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What determines euro area bank CDS spreads?

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What determines euro area bank CDS spreads?

by Jan Annaert, Marc De Ceuster, Patrick Van Roy and Cristina Vespro

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Abstract

This paper decomposes the explained part of the CDS spread changes of 31 listed euro area banks according to various risk drivers. The choice of the credit risk drivers is inspired by the Merton (1974) model. Individual CDS liquidity and other market and business variables are identified to complement the Merton model and are shown to play an important role in explaining credit spread changes. Our decomposition reveals, however, highly changing dynamics in the credit, liquidity, and business cycle and market wide components. This result is important since supervisors and monetary policy makers extract different signals from liquidity based CDS spread changes than from business cycle or credit risk based changes. For the recent financial crisis, we confirm that the steeply rising CDS spreads are due to increased credit risk. However, individual CDS liquidity and market wide liquidity premia played a dominant role. In the period before the start of the crisis, our model and its decomposition suggest that credit risk was not correctly priced, a finding which was correctly observed by e.g. the International Monetary Fund.

Key Words: credit default spreads, credit risk, financial crisis, financial sector, liquidity premia, structural model.

JEL Classification: G01, G12, G21.

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1. Introduction

This paper empirically addresses the determinants of credit default swap (CDS) spread changes for euro area credit institutions over the period 2004-2008, covering both tranquil times and the recent financial crisis. A CDS spread is the periodic rate a protection buyer pays on the notional amount to a protection seller for transferring the risk of a credit event. As such CDS spreads reflect market perceptions about the financial health of credit institutions (‘banks’ for short) and can be used by prudential authorities to extract warning signals regarding financial stability. However, very little is known about what actually drives credit spreads in general and bank CDS spreads in particular. Not only do variables that follow from structural credit risk models explain a limited part of credit spread variation (e.g. Eom, Helwege & Huang (2004)), their impact is also found to be strongly time-varying (e.g. González-Hermosillo (2008)). Moreover, variables that are found to affect credit spreads of non-financial companies often lose their explanatory power when applied to financials (e.g. Boss & Scheicher (2005) and Raunig & Scheicher (2008)). In order to fine-tune the potential signals that can be inferred from credit spreads, we distinguish the explanatory power of credit risk variables, liquidity, and business cycle indicators and market conditions. Although the traditional credit risk variables are important drivers of spread changes, adding liquidity and market and business cycle variables increases the explanatory power by up to 30%. Moreover, as our sample covers the recent financial crisis, we are able to study to what extent the relations are stable across time. Using simple rolling regressions we show that both the explanatory power of our variables and the time variation of their coefficients is huge. CDS spreads change very strongly due to a host of risk drivers. By studying the marginal contributions of each explanatory variable to the model, we show that during the 2004-2006 period, changes in CDS spreads are mainly dominated by credit risk drivers. In the period preceding the crisis, our model virtually breaks down and economically sensible variables hardly seem to explain variation in the CDS spreads. During the period of financial crisis, it is manifest that CDS spread changes cannot be explained by credit risk drivers alone. Liquidity and the overall perception of bank stability explain significant parts of their variation.

These findings are important for bank supervisors. First, knowledge of the precise causes of the CDS changes is a necessary condition for taking the right policy actions. Credit spread changes that are driven by the increased credit risk of individual financial institutions, call for additional monitoring of their financial health. On the other hand, liquidity-induced credit risk changes may merely point to an increase in market malfunctioning, for which no actions vis-à-vis the individual underlying names have to be taken. Instead, market wide measures may be more appropriate. Also, business cycle related CDS spread changes may constitute systemic risk warnings or may be additional signals for monetary authorities to review their monetary policy. Second, knowing when a reasonable model no longer works may also be important. When CDS spread changes are not related to fundamental variables, the market’s ability to correctly price for risk can be questioned.

Using market information to guide policy is hardly new (e.g. Bongini, Laeven & Majnoni (2002), Duca (1999), and Gropp, Vesala & Vulpes (2004)). Since long, central banks and supervisory authorities have been using financial market information such as the term structure of interest rates, implied volatilities
and option implied risk neutral distributions to guide their monetary policy actions. Also market-wide credit spreads have been recognized as indicators of the business cycle stance and therefore important for both monetary policy and financial stability purposes. Especially during the credit crisis, market variables helped supervisors to have timely indications of financial stress in the European banking industry. Depending on the signals, a wide range of policy actions were taken (Committee on the Global Financial System (2008)). More recently, credit spreads on individual names have been included on the supervisory dashboard. Especially CDS spreads have been closely monitored by prudential authorities, as the following quotes illustrate:

The “differentiation between banks is also reflected in market perceptions of credit risk, as proxied by credit default swap (CDS) premia” Bank of England (2007), p. 34.

“The impact of the sub-prime episode on market indicators of the financial soundness of global LCBGs was quite pronounced. CDS spreads on the debt of these institutions initially widened as a result of investor concern over exposure to sub-prime mortgages.” European Central Bank (2007), p. 46.

Their rise to a prominent role as market based credit indicator is in the first place thanks to the stellar growth to maturity of the CDS market. The Bank for International Settlements (BIS) estimates the notional amounts outstanding to have risen from about 6 trillion USD in December 2004 to 57 trillion USD in June 2008. Single name contracts, which are traded insurance contracts against the default of a single entity (‘name’), account for more than half of this amount (33 trillion USD).

Duffie (1999) and Hull, Predescu & White (2004) show that -under a set of restrictive assumptions- CDS spreads and credit spreads derived from bond prices should be closely related. However, CDS spreads have some advantages compared to bond spreads. First, CDS spreads are directly observable whereas bond spreads have to be computed vis-à-vis a riskless benchmark. Houweling & Vorst (2005) demonstrate that the choice of the risk-free reference asset may be problematic. Second, the estimation of the credit premium in bond spreads is presumably more confounded by market and institutional factors. Indeed, the precise measurement of bond spreads is known to be hampered by (ill)liquidity issues (e.g. Sarig & Warga (1989); Chen, Lesmond & Wei (2007)), tax effects (Elton, Gruber, Agrawal & Mann (2001)) and various market microstructure effects (maturity effects, coupon effects, …). Finally, CDS spreads have been found to react more rapidly to information regarding the changes in the credit quality of the underlying name compared to the bond market (Blanco, Brennan & Marsh (2005); Hull, Predescu & White (2004); Zhu (2006)). Long term bond ratings are also lead by CDS rate changes (Norden & Weber (2004)).
Credit spreads can be inferred from corporate bond markets.\(^1\) Empirical research, however, revealed that expected default losses only account for a small fraction of observed credit spreads (Anderson & Sundaresan (2000), Delianedis & Geske (2001), Huang & Huang (2003)). This observation is known as the credit spread puzzle (Amato & Remolona (2003)). Elton, Gruber, Agrawal & Mann (2001) e.g. show that only 17.8% of the 10 year A-corporate-treasury spread can be attributed to default. Another 36.1% was assigned to tax effects, leaving a residual spread of 46.2%. Also CDS spreads are too high to be attributed to credit risk alone (Berndt, Douglas, Duffie, Ferguson & Schranz (2005); Pan & Singleton (2005)). On the one hand, Tang & Yan (2007) and Acharya & Johnson (2007), suggest that liquidity may also be an issue. Bongaerts, de Jong & Driessen (2008) develop an asset pricing model for derivative securities that allows for liquidity. This model predicts a liquidity premium for derivative securities that can be zero, positive or negative, depending on heterogeneity of investors’ risk aversion, wealth and non-traded risk exposures. Testing the model on CDS portfolios they find that part of the CDS spread reflects a compensation for expected liquidity. On the other hand, also business cycle and market wide sentiments have been shown to be related to credit spread changes (e.g. Amato & Luisi (2006), Gilchrist, Yankov & Zakrajšek (2009)). Given these findings, it is of the utmost importance to study empirically the determinants of credit spread changes.

