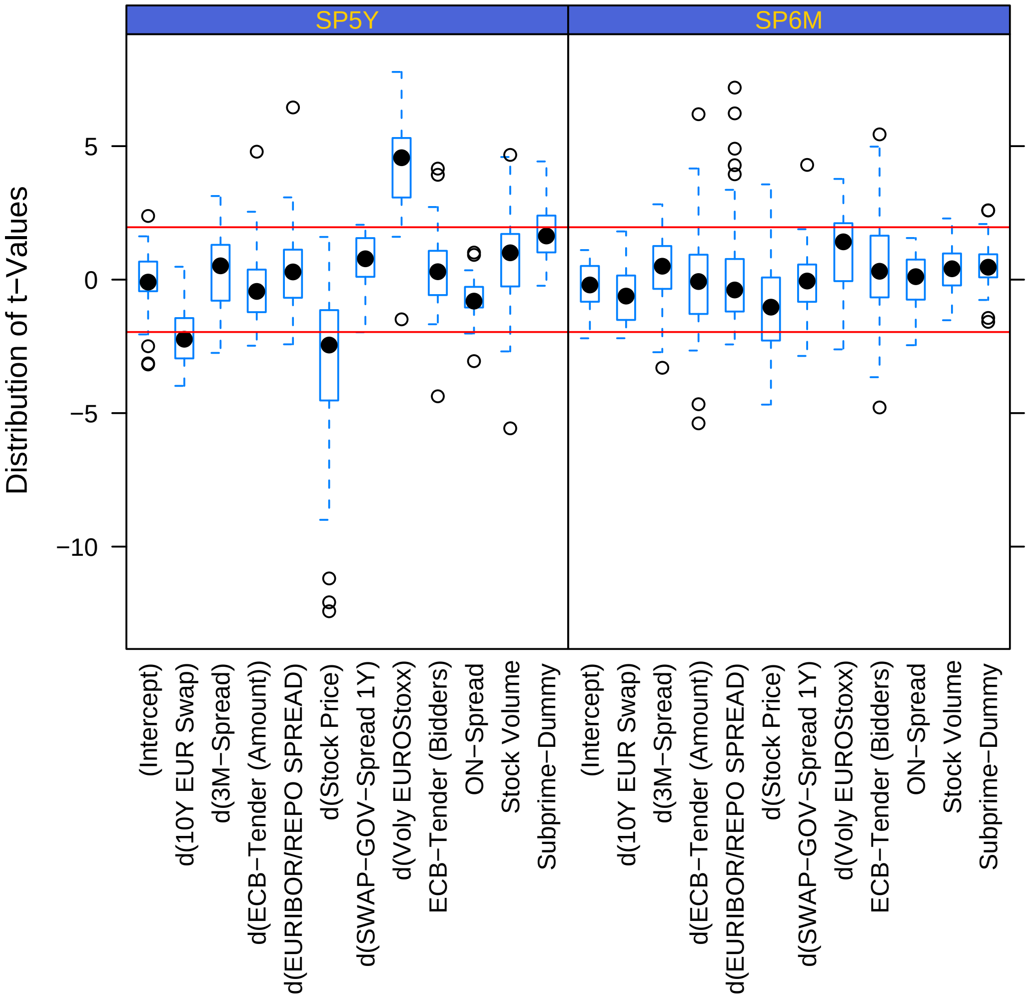

Figure 25: t-Values of Time Series Regressions

almost all regressions. Even the lowest t-values are still significant.

- Stock Price
  The majority of regressions show the negative relation between stock price and 5Y-spread. However, some regressions also have positive (insignificant) values.

- 10Y-Swap Rate
  We corroborate the negative relation. Analogously to stock prices, the majority of regressions have significant negative t-values. However, some regressions have small (insignificant) positive t-values.

- Subprime-Dummy
  Almost 50% of the regressions have a significant positive subprime dummy. This indicates that the subprime window has higher spreads that have not been explained by other factors.

The following statements summarize the findings of our time series regressions:

1. For the 5Y-segment, we confirm signs and significance of Merton factors (Stock Volatiltiy, Stock Price, Interest Rate). Furthermore, we confirm that the 5Y-segment is not sensitive to liquidity factors.

2. For the 6M-segment, none of our factors is significant. The fact that the Merton-factors are not significant either is an indication, that 6M-spreads are driven by other factors. Though we cannot say by which factors. None of our liquidity factors showed a significant response.

The following section discusses the robustness of our results by testing the OLS-assumptions.

4.3.4 Testing of OLS-Assumptions

Heteroscedasticity To test for heteroscedasticity, we use the Goldfeld-Quandt and the Breusch-Pagan test. For a confidence level of 1%, the critical values are 1,36 and 23,31[15], respectively. Figure 26 and 27 summarize 41 test statistics. The critical values are plotted as line. Both tests suggest that homoscedasticity can be rejected on a 1% error level: 90% of the Breusch-Pagan test statistics are beyond the critical value (see figure 27). The Goldfeld-Quandt test does not have any observations below the critical value. A consequence of heteroscedasticity is that our t-values and R^2s are likely to be biased.