Interestingly, hardly any attempt has been made to assess the determinants of bank credit spreads, probably because the financial industry is considered to be an opaque industry where traditional credit risk models are likely to be less successful. Notable exceptions are Boss & Scheicher (2005), Düllmann & Sosinska (2007) and Alexander & Kaeck (2008). Boss & Scheicher (2005) study credit spread changes of European corporate bond indices and find that although some variables affect both spreads on industrials and financials, other factors like implied stock market volatility have opposite effects in both samples. Düllmann & Sosinska (2007) explore the usefulness of CDS prices as market indicators of bank risk based on a very limited ad hoc chosen set of variables: (abnormal) stock returns, market index returns, the swap spread and the bid ask spread. Their sample, however, is limited to three German banks. Alexander & Kaeck (2008) advance a Markov switching model to capture the changes in the iTraxx Europe indices. For financials, however, the explanatory power of their regression models is low (R²s of 4% to 18%) and almost entirely due to adding the lagged credit spread. Variables that are significantly related to spreads of other indices do not enter the model for financials. Also Raunig & Scheicher (2008) find that CDS spreads of banks behave differently from those in other industries. By studying a large cross-section of euro area banks over a diverse period, covering both tranquil and turbulent months, we enlarge the experience with the empirical behavior of CDS spreads in general and of bank spreads in particular.

The remainder of this paper is structured as follows. Section 2 introduces the sample of banks under consideration, whereas section 3 discusses the determinants of the credit spread changes used in the

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\(^1\) Decompositions of bond spreads have been advanced in order to empirically disentangle the credit part from other residual risks (Webber & Churm (2007); Churm & Panigirtzoglou (2005)). The usefulness of these decomposition attempts depends crucially on the heroic assumption that the credit risk model is well specified and it gives an 'ad hoc' interpretation to the residual part. Duffie (1999) e.g. assumes that the unexplained part of the spread is liquidity related.
empirical analysis. Section 4 presents univariate regressions which put the importance of the separate variables into perspective, as well as a multivariate regression model used to explain the time variation in the determinants and to present a decomposition of the explanatory power based on the marginal contribution of each variable to the model. Finally, section 5 concludes and summarizes the policy implications of our findings.

2. Euro area bank CDS spreads

Our sample consists out of 31 listed euro area banks for which CDS contracts trade. The selection of the banks is made based on the data availability of stock prices and CDS quotes in the Thomson Datastream™ database. Our sample contains banks from Belgium (2), France (5), Germany (4), Greece (1), Ireland (4), Italy (7), The Netherlands (2), Portugal (3) and Spain (3). We select the 5 year CDS quotes for senior debt issues since these contracts are generally considered to be the most liquid segments of the market (E.g. Meng & Ap Gwilym (2008)). Thomson Datastream™ gets its data feeds from CMA New York, which provides closing bid and ask quotes. In addition, a veracity index that indicates the nature of the provided quote is available. In order to maximize data quality, we only retain quotes with the best veracity index (i.e. 1). Daily CDS rates are known to be scanty. Zhu (2006), footnote 6, e.g. reports valid daily quotes for 20% of the days in his sample period. Consequently, we use a weekly frequency with the last-observation-carried-forward principle of interpolation. Finally, only underlying names with at least 10 weekly credit spread changes are retained. Our data span the period starting from 1 January 2004 to 22 October 2008 resulting in 5214 (unbalanced) panel observations with an average of 20.6 observations per week. The sample starts on 1 January 2004 because few CDS quotes were available before that date. The sample stops in October 2008 because bank CDS spreads in the subsequent months have been affected by different government interventions whose application to specific banks is not always identifiable.

The levels of the credit spreads have evolved dramatically since the outbreak of the subprime crisis. Figure 1 (panel A) graphs the median euro area bank CDS credit spreads over time. It is clear that from the first quarter of 2007 onwards CDS spreads started to rise dramatically. Also the cross sectional variation in the credit spreads exploded. The average inter-decile spread between the 10% and the 90% quantiles rose from 14 bp in 2004 to 182 bp in 2008, a 13-fold increase. Figure 1 (panel B) reports the median CDS spread levels broken down by Fitch long term rating. As we would expect the median of A-rated banks reflects a credit premium vis-à-vis the median AA bank before the start of the financial turmoil. In the wake of the crisis, however, this premium seems to disappear and during the crisis the median CDS spreads on A and AA rated banks almost coincide.
As Figure 1 and Table 1 reveal, the cross-sectional variation in CDS spreads over the period studied is vast. The minimum spread recorded was a mere 2.8 bp (Dexia). The maximum ran up to 750 bp (IKB). In our sample the average spreads over the whole sample period varied between 14.13 bp (Banco Popolare) and 299.49 bp (Banca Italease). The variations over time are also huge for every bank in our sample. The overall standard deviation is 63.9 bp compared to an average overall spread of 38.5 bp. The spread changes are on average 0.44 bp. The average, however, masks large changes as testified by the overall standard deviation of 13.5 bp. Table 1 also illustrates the unbalanced nature of our panel. For 23 banks, we have more than 100 observations out of a potential of 250 weeks. For only 4 banks less than 50 time series observations are available.
Table 1: Descriptive statistics of the time series of the cross-sectional number of observations

<table>
<thead>
<tr>
<th>Bank/Region</th>
<th>CDS Spread Levels</th>
<th>CDS Spread Changes</th>
<th>Nobs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Belgium</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DEXIA</td>
<td>2.80</td>
<td>52.60</td>
<td>550.00</td>
</tr>
<tr>
<td>KBC GROUPE</td>
<td>7.50</td>
<td>21.88</td>
<td>282.20</td>
</tr>
<tr>
<td><strong>France</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BNP PARIBAS</td>
<td>5.20</td>
<td>20.29</td>
<td>121.30</td>
</tr>
<tr>
<td>CREDIT AGRICOLE</td>
<td>5.50</td>
<td>27.69</td>
<td>165.00</td>
</tr>
<tr>
<td>NATIXIS</td>
<td>7.50</td>
<td>40.79</td>
<td>335.00</td>
</tr>
<tr>
<td>SOCIETE GENERALE</td>
<td>5.90</td>
<td>25.34</td>
<td>149.20</td>
</tr>
<tr>
<td>UNIBAIL</td>
<td>23.00</td>
<td>73.79</td>
<td>320.00</td>
</tr>
<tr>
<td><strong>Germany</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BAYERHYPO</td>
<td>6.00</td>
<td>30.60</td>
<td>150.00</td>
</tr>
<tr>
<td>COMMERZBANK</td>
<td>7.40</td>
<td>32.50</td>
<td>165.00</td>
</tr>
<tr>
<td>DEUTSCHE BANK</td>
<td>9.00</td>
<td>30.13</td>
<td>186.20</td>
</tr>
<tr>
<td>IKB DEUTSCHE INDSTR.K.</td>
<td>10.00</td>
<td>140.40</td>
<td>750.00</td>
</tr>
<tr>
<td>EFG EUROBANK ERGASIAS</td>
<td>14.50</td>
<td>18.08</td>
<td>23.50</td>
</tr>
<tr>
<td><strong>Ireland</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ALLIED IRISH BANKS</td>
<td>6.30</td>
<td>42.04</td>
<td>275.00</td>
</tr>
<tr>
<td>ANG IR BK</td>
<td>3.00</td>
<td>107.46</td>
<td>605.00</td>
</tr>
<tr>
<td>BANK OF IRELAND</td>
<td>6.40</td>
<td>48.39</td>
<td>320.00</td>
</tr>
<tr>
<td>IRISH LIFE &amp; PERM.</td>
<td>115.00</td>
<td>191.24</td>
<td>319.20</td>
</tr>
<tr>
<td><strong>Italy</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BANCA ITALIAEISE</td>
<td>65.70</td>
<td>299.49</td>
<td>650.00</td>
</tr>
<tr>
<td>BANCA MONT DEI PASCHI</td>
<td>6.00</td>
<td>29.25</td>
<td>156.70</td>
</tr>
<tr>
<td>BANCA POPOLARE MILANO</td>
<td>11.50</td>
<td>25.17</td>
<td>125.00</td>
</tr>
<tr>
<td>BANCO POPOLARE</td>
<td>3.00</td>
<td>14.13</td>
<td>75.00</td>
</tr>
<tr>
<td>MEDIOBANCA</td>
<td>7.00</td>
<td>22.55</td>
<td>119.70</td>
</tr>
<tr>
<td>UBI BANCA</td>
<td>14.80</td>
<td>19.73</td>
<td>69.20</td>
</tr>
<tr>
<td>UNICREDITO ITALIANO</td>
<td>7.00</td>
<td>27.08</td>
<td>154.80</td>
</tr>
<tr>
<td><strong>The Netherlands</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ING GROEP</td>
<td>4.50</td>
<td>26.23</td>
<td>188.30</td>
</tr>
<tr>
<td>FORTIS NL</td>
<td>6.00</td>
<td>46.98</td>
<td>415.00</td>
</tr>
<tr>
<td><strong>Portugal</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BANCO BPI</td>
<td>10.50</td>
<td>16.25</td>
<td>32.00</td>
</tr>
<tr>
<td>BANCO COMERCIAL PORTUGUES</td>
<td>8.00</td>
<td>30.04</td>
<td>161.20</td>
</tr>
<tr>
<td>BANCO ESP. SANTO</td>
<td>8.50</td>
<td>34.00</td>
<td>182.80</td>
</tr>
<tr>
<td><strong>Spain</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BANCO DE SABADELL</td>
<td>21.00</td>
<td>197.66</td>
<td>321.70</td>
</tr>
<tr>
<td>BANCO SANTANDER</td>
<td>7.50</td>
<td>27.00</td>
<td>154.20</td>
</tr>
<tr>
<td>BBVA</td>
<td>7.80</td>
<td>25.97</td>
<td>152.50</td>
</tr>
<tr>
<td><strong>ALL</strong></td>
<td>2.80</td>
<td>38.50</td>
<td>790.00</td>
</tr>
</tbody>
</table>