Autocorrelation of Residuals We applied the Breusch-Godfrey test for analysing whether the residuals are correlated or not. Figure 28 summarizes the results of the test. The critical value for the 1% level is 6.65 and is displayed as a red line. We conclude that for 70% of the regressions the Breusch-Godfrey-value is beyond the critical value. Hence, for the large majority, the assumption of uncorrelated residuals has to be rejected. As a consequence, the reported t-values might be biased.

[15] 11 factors, 99%-confidence level

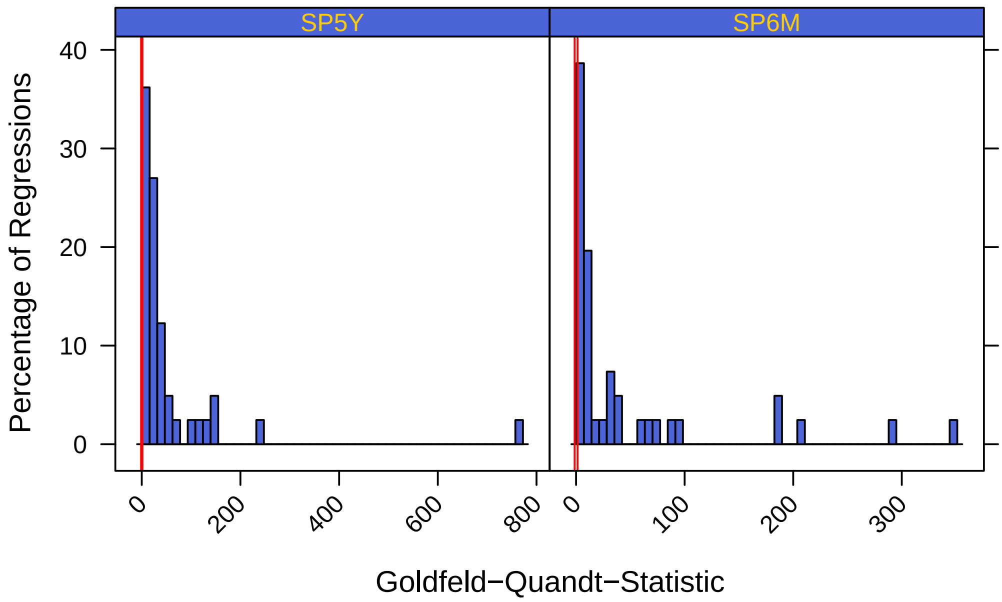

Figure 26: GoldfeldQuandt, N = 41

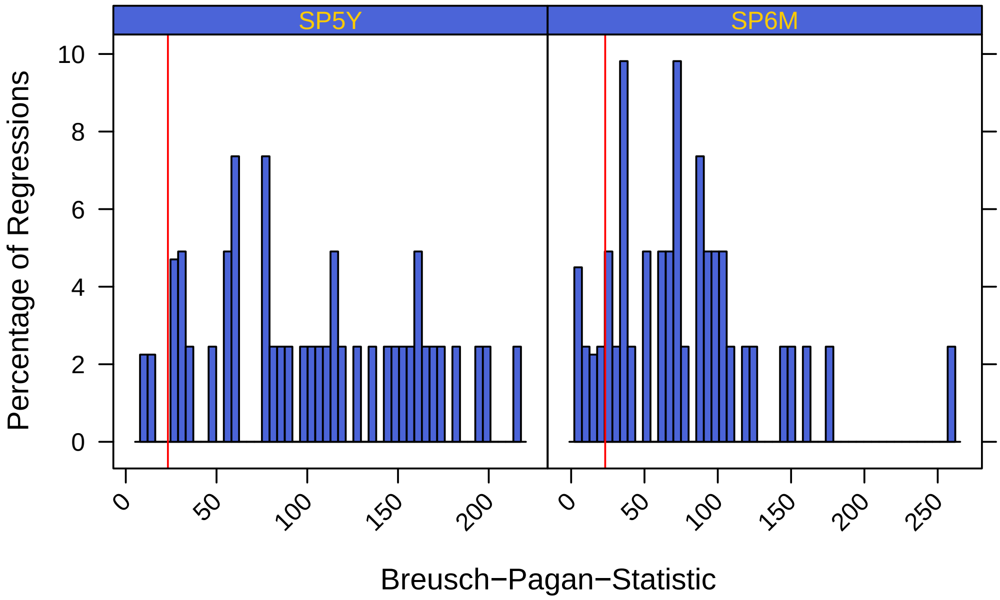

Figure 27: BreuschPagan, , N = 41

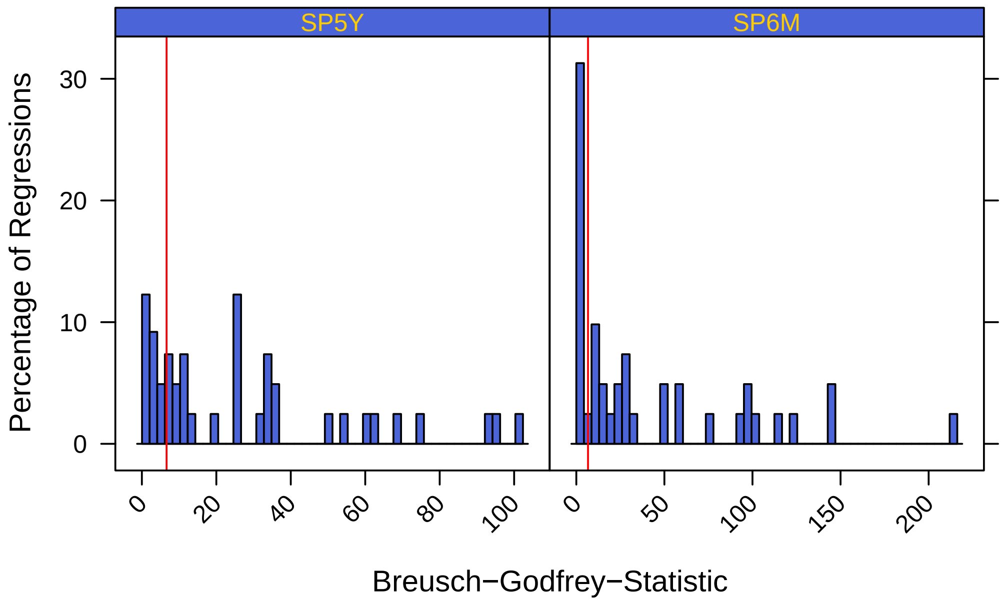

Figure 28: BreuschGodfrey, N = 41

4.4 Cross-Sectional Regressions

4.4.1 Factor Description

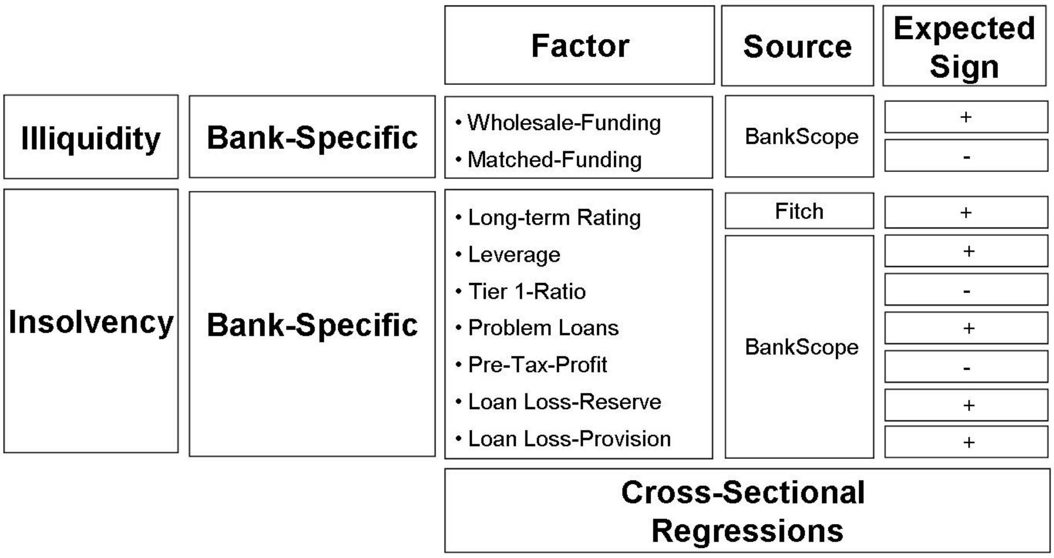

Figure 29: Factors used in Cross-Sectional Regressions

The factor set for cross-sectional regressions consists of balance sheet factors and one rating factor. Due to their balance sheet and rating character, they are all bank-specific. Systematic, low frequency factors are not at our disposal. We obtain balance sheet information for 2004 to 2007 from BankScope. Long-term Ratings are obtained from Fitch. Due to different accounting schemes, we do not have observations for all banks and all years. Table B in the appendix shows the distribution of observations across factors and years. It also shows that the data coverage increases every year. However, the coverage in 2004 is not sufficient to perform OLS-regressions. That is why we drop this year. In the following, we establish and explain our factors starting with the illiquidity factors.

Illiquidity Factors

- % of matched funding (MF)

$$MF = \frac{\text{Liquid Assets}}{\text{Short-term Funding}}$$

  The % of matched funding measures the liquidity mismatch between assets and liabilities. Bank's liquidity risk primarily stems from a liquidity mismatch between assets and liabilities. A bank that only holds illiquid assets or only liquid liabilities does not necessarily bear a liquidity risk. Only if the illiquid assets are funded with liquid liabilities (and vice versa). Therefore, our factor accounts for both sides taking into account assets and liabilities. The higher the liquid asset proportion, the lower the liquidity risk and spread implying a

negative sign. 'Liquid Assets' and 'Short-term funding' are already aggregated positions.
We define 'Liquid Assets' as:

$$\begin{aligned} LF = &\text{ Government Securities} \\ &+ \text{Trading Securities} + \text{Cash and Due from Banks} \\ &+ \text{Due from Other Banks} \end{aligned}$$

We define 'Short-term Funding' as:

$$\begin{aligned} SF = &\text{ Customer Deposits} + \text{Banks Deposits} \\ &+ \text{Total Money Market Funding} \end{aligned}$$

- % of Wholesale Funding (WF)

$$WF = \frac{\text{Total Money Market Funding}}{\text{Total Liabilities}}$$

  Our second liquidity factor is an exclusive liability factor. It measures the percentage of wholesale funding on total funding and captures the stability of the funding base. We argue that wholesale funding is more volatile than retail funding. We use money market funding as a proxy for wholesale funding. We expect that a high money market dependence leads to higher short-term CDS-spreads (positive sign). Both positions 'Total Money Market Funding' and 'Total Liabilities' are pre-defined by BankScope.

With these factors, we are close to [Covitz and Downing, 2007] who test the following factors in cross-sectional regressions:

1. (log) current assets - (log) current liabilites
2. (current assets - current liabilities)/asset volatility
3. (log) current assets - (log) total assets

[Kashyap et al., 2002] analyse the relation between liquidity options (demand deposits and credit lines) and liquidity reserve. They approximate the liquidity reserve by the sum of cash, securities and FED-funds sold, normalised by total assets.

Insolvency Factors

- Loan Loss Reserves [%]
  Loan loss reserves measure the reserves for expected and unexpected credit losses. They are accumulated across years. In order to de-level the series, we standardize by 'Total Equity'. Higher reserves indicate a low credit quality of banks' assets and therefore higher spreads. Hence we expect a positive sign.

- Loan Loss Provision [%]
  Loan loss provisions are the new loss reserves that only date from the reporting year. We also standardize by 'Total Equity'. We expect a positive sign.

- Tier 1-Capital Ratio
  Tier1-Capital Ratio measures the ability of the bank to absorb (any) losses. The higher the ratio, the higher the risk buffer and the lower the CDS-spreads. Hence we expect a negative sign.

- % of Problem Loans
  The volume of problem loans to total loans measures the credit quality of banks' loan portfolios. However, it is not homogenous: it comprises problem loans (that could default)/overdue loans (that have entered the default status) and restructured loans (that are beyond default). We expect a positive sign.

- Pre-Tax-Profit [%]
  The Pre-Tax-Profit measures the profitability of the bank and thus also its capacity to absorb losses. We standardize the profit by 'Total Equity'. We expect a negative sign.

- Leverage
  We define leverage as:

$$\text{Leverage} = \frac{\text{Total Assets}}{\text{Total Equity}}$$

  The position 'Total Assets' is an accounting position and not risk-weighted. We use this factor to be in line with former studies. The higher the leverage, the higher the default risk (c.p.). Hence we expect a positive sign.

- Long-term Rating
  We linearly map ratings to values ('Rating Value'). Thus we neglect the fact that default probabilities are not linearly increasing with the rating. We expect a positive sign as a lower rating quality refers to a higher rating value, implying a higher CDS-spread.

[Covitz and Downing, 2007] use the following insolvency factors:

1. (log) KMV-EDF

We could not access KMV-EDF. For robustness tests they also use:

1. (log) total assets/ total liabilities
2. (log) Interest rate coverage
3. long-term rating of each firm.

From these factors, we use the long-term rating.
The study of [Krishnan et al., 2006] raises the question if the slope of the credit spread of corporate bonds predicts future bank (default) risk. From a sample of 50 firms across 5 years, they proxy default risk with the following factors:

1. Return on Assets
2. Loans to Total Assets

3. Non-performing Assets

4. Net charge-offs

5. Leverage

From this factor set, we use % of Problem Loans (Problem loans/ Total Loans) and Leverage.