The table contains the minimum (Min.), mean, maximum (Max.) and the standard deviation (St.Dev.) of both the levels and the changes in the weekly CDS spreads (in basis points) by bank. Banks are assigned to countries based on the Bankscope classification. Nobs refers to the available number of observations in the changes. The period runs from 1 January 2004 to 22 October 2008.
Table 2: Descriptive Statistics Credit Spread Changes - Break up by Rating and Period

<table>
<thead>
<tr>
<th>Fitch Long Term Rating</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>Missing</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Pre-crisis</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>-0.04</td>
<td>-0.05</td>
<td>-</td>
<td>-0.08</td>
<td>-0.05</td>
</tr>
<tr>
<td>Max</td>
<td>9.80</td>
<td>17.00</td>
<td>-</td>
<td>9.50</td>
<td>17.00</td>
</tr>
<tr>
<td>Min.</td>
<td>-4.30</td>
<td>-14.50</td>
<td>-</td>
<td>-9.70</td>
<td>-14.50</td>
</tr>
<tr>
<td>St. Dev.</td>
<td>0.95</td>
<td>1.80</td>
<td>-</td>
<td>1.48</td>
<td>1.41</td>
</tr>
<tr>
<td>Nobs</td>
<td>1684</td>
<td>1384</td>
<td>-</td>
<td>461</td>
<td>3529</td>
</tr>
<tr>
<td><strong>Panel B: Crisis</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>1.32</td>
<td>1.22</td>
<td>30.64</td>
<td>1.71</td>
<td>1.48</td>
</tr>
<tr>
<td>Max</td>
<td>156.70</td>
<td>262.50</td>
<td>112.50</td>
<td>110.00</td>
<td>262.50</td>
</tr>
<tr>
<td>Min.</td>
<td>-155.00</td>
<td>-251.20</td>
<td>-87.50</td>
<td>-143.30</td>
<td>-251.20</td>
</tr>
<tr>
<td>St. Dev.</td>
<td>21.01</td>
<td>24.73</td>
<td>64.19</td>
<td>25.95</td>
<td>23.61</td>
</tr>
<tr>
<td>Nobs</td>
<td>804</td>
<td>687</td>
<td>9</td>
<td>185</td>
<td>1685</td>
</tr>
<tr>
<td><strong>Panel C: All</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.40</td>
<td>0.37</td>
<td>30.64</td>
<td>0.43</td>
<td>0.44</td>
</tr>
<tr>
<td>Max</td>
<td>156.70</td>
<td>262.50</td>
<td>112.50</td>
<td>110.00</td>
<td>262.50</td>
</tr>
<tr>
<td>Min.</td>
<td>-155.00</td>
<td>-251.20</td>
<td>-87.50</td>
<td>-143.30</td>
<td>-251.20</td>
</tr>
<tr>
<td>St. Dev.</td>
<td>11.98</td>
<td>14.32</td>
<td>64.19</td>
<td>13.94</td>
<td>13.49</td>
</tr>
<tr>
<td>Nobs</td>
<td>2438</td>
<td>2071</td>
<td>9</td>
<td>646</td>
<td>5214</td>
</tr>
</tbody>
</table>

The table reports summary statistics for the weekly CDS spread changes (in basis points) segmented by Fitch long term ratings and sub periods. It contains the minimum (Min.), mean, maximum (Max.) and the standard deviation (St.Dev.) Nobs refers to the available number of observations. The pre-crisis period runs from 1 January 2004 to 1 April 2007. The crisis period starts on 2 April 2007 and ends on 22 October 2008.

Table 2 breaks down the descriptive statistics by Fitch long term rating and sub-period. Acknowledging significant strains on smaller US subprime lenders in February and March 2007, we follow Borio (2008) in recognizing the filing for Chapter 11 bankruptcy of New Century Financial Corporation, the second largest US subprime lender, on 2 April 2007 as the first major subprime crisis event. We use this date as a delineation of the crisis period versus a pre-crisis period. Of course, the choice of this structural break is somewhat arbitrary, but shifting the break point a couple of months does not materially affect any of our findings. Table 2 shows that the volatility of AA spread changes is smaller than the volatility of the CDS spread changes for A rated banks, which shows up both in the lower standard deviation and the smaller ranges. Note that, for some of our banks, a long term rating was not available from Fitch (646 bank-week observations), whereas BBB ratings occur only at the very end of our sample period (only 9 bank-week observations). The average changes are small given the weekly frequency. The standard deviation however boosts during the crisis periods for each rating category.

Whereas most authors would date the start of the crisis somewhat later, others such as Acharya, Philippon, Richardson & Roubini (2009) date it even earlier. In any case, the rolling regressions presented in section 4 below provide some robustness analysis.
3. Explanatory variables

Most theoretical models, spurred by the seminal paper Merton (1974), relate credit spreads to default losses. Empirical papers testing these models therefore use proxies for the determinants advanced by these models. Most of these variables are firm-specific and focus on leverage and asset volatility. Empirically, they are usually found to be significantly related to credit spread (changes), but their explanatory power is weak (see e.g. Eom, Helwege & Huang (2004), who find that structural models tend to underestimate spreads on bonds that are deemed safe and overestimate spreads on the bonds that are considered to be very risky). Many authors have argued that adding variables describing market conditions should improve the fit (e.g. Jarrow & Turnbull (2000)), as it has been documented that credit spreads (Fama & French (1989)), default probabilities and recovery rates vary through the business cycle (Pesaran, Schuermann, Treutler & Weiner (2006); Altman, Brady, Resti & Sironi (2005); see e.g. Hackbarth, Miao & Morellec (2006) for a theoretical discussion and model). In addition, investors’ risk aversion may also vary in relation to the business cycle and thereby affecting credit spreads. Finally, also the liquidity of the traded contracts can impact prices. We therefore organize our more detailed discussion of the various determinants into three groups: credit risk, marketability (trading liquidity), and market wide (economic) factors (including business cycle variables and market conditions). Note that the goal of this paper is not to predict but to explain credit spreads, hence, we use contemporaneous explanatory variables. When selecting these variables, we try to choose variables which are available on a sufficiently frequent basis, as we work with a weekly frequency for credit spreads.

3.1 Credit risk variables

Credit risk variables are introduced following the Merton (1974) model. This model derives a closed form formula for the credit spread on a risky zero bond using asset growth, asset volatility and leverage as the key economic drivers for bankruptcy. The assets of the firm are assumed to follow a geometric Brownian motion with a risk-neutral drift rate equal to the risk free rate. To finance the assets, the firm has issued a zero bond and equity shares. The default boundary is given by the leverage. The firm defaults on its zero bond when the value of the assets is below the default boundary at maturity. Following Christie (1982), the changes in the degree of financial leverage is measured by the bank stock return. Because we work with weekly data over a relatively short horizon, it is difficult to include a “clean” measure of market value leverage (note that Collin-Dufresne, Goldstein & Martin (2001) and Alexander & Kaecck (2008) also use bank stock returns to proxy for leverage). If stock returns are negative, the leverage measured in market values will be positively affected. In turn, higher leverage leads to higher credit spreads. A negative relation between stock returns and credit spreads is thus expected.