4.4.2 Results

The stationarity issue from time series regression does not apply in the cross-sectional setup. Therefore, all factors are regressed in their original form.
Cross-sectional regressions are performed across all banks for selected dates. The selected time-points are preferably around the dates, that the low frequency data are updated. We therefore use the first observation in each January (2005, 2006, 2007) as key dates. As our explained variables (6M- and 5Y-CDS spreads) are of a high frequency, spreads on a particular key date might be exposed to a daily noise. In order to smooth such noise away, we average spreads from 1.12.(t) till 31.1.(t+1) and regress on these averages.
The cross-sectional regressions of 2005 (beginning of January 2005) and 2006 (beginning of January 2006) across 41 entities lead to the t-values given in figure 30. We make the following observations:

1. The t-Values of 2006 are larger than those of 2005.
   Particularly, we do not have any significant (99%-level) relation in 2005. By contrast, in 2006 we have the following significant relations:

   $$\begin{aligned} \text{6M-/5Y-Spread} &\sim \text{Long-Term Rating} \\ \text{6M-/5Y-Spread} &\sim \text{Loan Loss Reserves [\%]} \\ \text{6M-Spread} &\sim \text{Problem Loans} \\ \text{5Y-Spread} &\sim \text{Loans Loss Provisions} \end{aligned}$$

   These factors are all insolvency factors. These factors influence 6M-spreads as well.

2. Small t-values have a tendency to have different signs in 2005 and 2006.
   This is true for 'Leverage', 'Tier1-Ratio', 'Pre-Tax-Profit' and 'Matched-Funding'. An exception is 'Wholesale Funding' where small t-values have consistent signs in 2005 and 2006.

3. Large t-values have consistent signs
   Large t-values usually have the same sign in 2005 and 2006 and for 6M- and 5Y-maturities.

4. Liquidity Factors do not have a significant impact on either 6M- or 5Y-spreads.

Similar to time series regressions, we do not find empirical support for the assumption that 5Y-spreads are particularly sensitive to insolvency and 6M-spreads to illiquidity

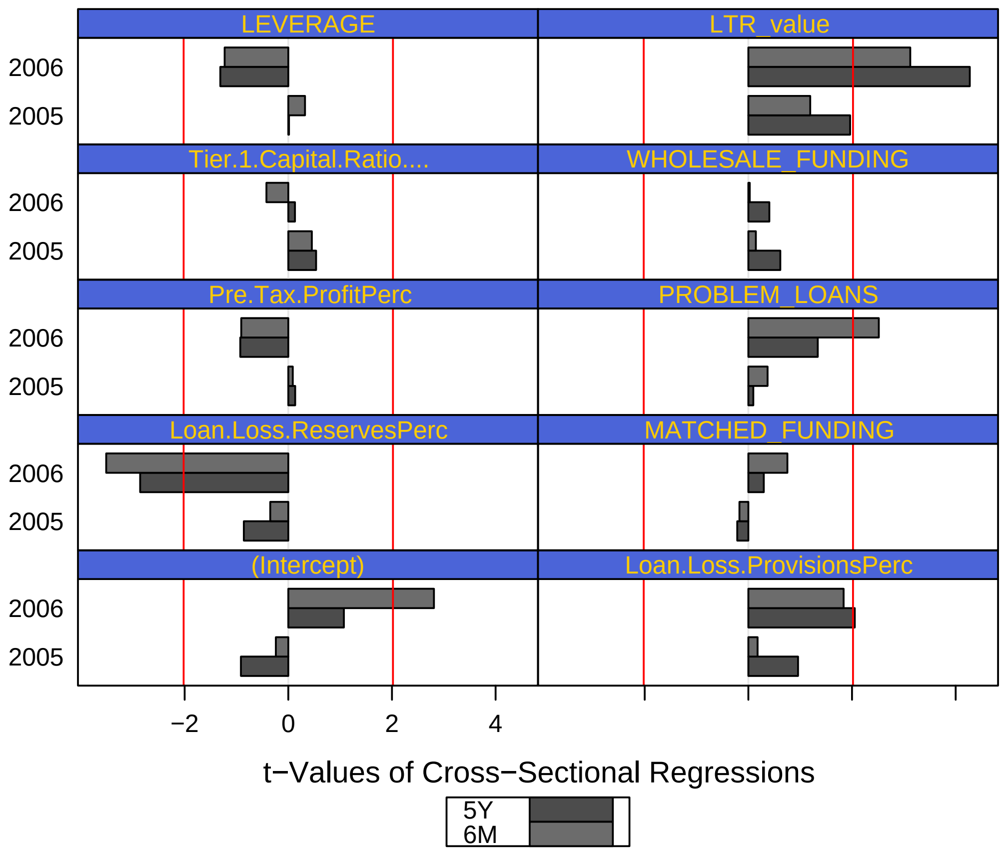

Figure 30: t-Values of Cross-Sectional Regressions, N=41

factors. Insolvency factors have an impact on both maturities, whereas we do not find any significant impact of illiquidity factors on either maturity.
Concerning the R^2, we obtain 56% (6M)/ 81,7% (5Y) for 2005 and 75,3% (6M)/ 83,55% (5Y) for 2006. The higher R^2 for 2006 is consistent with the better t-values. However, the t-significance does not seem to justify such high R^2. Unfortunately, we could not determine the reason of that phenomenon. We eliminated a possible level bias[16] by using ratios as explaining factors.
We also tested for multicollinearity calculating the pairwise factor correlations of 2006. They are reported in table . We consider correlations of 60% and more as critical. The reported correlations are however below that value. Furthermore, the correlation of 2005 is similar, as the delta-correlation matrix of table 4.4.2 reveals.

	MF	WF	LLR	LLP	T1	PL	PTP	LEV	LTR
MF	1.00	0.45	−0.26	−0.26	0.29	0.06	0.05	0.28	−0.04
WF	0.45	1.00	−0.26	−0.04	0.23	0.06	0.14	0.23	−0.20
LLR	−0.26	−0.26	1.00	0.17	−0.32	0.75	−0.29	0.00	0.28
LLP	−0.26	−0.04	0.17	1.00	0.24	0.07	0.57	−0.34	0.30
T1	0.29	0.23	−0.32	0.24	1.00	−0.31	0.56	0.12	0.13
PL	0.06	0.06	0.75	0.07	−0.31	1.00	−0.45	0.05	0.25
PTP	0.05	0.14	−0.29	0.57	0.56	−0.45	1.00	−0.22	0.22
LEV	0.28	0.23	0.00	−0.34	0.12	0.05	−0.22	1.00	−0.38
LTR	−0.04	−0.20	0.28	0.30	0.13	0.25	0.22	−0.38	1.00

Table 1: Correlation of Low-Frequency Factors, 2006(N=41)

	MF	WF	LLR	LLP	T1	PL	PTP	LEV	LTR
MF	0.00	0.02	0.07	0.10	0.07	−0.22	0.05	0.12	−0.16
WF	0.02	0.00	−0.17	0.15	0.02	0.01	−0.11	−0.09	−0.14
LLR	0.07	−0.17	0.00	−0.10	0.06	0.19	−0.05	−0.22	0.05
LLP	0.10	0.15	−0.10	0.00	0.07	0.08	0.24	−0.13	−0.09
T1	0.07	0.02	0.06	0.07	0.00	−0.01	−0.04	0.09	0.01
PL	−0.22	0.01	0.19	0.08	−0.01	0.00	−0.08	−0.21	0.08
PTP	0.05	−0.11	−0.05	0.24	−0.04	−0.08	0.00	−0.18	0.20
LEV	0.12	−0.09	−0.22	−0.13	0.09	−0.21	−0.18	0.00	−0.11
LTR	−0.16	−0.14	0.05	−0.09	0.01	0.08	0.20	−0.11	0.00

Table 2: Correlation-Deltas (2006-2005) of Low-Frequency Factors (N=41)

[16] A level bias occurs if absolute factors are used instead of relative ones. As CDS-spreads are a sort of rate, factors should be rates or ratios as well.

5 Conclusion

Our paper studied 'Stylised Facts' and 'Determinants' of short- and long-term CDS-spreads of banks. We got inspired by a paper of [Covitz and Downing, 2007] that studied short-term commercial paper and long-term bond spreads of non-financial companies.
Using short- and long-term spreads of the same asset class eliminates potential instrument biases. [Covitz and Downing, 2007] first showed that short- and long-term spreads are not perfectly correlated. They hypothesized that short-term spreads might reflect illiquidity risk whereas long-term spreads rather reflect insolvency risk. As banks bear a higher liquidity risk (higher cash flow volatility due to products with liquidity options and no re-negotiating of payment obligations), banks are a natural choice to test for liquidity risk.
Using a sample of 58 banks with daily CDS-spreads covering the period 1.1.2004-31.12.2007, we obtained the following 'Stylised Facts':

- Short- and long-term spreads have a high correlation (97%) on the total period.
- Splitting up the total period into sub-periods, we obtain a wide spectrum of correlations (-99% ... 99 %).
- In turbulent markets, spreads have a tendency to co-move. In calm markets, they seem independent.
- In 39%, spreads went into different directions. This result is robust, even if small changes ($\leq 10\%$) are excluded.

The second point corroborates the findings of [Covitz and Downing, 2007]. However, the third point sharply contrasts them, as they report that negative correlation is most pronounced in turbulent markets. We showed, that for CDS-spreads exactly the opposite is the case.
Having shown that CDS-spreads are not always perfectly correlated, we tested for potential determining factors in the section 'Determinants'. We split up our factor set into (daily) high frequency and low frequency factors. High-frequency factors were regressed in a time series-framework, whereas low frequency factors were regressed cross-sectional for selected dates.
Prior to the time series regressions, we tested for spread and factor stationarity. We found that the majority of series are non-stationary at the 1%-level. Therefore, we used the delta-series in the regressions.
We find empirical support for the following statements:

- 5Y-spreads are significantly sensitive to Merton-insolvency factors (firm value volatility, stock-price, interest rate level).
- 5Y-spreads are not sensitive to liquidity factors.
- 6M-spreads are neither sensitive to insolvency nor to illiquidity factors.
  This finding suggest that 6M-spreads are (partly) driven by other factors than 5Y-spreads. However, none of our factors seems to significantly explain 6M-spreads.