See also Chen, Fabozzi, Pan & Sverdlove (2006) who use CDS spreads to estimate and compare structural credit models. They also find that the models both overestimate some contracts and underestimate others. Spreads for firms that are deemed to be less risky are generally estimated more accurately.
Although weekly stock returns are used to proxy for leverage, it is possible that they also capture other factors. For instance, to the extent that equity returns reflect a firm’s future prospects, positive returns indicate lower default risk and may thus lead to lower (and not higher) spreads. To take this possibility into account, we also experiment with excess stock returns in our regressions, as common market return may blur the information the stock market conveys regarding the outlook of an individual bank. As the results for the excess returns are very comparable to those of the total return, we choose to report only the latter.

Higher asset volatility theoretically leads to higher credit spreads because it increases the likelihood that the default threshold is hit. We follow Covitz & Downing (2007) and Chen, Lesmond & Wei (2007) among others, and use various estimators of historical volatilities. First, we compute weekly historical standard deviations based on the intraweek daily stock returns. Alternatively, we compute volatilities based on larger windows of daily data (25 days and 50 days). We also use absolute weekly returns, squared weekly returns, ranges, mean absolute deviations, but none of these proxies improves the results reported based on weekly historical standard deviations. Hence, we only report the latter.

In Merton (1974), the risk free interest rate constitutes the drift in the risk neutral world. The higher it is, the less likely default becomes. Hence higher risk free rates lead to decreasing credit spreads. This negative relationship can also be explained in a macro-economic setting. Interest rates are positively linked to economic growth and higher growth should, ceteris paribus, imply lower default risk (see e.g. Tang & Yan (2006) for a theoretical model that implies this conclusion). We proxy the risk free rate with the Datastream benchmark 2 year government redemption yield, although we also try 5 and 10 year yields with virtually similar results.

3.2 Marketability

Liquidity is a multidimensional concept that can be assessed in various ways. First, Longstaff, Mithal & Neis (2005) and Chen, Lesmond & Wei (2007) argue that individual bond illiquidity is priced and consider liquidity as marketability of a particular bond issue. The theoretical asset pricing model of Bongaerts, de Jong & Driessen (2008) predicts that also derivative securities may contain liquidity premia. In their empirical tests using CDS portfolios they show that part of the CDS spread is indeed due to liquidity. Second, Campbell and Taksler (2003) take aggregate liquidity measures into account to model credit spreads.

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4 We compute excess returns either by correcting for the market return or for the bank industry return. In both cases we use Datastream global equity indices. For the market return we take the euro area index. Likewise, the bank industry return is derived from the euro area bank equity index (level 3 sector classification).
5 We also try the square root of the sum of squared daily returns to avoid estimating the average return. This gives nearly identical results.
6 Following Cao, Yu & Zhong (2007), who find that implied volatility of individual stock options has significant explanatory power for CDS spreads, we would have liked to study the implied volatility of the banks’ stock options. Unfortunately, lack of data prevents this.
In this study, we measure liquidity both at the individual and aggregate level. We measure bank specific liquidity as the bid-ask spread of the CDS quotes, i.e. the difference between ask and bid quote. Our choice to use the bid-ask spread is primarily motivated by the lack of data on other proxies of liquidity at the individual level; however, there are at least two other reasons for relying on this variable. First, Bongaerts, de Jong & Driessen (2008) and Tang & Yan (2008) report substantial correlations between the bid-ask spread and other liquidity proxies (e.g. number of quotes per CDS, data on trades or volume of orders). Second, unreported regressions show that the CDS bid-ask spread appears to be unrelated to the other determinants of CDS spreads in our sample. This suggests that the bid-ask spread broadly captures liquidity at the individual level and is not being "contaminated" by variables implied by structural credit risk models and by market wide factors.

Market wide liquidity is not measured directly but indirectly through swap and corporate bond spreads. We discuss them in the next section.

### 3.3 Market wide factors

Most empirical papers exploring the explanatory power of credit risk variables for bond and CDS spreads find that the residuals in their model still contain common variation, which indicates some missing common factor(s) (Collin-Dufresne, Goldstein & Martin (2001)). It is likely that this common variation is linked to the economic environment, capturing general market and economic conditions. The business cycle may impact credit spreads at least through two channels. First, as default risk depends on economic circumstances, credit spreads should reflect this. Second, risk aversion is also shown to vary through the cycle, which should impact the risk premia investors require for assuming credit risk. Berndt, Douglas, Duffie, Ferguson & Schranz (2005) provide evidence consistent with highly time-varying risk premia in the CDS market. An alternative interpretation refers to the existing frictions in capital markets. When capital freely flows across the different market segments unexpectedly higher risk premia in one segment should immediately attract new capital, thereby reducing the risk premia to more normal levels. When due to frictions this adjustment does not incur immediately higher premia persist for some time. It is likely that such frictions are more important when there is a lot of uncertainty in the market, inhibiting investors to build up positions in markets less familiar to them. Given this evidence and conjectures we introduce several variables that are known to proxy for business conditions, market conditions and/or uncertainty.

The slope of the term structure is widely acknowledged as a business cycle predictor (see e.g. Estrella & Mishkin (1997)). A high slope anticipates improved economic growth. Therefore, a negative relationship is expected with credit spreads. Moreover, to the extent that the slope carries information about future interest rate levels, again a negative relation with credit spread follows: an increase in the slope would then indicate higher future interest rates which, using the arguments above, implies lower credit risk. Theory of course does not provide an answer as to which points on the term structure should be used to

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7 We also try the relative bid-ask spread, by dividing through the mid-quote, but find that it is not significantly related to credit spreads. In addition, we measure both variables in excess of their cross-sectional average (across all banks in the sample) to capture issue-specific liquidity, but although qualitatively similar, these results are weaker than those for the total bid-ask spread, which is reported.
measure the slope. Many different combinations have been proposed in the literature. We consider the difference between the 10 year and 5 year redemption yields of the benchmark series, but we also carry out robustness checks using the 5 minus 2 year and 10 minus 2 year yields, with similar but weaker (not reported) results.

**General business climate improvements** will decrease the probabilities of default and will also increase the recovery rates. A negative relation with credit spreads thus follows. We follow Collin-Dufresne, Goldstein & Martin (2001), Ericsson, Jacobs & Oviedo (forth), Duffie, Saita & Wang (2007), Campbell & Taksler (2003), Cremers, Driessen, Maenhout & Weinbaum (2004), Avramov, Jostova & Philipov (2007), Boss & Scheicher (2005) and Düllmann & Sosinska (2007) by including a market wide stock index return as control variable. Again we use the euro area stock market index return from the Datastream global equity index family. In unreported results, we also use the bank industry stock return as proxy. It could be argued that the individual stock return, included as proxy for financial leverage, already captures this information. However, firm stock returns are quite noisy and the danger exists that the firm-specific returns swamp the economy-wide content of an index return.

Also **market wide volatility** is used as a proxy for the business climate. The higher the volatility, the higher the uncertainty about the economic prospects is the assumption. A positive relation with credit spreads therefore follows. In addition, it can also proxy for market strains that limit capital mobility across different market segments, thereby sustaining temporary high risk premia. Following Berndt, Douglas, Duffie, Ferguson & Schranz (2005), Boss & Scheicher (2005), González-Hermosillo (2008), and Tang & Yan (2008) we use the VSTOXX index to measure market wide implied volatility. VSTOXX captures the expected volatility for the Dow Jones EuroStoxx 50 index. Alternatively, it can be seen as an indicator of the investors’ risk aversion (Pan & Singleton (2008)).

Similar to Collin-Dufresne, Goldstein & Martin (2001) and Cremers, Driessen, Maenhout & Weinbaum (2004), we finally include some corporate bond market and swap spreads into our regressions. The economic interpretation of these proxies is not crystal clear. Swap spreads are considered to be an indicator of general **banking stability** (Denkert (2004)), whereas the AAA-BBB spread reflects the overall credit risk level. Both spreads, however, also may absorb market wide liquidity strains. This should be taken into account when interpreting the decomposition results. To calculate the swap spreads, we use the middle rate of the 5 year euro interest rate swaps and the benchmark government bond redemption yields of the same maturity. For the corporate yield spread, the Merrill Lynch 5 year corporate redemption yield series are employed.
3.4 Descriptive statistics

Table 3: Descriptive statistics explanatory variables

<table>
<thead>
<tr>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk free rate</td>
<td>0.00</td>
<td>0.01</td>
<td>-0.58</td>
<td>0.41</td>
<td>-0.62</td>
<td>6.84</td>
<td>-5.55</td>
<td>2.20</td>
<td></td>
</tr>
<tr>
<td>Leverage</td>
<td>-0.04</td>
<td>0.28</td>
<td>-81.09</td>
<td>75.42</td>
<td>0.09</td>
<td>1.03</td>
<td>35.18</td>
<td>-7.95</td>
<td>2.85</td>
</tr>
<tr>
<td>Equity volatility</td>
<td>0.04</td>
<td>0.01</td>
<td>-22.93</td>
<td>33.67</td>
<td>1.59</td>
<td>3.31</td>
<td>100.27</td>
<td>1.69</td>
<td>3.42</td>
</tr>
<tr>
<td>Bid-ask spread</td>
<td>0.09</td>
<td>0.00</td>
<td>-75.00</td>
<td>100.00</td>
<td>4.27</td>
<td>4.25</td>
<td>169.42</td>
<td>1.65</td>
<td>3.60</td>
</tr>
<tr>
<td>Term structure slope</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.19</td>
<td>0.16</td>
<td>0.04</td>
<td>-0.44</td>
<td>7.47</td>
<td>7.55</td>
<td>1.97</td>
</tr>
<tr>
<td>Swap spread</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.15</td>
<td>0.23</td>
<td>0.04</td>
<td>0.84</td>
<td>14.62</td>
<td>5.33</td>
<td>3.32</td>
</tr>
<tr>
<td>Corporate bond spread</td>
<td>0.01</td>
<td>0.00</td>
<td>-0.51</td>
<td>0.66</td>
<td>0.09</td>
<td>1.38</td>
<td>24.16</td>
<td>8.28</td>
<td>1.72</td>
</tr>
<tr>
<td>Market return</td>
<td>0.06</td>
<td>0.47</td>
<td>-10.98</td>
<td>5.12</td>
<td>2.26</td>
<td>-1.10</td>
<td>5.48</td>
<td>-12.81</td>
<td>1.72</td>
</tr>
<tr>
<td>Market volatility</td>
<td>0.16</td>
<td>-0.11</td>
<td>-8.90</td>
<td>15.99</td>
<td>2.95</td>
<td>1.54</td>
<td>9.86</td>
<td>5.97</td>
<td>2.02</td>
</tr>
</tbody>
</table>

The table reports the mean, the median, the minimum (Min.), the maximum (Max.), the standard deviation (St.Dev.), the skewness (Skew.) and the kurtosis (Kurt.) of the explanatory variables over the period 1 January 2004 to 22 October 2008. The risk free rate is the weekly change in the Datastream benchmark 2 year government redemption yield measured in percentage points. The leverage is the weekly bank stock return (in percentage points). The equity volatility is measured as the changes in the weekly historical standard deviation computed using the daily stock returns of the underlying bank (in percentage points). The bid-ask spread is the weekly change in the difference between the ask and the bid CDS spread quote measured in basis points. The term structure slope is the weekly change in the difference (in percentage points) between the 10 year and 5 year government redemption yields of the Datastream benchmark series. The corporate bond spread is defined as the weekly change of the difference between the Merrill Lynch 5 year BBB and AAA corporate redemption yield series (measured in percentage points). The market return is proxied by the Datastream euro area stock market index return (in percentage points). Finally, the market volatility is computed based on the weekly change of the VSTOXX index. The penultimate column presents the t-test on the difference between the mean in the crisis period versus the pre-crisis period. The last column displays the ratio of the standard deviation in the crisis period to its value in the pre-crisis period. The pre-crisis period runs from 1 January 2004 to 1 April 2007. The crisis period starts on 2 April 2007 and ends on 22 October 2008.

In Table 3 we present summary statistics for the explanatory variables used. The average changes are relatively small, definitely compared to their standard deviations. Moreover, the Jarque-Bera test (not reported) rejects normality in all cases, not in the least because of the high kurtosis. The last two columns indicate that the explanatory variables behave differently across the two sub periods. The penultimate column reports the t-test on the means across both sub periods. A positive value indicates that the variable is on average larger in the crisis period. Almost all differences are more than two standard deviations from zero. The last column reports the ratio of the variable’s standard deviation in the crisis period to its pre-crisis value. It learns that also the volatility of the explanatory variables strongly picks up in the crisis period. Although these time-varying characteristics contribute to the high kurtosis coefficients in the overall period, we can still strongly reject normality in both sub periods.

4. Empirical results

In order to examine the relationship between changes in the potential explanatory variables and the changes in credit spreads, we first perform a univariate analysis. Next, a multivariate model is presented.
4.1 Estimation technique

Our sample lends itself to panel estimation techniques. More specifically, we posit the following generic model:

\[ y_{jt} = \alpha_j + \sum_{k=1}^{K} \beta_{jk} x_{jkst} + \sum_{g=1}^{G} \gamma_{g} z_{gt} + \varepsilon_{jt}, \]

where \( j \) is the subscript identifying the bank and \( t \) indicates the time period. In this model we introduce both time-varying bank-specific explanatory variables \( x_{jkst} \) and time-varying common explanatory variables \( z_{gt} \). The latter have the advantage that they pick up any fixed effects across time. Note that the intercept term has a bank subscript, which allows estimating bank-specific fixed effects. However, in the reported results below we will restrict the intercept term to be constant across banks because an \( F \)-test never rejects this restriction at any conventional significance level. Moreover, both the estimated coefficients and the R-squared coefficients are almost similar across both series of estimates. This is not surprising as by studying CDS spread changes, we filter out any constant fixed effects. We did not estimate random effects, essentially for three reasons. First, our sample includes all banks having both sufficient valid CDS quotes and their stock listed. Hence, it is not a random sample and we do not see how we could generalize our results to other banks. Second, in contrast to many other panel applications we have relatively many time series observations certainly compared to the number of banks. It is well known that the Generalized Least Squares estimator for random effects converges to the Ordinary Least Squares estimator for fixed effects when the number of time series observation grows (Hsiao (2005), p. 37). Third, any missing firm specific effects are likely to be very persistent or even constant, certainly taking into account that we study the data on a weekly frequency. Computing credit spread changes therefore eliminates most if not all of these effects. To compute \( t \)-statistics for the estimated coefficients clustered standard errors are used. More specifically, the White cross-section method is used. In this approach the unconditional contemporaneous covariance matrix of the residuals is unrestricted and the conditional covariance matrix is allowed to depend in an arbitrary, unknown way on the explanatory variables (Wooldridge (2002), pp. 148-153). These standard errors are consistent as the number of clusters, i.e. weeks in our case, increases. Here, the number of clusters ranges between 79 and 178 depending on the period studied. According to Figure 3 in Petersen (2009) this assures that the finite sample standard error estimates should be very close to their asymptotic values.

Of course, as Table 1 clearly shows, our panel is unbalanced. Whereas the estimation procedure can easily accommodate unbalanced data sets, a more important concern is the possibility that data selection is endogenous, which may lead to biased and inconsistent estimates of the explanatory variables’ effect on CDS spread changes. To investigate this possibility we compute univariate logit regressions to test whether the probability to have a quote is systematically linked to the explanatory variables.\(^8\) For most variables we do not find any significant links at the two-sided 10% level.