Testing for 'Homoscedasticity' and 'Independence of Residuals' revealed that these assumptions were not fulfilled for our regressions. As a consequence, our t-values and R^2 are likely to be biased.
The majority of bank-specific factors were of low-frequency. In order to eliminate any level bias, we transformed all balance sheet factors to ratios or rates. Due to low data coverage, we had to exclude the 2004-values.
The cross-sectional regressions lead to the following results:

- The t-values of 2006 are larger than those of 2005.
  Particularly, we do not find any significant (99%-level) relation in 2005. By contrast, for 2006 we found:

$$\begin{aligned} \text{6M-/5Y-Spread} &\sim \text{Long-Term Rating} \\ \text{6M-/5Y-Spread} &\sim \text{Loan Loss Reserves [\%]} \\ \text{6M-Spread} &\sim \text{Problem Loans} \\ \text{5Y-Spread} &\sim \text{Loans Loss Provisions} \end{aligned}$$

In contrast to our time series regressions, the cross-sectional regressions find some significant factors for 6M-spreads. However, these relations are not observable for all years. The fact that relations can be found for 2006 might be due to the better data quality for both balance sheet factors and 6M-CDS-spreads. In line with the time series regressions, none of our liquidity factors is significant for either maturity. Hence, we cannot corroborate [Covitz and Downing, 2007] who state that short-term spreads are also sensitive to liquidity factors whereas 5Y-spreads are not. We do not find this 6M-sensitivity.
Our cross-sectional regressions show very high R^2 that do not seem to be consistent with the rather poor t-values. Unfortunately, we did not find the reason for that phenomenon.
The imperfect correlation between short- and long-term factors can be easily shown. However, we did not find any factor that significantly drives 6M-spreads. The 5Y-insolvency factors did not drive them either. Future research should concentrate on identifying the factors behind short-term CDS-spreads. This requirement does not only apply for empirical studies, but also for modelling efforts: credit risk models should describe short-term spreads by another risk factor than long-term spreads. Distinguishing 'Jump-to-Default'-risk for short-term and 'Credit Deterioration' for long-term spreads are promising ways to pursue. However, our research well integrates into the 'Jump-to-Default'-philosophy as we tested whether the 'Jump-to-Default' might be triggered by liquidity risk. We cannot report any empirical evidence that short-term CDS-spreads are particularly sensitive to either systematic or bank-specific liquidity factors, though.

A Spread Coverage

B Factor Coverage

Bank	6M				5Y			
	2004	2005	2006	2007	2004	2005	2006	2007
ABN AMRO Bk N V	261	260	256	216	262	260	260	261
Allied Irish Bks PLC	229	259	260	222	262	260	260	261
Amern Express Co	256	260	260	247	262	260	260	261
Barclays Bk plc	261	249	260	248	262	260	260	261
Bay Landbk Giroz	153	257	260	214	259	260	260	261
Bca Monte dei Paschi di Siena S p A	255	257	252	248	262	260	260	261
Bca Naz del Lavoro S p A	243	258	259	253	262	260	260	261
Bca Pop di Milano Soc Coop a r l	213	256	260	255	262	260	260	261
Bco Bilbao Vizcaya Argentaria S A	260	256	257	244	262	260	260	261
Bco Comercial Portugues SA	258	259	260	224	262	260	260	261
Bco Espirito Santo S A	259	258	260	243	262	260	260	261
Bco Santander Cen Hispano S A	262	257	260	169	262	260	260	169
Bk Austria Cred AG	210	206	242	30	262	260	260	261
BNP Paribas	257	260	244	156	262	260	260	261
Cap One Bk	260	219	240	244	262	260	260	261
CIT Gp Inc	257	256	259	261	262	260	260	261
Citigroup Inc	252	258	260	261	262	260	260	261
Commerzbank AG	260	260	257	242	262	260	260	261
Cr Agricole SA	142	220	252	170	262	260	260	261
Cr Suisse Gp	254	260	256	254	262	260	260	261
Deutsche Bk AG	262	260	260	260	262	260	260	261
Dresdner Bk AG	258	260	259	247	262	260	260	261
Erste Bk Der Ost Sparkassen AG	185	249	257	257	262	260	260	261
Fortis NV	229	240	258	261	262	260	260	261
Goldman Sachs Gp Inc	257	260	260	239	262	260	260	261
Gov & Co Bk Irlnd	206	232	257	260	262	260	260	261
Gov & Co Bk Scotland	242	250	246	166	262	260	260	185
HSBC Bk plc	262	252	243	197	262	260	260	261
HSBC Hldgs plc	202	204	244	35	262	260	260	261
ING Bk N V	260	260	244	169	262	260	260	261
KBC Bk	41	243	244	169	260	260	260	261
Landbk Hessen thueringen Giroz	15	170	250	258	255	247	260	261
Lehman Bros Hldgs Inc	261	260	260	252	262	260	260	261
Lloyds TSB Bk plc	256	250	248	197	262	260	260	261
Mediobanca SpA	201	258	259	254	262	260	260	261
Merrill Lynch & Co Inc	257	258	260	259	262	260	260	261
Morgan Stanley	249	260	260	255	262	260	260	261
Nomura Secs Co Ltd	107	218	257	244	262	260	260	261
Nordea Bk Norge ASA	0	114	0	232	75	222	260	256
Q B E Ins Gp Ltd	29	255	250	246	262	260	260	261
Rabobank Nederland	252	258	245	201	262	260	260	261
Royal Bk Scotland plc	252	260	248	204	262	260	260	261
Skandinaviska Enskilda Banken AB	79	255	245	202	245	260	260	261
SNS Bk NV	227	257	259	246	262	260	260	261
Societe Generale	261	260	259	246	262	260	260	261
Std Chartered Bk	254	251	258	228	262	260	260	261
Svenska Handelsbanken AB	26	224	250	55	260	260	260	261
UBS AG	255	259	260	242	262	260	260	261
UniCredito Italiano S p A	259	258	260	185	262	260	260	195
Wachovia Corp	244	256	260	244	262	260	260	261
WestLB AG	174	256	244	187	262	260	260	261
Zurich Ins Co	259	256	258	248	262	260	260	261