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\(^8\) We also run the logit regressions adding year dummies to take into account time variation in the availability of quotes, resulting in identical conclusions.
Table 4: Univariate regression results

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Pre-crisis</th>
<th>Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>c</td>
<td>t-stat</td>
<td>Adj. R²</td>
</tr>
<tr>
<td>Risk free rate</td>
<td>-25.51</td>
<td>-2.13</td>
<td>4.87%</td>
</tr>
<tr>
<td>Leverage</td>
<td>-0.78</td>
<td>-2.31</td>
<td>8.63%</td>
</tr>
<tr>
<td>Equity volatility</td>
<td>-1.32</td>
<td>-1.12</td>
<td>2.40%</td>
</tr>
<tr>
<td>Bid-ask spread</td>
<td>1.05</td>
<td>4.25</td>
<td>10.54%</td>
</tr>
<tr>
<td>Term structure slope</td>
<td>38.16</td>
<td>1.43</td>
<td>1.52%</td>
</tr>
<tr>
<td>Swap spread</td>
<td>133.64</td>
<td>5.29</td>
<td>12.66%</td>
</tr>
<tr>
<td>Corporate bond spread</td>
<td>-6.40</td>
<td>-0.47</td>
<td>0.15%</td>
</tr>
<tr>
<td>Market return</td>
<td>-1.19</td>
<td>-2.35</td>
<td>3.98%</td>
</tr>
<tr>
<td>Market volatility</td>
<td>0.51</td>
<td>0.93</td>
<td>1.22%</td>
</tr>
</tbody>
</table>

The table reports the coefficients (columns "c") estimated using pooled regression (no fixed effects). The t-statistics (columns "t-stat") are computed using standard errors robust for contemporaneous correlation (White cross-section). The adjusted R-squared is reported in the column "Adj. R²". The last column reports the t-statistic testing the equality of the slope coefficients in both sub periods. The risk free rate is the weekly change in the Datastream benchmark 2 year government redemption yield measured in percentage points. The leverage is the weekly bank stock return (in percentage points). The equity volatility is measured as the changes in the weekly historical standard deviation computed using the daily stock returns of the underlying bank (in percentage points). The bid-ask spread is the weekly change in the difference between the ask and the bid CDS spread quote measured in basis points. The term structure slope is the weekly change in the difference (in percentage points) between the 10 year and 5 year government redemption yields of the Datastream benchmark series. The corporate bond spread is defined as the weekly change of the difference between the Merrill Lynch 5 year BBB and AAA corporate redemption yield series (measured in percentage points). The market return is proxied by the Datastream euro area stock market index return (in percentage points). Finally, the market volatility is computed based on the weekly change of the VSTOXX index. The pre-crisis period runs from 1 January 2004 to 1 April 2007. The crisis period starts on 2 April 2007 and ends on 22 October 2008.

4.2 Univariate analysis

Table 4 above reports the results of the univariate analysis. We first run the regression on the overall sample, then on the two sub periods. The pre-crisis period runs from the start of the sample to 1 April 2007, whereas the remainder of the sample is called the crisis period. Two of the three credit risk variables, the risk free rate and the leverage, are statistically significant in the overall sample. They both carry a negative sign, which is predicted by structural credit risk models. Lower leverages and higher interest rates lead to reduced default risk and hence in CDS spreads. For changes in equity volatility, we cannot reject the null: equity volatility does not seem to affect CDS spreads – it even has the “wrong” sign. As noted above, we have tried other methods to compute equity volatility, to no avail.

Looking at the results for the sub periods, only the leverage variable (i.e. the stock return) is always highly significant. However, it should be noticed that its coefficient is dramatically higher (in absolute value) in the crisis period. This is also consistent with the structural credit risk models. Lower leverages and higher interest rates lead to reduced default risk and hence in CDS spreads. For changes in equity volatility, we cannot reject the null: equity volatility does not seem to affect CDS spreads – it even has the “wrong” sign. As noted above, we have tried other methods to compute equity volatility, to no avail.

The risk free rate is only significant in the crisis period and its effect is negative throughout.
Again, its coefficient increases strongly in the crisis period in absolute value, consistent with the option theoretic interpretation of default risk.

Liquidity, as measured by the CDS bid-ask spread, is highly and positively significant in both sub periods and the overall period. Changes in the bid-ask spread explain up to 12% of the variation in CDS spread changes. This finding already confirms the results of Bongaerts, de Jong & Driessen (2008) that CDS premia also encompass a liquidity component. The higher coefficient in the crisis period is consistent with this interpretation and with the results of Scheicher (2008) where CDS index tranches are studied. Arguably, the financial crisis has made it more difficult (if not impossible) for protection sellers to hedge their credit exposure by trading in the equity of the underlying name.

Several market and business cycle related variables turn out to be related to the CDS spread changes, albeit not always with the expected sign. The results show that, contrary to what we would expect, the term structure slope receives positive coefficients, although not significantly. However, we retain this variable in our analysis, as its impact will become significantly negative in the multivariate model. The swap spread, our proxy for market wide banking risk, is highly significant in all regressions. Higher banking risks translate into higher CDS spreads. Again, its impact rises dramatically in the crisis period. In contrast, the corporate bond spread does not show a consistent picture. Overall, its coefficient is negative but insignificant. This hides a significantly positive effect before the crisis and an insignificant negative effect during the crisis period. In the latter period and in the overall sample the adjusted R squared coefficient for this regression is close to zero. However, closer inspection shows that the disappointing results of this explanatory variable are entire due to the last four weeks of our sample. When we end the sample on 15 September 2008 (Lehman default) its coefficient is significantly positive both in the entire period and in the crisis period. Moreover, its explanatory power in the latter period jumps to 7.3%. We therefore retain it in the multivariate analysis. The effects of the two stock market variables are estimated with the expected signs. The overall stock market return receives a significantly negative coefficient in all regressions. Again, its absolute value is higher in the crisis period, which is consistent with the interpretation that the default option becomes less out-of-the-money. Changes in implied stock market volatility has the expected positive sign in all regressions. Surprisingly, though, this effect is only statistically significant in the pre-crisis period.

Summarizing, the univariate results clearly show that variables that have been proposed in the theoretical literature are empirically linked to CDS spread changes for banks, although—as expected—their explanatory power is limited in periods when there is hardly credit risk. In the crisis period, both the risk free rate and the leverage variable explain a non-negligible part of spread changes. Only the equity volatility, used as a proxy for asset volatility, seems not to be related to spread changes. Also other control variables that have been proposed in the empirical literature should be taken into account when studying bank CDS spread changes. Especially the swap spread, our proxy for banking sector

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9 This result is consistent with papers studying non-financial CDS and bond spreads and that find very weak explanatory power for highly rated companies. The banks have relatively high ratings almost throughout the entire period and certainly in the pre-crisis many market participants thought it very unlikely that any large bank would actually default.
strains, turns out to explain a major part of CDS spread changes, albeit mostly in the crisis period – which is consistent with our interpretation as an overall bank risk proxy. Finally, a less frequently studied variable, individual CDS liquidity (as measured by the bid-ask spread), is important throughout the entire sample, but as expected even more so in the crisis period when hedging difficulties increase the premium protection sellers require. As is clear from our discussion in this section, there is ample evidence that the relations between spread changes and the determinants are not constant over time. The $t$-statistics in the last column of Table 4, which report the results of a test of equality of the coefficients in both subperiods, corroborate this. We take this observation into account in the remainder of this paper where the joint explanatory power of the variables is explored. Although we still report results for the entire period, we will continue supplementing them with the sub period results. In addition, we present more detailed evidence about the time variation of the effects by studying rolling regressions.

4.3 Multivariate Analysis

In our multivariate approach, reported in Table 5, we first assess the relative importance of the three blocks of risk drivers we advanced: the credit risk, the liquidity risk, and the business cycle and market wide variables. We report results for the overall period and our full sample of banks, as well as results for sub samples based on ratings and two time periods.

In the overall period, the credit risk variables are able to explain up to 11.79% of the variation in CDS spread changes across all banks. Similar to the univariate analysis, the risk free rate and the leverage variable carry the right sign, but only leverage stands out with respect to statistical significance. Since CDS spreads are intimately related to credit risk, we will keep these three variables in our model regardless of their performance. The second panel retakes the results of the bid-ask spread from the univariate analysis, explaining 10.54%. The last panel shows that the business cycle and market related variables explain 15.23%. Term structure slope, swap spread and market returns carry the right sign. Two of them, the swap spread and the market return, also are statistically significant. In contrast to the univariate results, the term structure slope now reflects the expected negative relationship with the changes in CDS spreads. The results for the corporate bond spread and market volatility are disappointing.

Looking at the sub periods, the explanatory power of all three blocks of variables is very low in the pre-crisis period, as it ranges from 0.3% to 3.6%. In the crisis period, however, adjusted $R^2$’s vary from 12.04% to 17.88%. In both sub periods, the signs of the estimated coefficients remain consistent with those of the overall period except for the corporate bond spread. In the pre-crisis period, it receives the expected positive sign and becomes significant.
The table reports the results of multivariate pooled regressions (no fixed effects) by the subsets of explanatory variables. Robust t-statistics are reported in parentheses. Regressions are run by period and by Fitch long-term rating. The “Adj. R²” rows denote the adjusted R-squared coefficients of the different blocks of explanatory variables. The risk free rate is the weekly change in the Datastream benchmark 2 year government redemption yield measured in percentage points. The leverage is the weekly bank stock return (in percentage points). The equity volatility is measured as the changes in the weekly historical standard deviation computed using the daily stock returns of the underlying bank (in percentage points). The bid-ask spread is the weekly change in the difference between the ask and the bid CDS spread quote measured in basis points. The term structure slope is the weekly change in the difference (in percentage points) between the 10 year and 5 year government redemption yields of the Datastream benchmark series. The corporate bond spread is defined as the weekly change of the difference between the Merrill Lynch 5 year BBB and AAA corporate redemption yield series (measured in percentage points). The market return is proxied by the Datastream euro area stock market index return (in percentage points). Finally, the market volatility is computed based on the weekly change of the VSTOXX index. The pre-crisis period runs from 1 January 2004 to 1 April 2007. The crisis period starts on 2 April 2007 and ends on 22 October 2008.

Similar to the results for the full sample, the results for AA and A rated banks show that the explanatory power of each block of variables jumps to much higher levels when moving from the pre-crisis to the crisis period. Interestingly, the liquidity block explains more for the A-rated banks compared to the AA rated banks in all periods. In contrast, the common factors, i.e. the business cycle and market variables, have more explanatory power for the higher rated banks. In general, all suggested variables except the volatilities and the corporate bond spread, consistently carry the right signs. The corporate bond spread is only correctly related to the CDS spread changes in the pre-crisis period.

So far it is clear that CDS spread changes are not uniquely driven by credit risk related variables. Each of the three risk drivers are able to explain 10%-15% of the variation of the CDS spreads. The kitchen sink regression, reported in Table 6, produces an adjusted R² of about 28%, which is a very reasonable result.
bearing in mind that we work with weekly data and that the banking industry is perceived as being very opaque.

Table 6: Multivariate kitchen sink model

<table>
<thead>
<tr>
<th>Credit Risk Variables</th>
<th>Full period</th>
<th></th>
<th>Pre-Crisis</th>
<th></th>
<th>Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ALL</td>
<td>AA</td>
<td>A</td>
<td>ALL</td>
<td>AA</td>
</tr>
<tr>
<td>Risk free rate</td>
<td>-12.71</td>
<td>-13.94</td>
<td>-12.78</td>
<td>-0.45</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>(-1.54)</td>
<td>(-1.26)</td>
<td>(-1.99)</td>
<td>(-0.36)</td>
<td>(0.45)</td>
</tr>
<tr>
<td>Leverage</td>
<td>-0.44</td>
<td>-0.57</td>
<td>-0.38</td>
<td>0.00</td>
<td>-0.05</td>
</tr>
<tr>
<td></td>
<td>(-1.54)</td>
<td>(-1.56)</td>
<td>(-1.47)</td>
<td>(-0.16)</td>
<td>(-3.16)</td>
</tr>
<tr>
<td>Equity volatility</td>
<td>-1.03</td>
<td>-0.81</td>
<td>-1.02</td>
<td>-0.01</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>(-1.27)</td>
<td>(-0.80)</td>
<td>(-1.34)</td>
<td>(-0.11)</td>
<td>(0.45)</td>
</tr>
</tbody>
</table>

Liquidity

<table>
<thead>
<tr>
<th></th>
<th>Full period</th>
<th></th>
<th>Pre-Crisis</th>
<th></th>
<th>Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ALL</td>
<td>AA</td>
<td>A</td>
<td>ALL</td>
<td>AA</td>
</tr>
<tr>
<td>Bid-ask spread</td>
<td>0.82</td>
<td>0.56</td>
<td>1.18</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(4.05)</td>
<td>(1.79)</td>
<td>(3.71)</td>
<td>(1.09)</td>
<td>(0.31)</td>
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</table>

Business cycle and market wide variables

<table>
<thead>
<tr>
<th></th>
<th>Full period</th>
<th></th>
<th>Pre-Crisis</th>
<th></th>
<th>Crisis</th>
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</thead>
<tbody>
<tr>
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<td>ALL</td>
<td>AA</td>
<td>A</td>
<td>ALL</td>
<td>AA</td>
</tr>
<tr>
<td>Term structure slope</td>
<td>-39.13</td>
<td>-46.45</td>
<td>-41.77</td>
<td>-2.31</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>(-1.90)</td>
<td>(-1.66)</td>
<td>(-2.10)</td>
<td>(-0.71)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Swap spread</td>
<td>115.87</td>
<td>149.16</td>
<td>113.25</td>
<td>6.20</td>
<td>3.15</td>
</tr>
<tr>
<td></td>
<td>(5.89)</td>
<td>(5.60)</td>
<td>(6.10)</td>
<td>(1.22)</td>
<td>(0.80)</td>
</tr>
<tr>
<td>Corporate bond spread</td>
<td>-10.55</td>
<td>-8.17</td>
<td>-16.29</td>
<td>3.68</td>
<td>3.29</td>
</tr>
<tr>
<td></td>
<td>(-1.60)</td>
<td>(-0.97)</td>
<td>(-1.90)</td>
<td>(2.72)</td>
<td>(3.55)</td>
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<tr>
<td>Market return</td>
<td>-0.49</td>
<td>-0.69</td>
<td>-0.18</td>
<td>-0.04</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(-1.03)</td>
<td>(-1.21)</td>
<td>(-0.44)</td>
<td>(-0.68)</td>
<td>(-0.35)</td>
</tr>
<tr>
<td>Market volatility</td>
<td>-0.01</td>
<td>-0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(-1.09)</td>
<td>(-1.66)</td>
<td>(0.02)</td>
<td>(0.69)</td>
<td>(-0.05)</td>
</tr>
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</table>

Adj. R²

<table>
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<th></th>
<th>Full period</th>
<th></th>
<th>Pre-Crisis</th>
<th></th>
<th>Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ALL</td>
<td>AA</td>
<td>A</td>
<td>ALL</td>
<td>AA</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>27.79%</td>
<td>30.60%</td>
<td>36.48%</td>
<td>5.00%</td>
<td>7.86%</td>
</tr>
<tr>
<td>Nobs</td>
<td>4484</td>
<td>2143</td>
<td>1794</td>
<td>2904</td>
<td>1384</td>
</tr>
</tbody>
</table>

P values Wald tests

<table>
<thead>
<tr>
<th></th>
<th>Credit risk variables</th>
<th>Liquidity</th>
<th>Bus. cycle &amp; market wide</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>6.51%</td>
<td>6.15%</td>
<td>8.17%</td>
</tr>
<tr>
<td></td>
<td>0.01%</td>
<td>7.27%</td>
<td>0.02%</td>
</tr>
<tr>
<td></td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

The table reports the results of the multivariate pooled regressions (no fixed effects). Robust t-statistics are reported in parentheses. Regressions are run by period and by Fitch long-term rating. The “Adj. R²” row reports the adjusted R-squared coefficients and the “Nobs” row denotes the number of observations. The sum of AA and A-rated observations does not equal the total, as the sample also includes observations for which the rating was either missing or BBB. The risk free rate is the weekly change in the Datastream benchmark 2 year government redemption yield measured in percentage points. The leverage is the weekly bank stock return (in percentage points). The equity volatility is measured as the changes in the weekly historical standard deviation computed using the daily stock returns of the underlying bank (in percentage points). The bid-ask spread is the weekly change in the difference between the ask and the bid CDS spread quote measured in basis points. The term structure slope is the weekly change in the difference (in percentage points) between the 10 year and 5 year government redemption yields of the Datastream benchmark series. The corporate bond spread is defined as the weekly change of the difference between the Merrill Lynch 5 year BBB and AAA corporate redemption yield series (measured in percentage points). The market return is proxied by the Datastream euro area stock market index return (in percentage points). Finally, the market volatility is computed based on the weekly change of the VSTOXX index. The pre-crisis period runs from 1 January 2004 to 1 April 2007. The crisis period starts on 2 April 2007 and ends on 22 October 2008.