Table 3: Number of Spread Observations for 'Stylised Facts'

Bank	2004	2005	2006	2007
ABN AMRO Bk N V	257	257	255	252
Allied Irish Bks PLC	0	24	253	253
Amern Express Co	252	252	251	251
Barclays Bk plc	0	0	0	60
Bay Landbk Giroz	0	0	0	0
Bca Monte dei Paschi di Siena S p A	0	17	254	252
Bca Naz del Lavoro S p A	0	0	0	0
Bca Pop di Milano Soc Coop a r l	257	256	254	252
Bco Bilbao Vizcaya Argentaria S A	251	256	254	253
Bco Comercial Portugues SA	0	0	254	255
Bco Espirito Santo S A	259	257	255	255
Bco Santander Cen Hispano S A	251	256	254	165
Bk Austria Cred AG	0	29	246	247
BNP Paribas	259	257	255	255
Cap One Bk	0	29	251	251
CIT Gp Inc	252	252	251	251
Citigroup Inc	252	252	251	251
Commerzbank AG	257	257	255	252
Cr Agricole SA	259	257	255	255
Cr Suisse Gp	0	1	250	252
Deutsche Bk AG	257	257	255	252
Dresdner Bk AG	0	0	0	0
Erste Bk Der Ost Sparkassen AG	0	0	242	247
Fortis NV	259	257	255	255
Goldman Sachs Gp Inc	252	252	251	251
Gov & Co Bk Irlnd	254	253	253	253
HSBC Bk plc	254	252	252	253
HSBC Hldgs plc	0	0	0	0
ING Bk N V	259	257	255	255
KBC Bk	259	257	255	255
Landbk Hessen thueringen Giroz	0	0	0	0
Lehman Bros Hldgs Inc	252	252	251	251
Lloyds TSB Bk plc	254	252	252	253
Merrill Lynch & Co Inc	0	0	241	251
Morgan Stanley	252	252	251	251
Nomura Secs Co Ltd	0	0	238	245
Nordea Bk Norge ASA	0	0	244	250
Rabobank Nederland	0	0	0	0
Royal Bk Scotland plc	254	252	252	253
Skandinaviska Enskilda Banken AB	0	10	251	250
SNS Bk NV	0	22	68	75
Societe Generale	259	257	255	255
Std Chartered Bk	0	0	243	253
Svenska Handelsbanken AB	0	0	238	250
UBS AG	257	257	255	252
UniCredito Italiano S p A	257	256	254	190
Wachovia Corp	0	10	251	251

Table 4: Number of Stock Price Observations for 'Spread Determinants'

	Factor	Y2004	Y2005	Y2006
1	Inflation Index	40	40	41
2	Unemployment Rate	40	40	41
3	Gross Domestic Product	40	40	41
4	Housing Prices	40	40	41
5	Matched Funding	15	38	41
6	Wholesale Funding	15	35	41
7	Loan Loss Reserves [%]	11	26	29
8	Loan Loss Provisions [%]	14	37	38
9	Tier-1-Capital Ratio	8	26	30
10	Problem Loans	9	23	32
11	Pre-Tax Profit [%]	15	38	41
12	Leverage	15	38	41
13	Long-Term Rating (Value)	15	38	41

Table 5: Observations of Low-Frequency Factors (N=41)

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