The significance of the risk free rate and the leverage almost vanishes. Although our liquidity proxy (bid-ask spread) loses a bit of statistical significance, the relationship remains very strong and positive. The
business cycle and market related variables show some puzzling findings. Many authors find the term structure slope to be ill-behaved. Either it is not significant or its sign depends on the exact regression specification and the choice of other explanatory variables (Avramov, Jostova & Philipov (2007)). For the full sample, the slope coefficient is negative and almost significant at the 5% level. Consistent with Düllmann & Sosinska (2007) the swap spread is positively and significantly related to bank CDS spread changes. The results for the stock market variables, the market return and the market volatility, are disappointing. The market return coefficient becomes non significant and market volatility retains its (insignificant) negative sign. These results are consistent with those reported for European financial Itraxx CDS index spread changes by Alexander & Kaeck (2008). Market volatility nor stock market return has a significant influence on spread changes (although the former’s sign is positive).

Breaking down the sample according to rating confirms that our model has a somewhat better explanatory power for A-rated banks than for AA-rated banks (adjusted $R^2$ of 36.5% versus 30.6%). All variables (except for the market volatility) keep the same sign as the regression performed on the full period. The relationship between the explanatory variables and the CDS spread changes is in general somewhat stronger. Note the increased economic importance of some variables: the coefficient of the bid-ask spread and the corporate bond spread doubles when a bank moves from an AA rating to an A rating.\(^\text{10}\)

Splitting the sample in the pre-crisis and the crisis period again reveals a highly time varying behavior of the parameter estimates. While some coefficients lose their statistical significance (e.g. the risk free rate for A-rated banks), others become prominent determinants (e.g. the corporate bond spread). In order to illustrate the time variation, we perform a rolling regression analysis of our kitchen sink model. We run the rolling regressions with various window sizes (26, 52 and 104 weeks). Taking into account the very similar results, we report the one-year (52 weeks) window. Figure 2 reports the time series of the regression coefficients. The shaded areas represent the periods during which the coefficient is statistically significant at the one-sided 95% confidence level. The graphs confirm the widely time varying character of the credit risk drivers. In general, the volatility of the parameter estimates severely increased since the outbreak of the crisis. For the credit risk block, the rolling regressions show that especially during the crisis period, credit risk variables became significant drivers of credit risk. The coefficients of both the risk free rate and the leverage hover around zero in the pre-crisis period but they become strongly negative during the crisis. Note that the coefficient of the equity volatility predominantly carries a positive sign (albeit not significantly different from zero). Liquidity clearly not only plays a role during crisis situations. In the crisis period, its coefficient, however, reaches levels that quadruple vis-à-vis the pre-crisis period. This is consistent with the results of Beber, Brandt & Kavajecz (2009) who study sovereign bond yield spreads for the euro area. They find that the role of liquidity is nontrivial, especially in times of heightened market uncertainty. Swap and corporate bond spreads both carry positive coefficients during substantial periods. The stock market return and volatility show

\(^{10}\) Even though the results for A banks are somewhat stronger, they do not markedly differ from those for AA banks. A reason for this may be that AA and A banks have very similar probabilities of default. Existing studies on the determinants of CDS spreads often find more divergent results for firms which belong to rating categories whose probabilities of default lie much further apart (e.g. AA and BBB).
strange results. The stock market return coefficient is most of the time slightly negative but it swings to large (anomalously) positive values at the start of the crisis. The coefficient of market volatility is predominantly positive but only gains statistical significance during very short periods.

Figure 2: Regressions by group of explanatory variables
The table reports the results of multivariate pooled regressions (no fixed effects) by the subsets of explanatory variables. Robust t-statistics are reported in parentheses. Regressions are run by period and by Fitch long-term rating. The “Adj. R²” rows denote the adjusted R-squared coefficients of the different blocks of explanatory variables. The risk free rate is the weekly change in the Datastream benchmark 2 year government redemption yield measured in percentage points. The leverage is the weekly bank stock return (in percentage points). The equity volatility is measured as the changes in the weekly historical standard deviation computed using the daily stock returns of the underlying bank (in percentage points). The bid-ask spread is the weekly change in the difference between the ask and the bid CDS spread quote measured in basis points. The term structure slope is the weekly change in the difference (in percentage points) between the 10 year and 5 year government redemption yields of the Datastream benchmark series. The corporate bond spread is defined as the weekly change of the difference between the Merrill Lynch 5 year BBB and AAA corporate redemption yield series (measured in percentage points). The market return is proxied by the Datastream euro area stock market index return (in percentage points). Finally, the market volatility is computed based on the weekly change of the VSTOXX index. The pre-crisis period runs from 1 January 2004 to 1 April 2007. The crisis period starts on 2 April 2007 and ends on 22 October 2008.

A simple but yet instructive way to assess the importance of each variable is proposed by Düllmann & Sosinska (2007). In order to determine the relative importance of various risk drivers, we measure the marginal contribution $mc_k = R^2 - R_k^2$, of the $k$th risk driver block (credit, liquidity, market and business cycle) to the total $R^2$. $R_k^2$ is the $R^2$ of the kitchen sink regression, when the variables of the $k$-th block are omitted. The ratio

$$\frac{R^2 - R_k^2}{\sum_{k=1}^{K} (R^2 - R_k^2)}$$

gives the relative contribution of these blocks to the sum of the marginal contributions. In order to prevent negative contributions, we focus on the $R^2$ instead of the adjusted $R^2$.

The upper part of Figure 3 shows this decomposition; the lower part of the figure further decomposes the credit risk block in the relative marginal contributions of the Merton variables. Several conclusions emerge. First, we notice that there is substantial time variation in the $R^2$, which becomes close to 0 for about one year, between May 2006 and May 2007. Second, credit risk is not the sole source of CDS spread changes: in most circumstances, it is even not the most important source of the variation. However, the Merton variables did become more important when the credit status of financials was under strain. The lower part of Figure 3 further shows that among the credit risk drivers, big time variations take place. Third, liquidity is priced but especially in conditions of market turbulence. Fourth, the business cycle and market variables also play a non trivial role. Of course their interpretation is less clear since they might disguise both credit and liquidity effects.
The figure on top shows the marginal contributions of the different variable blocks as defined in Table 6. The bottom figure further decomposes the credit risk contribution into its three components. The regressions are run using moving 52 week windows. The dates on the horizontal axes report the ending date of the rolling regressions. The marginal contribution of a single block $k$ is defined as $\left( R^2 - R^2_k \right) / \sum_{k=1}^{K} \left( R^2 - R^2_k \right)$.

5. Policy Recommendations

In recent years, market participants and regulators alike have begun to look to bank credit default swap spreads as indicators of bank credit risk and of the market's "collective view of credit risk" (IMF, 2006). However, like bond spreads, CDS spreads may also reflect other factors, including a liquidity premium, systematic credit risk or risk aversion. This paper presents an empirical analysis of the determinants of euro area bank CDS spread changes before and after the start of the financial crisis. In analyzing changes in CDS premia, we use variables suggested by structural credit risk models as well as an indicator of liquidity in the CDS market and several variables proxying for general economic conditions.

A first result is that the determinants of bank CDS spreads vary strongly across time (but not so much across rating categories). This finding, which echoes similar results in studies for bond spreads, implies that models which attempt to explain changes in bank CDS spreads must be re-estimated frequently in order to give the right "signals". This is especially important since supervisors and monetary policy makers may take different actions depending on whether changes in CDS spreads appear to be driven by credit risk, liquidity or business cycle factors.
A second finding is that the variables suggested by structural credit risk models became significant drivers of CDS spreads mostly after the start of the crisis, as shown by the rolling regressions. In addition, some of the variables proxying for general economic conditions are significant, but the sign of the coefficient estimates or their significance changed when the crisis started. These findings suggest that policy-makers should not rely solely on financial institutions’ CDS spreads to monitor their credit risk. Ideally, the behavior of CDS spreads should be examined together with other market indicators (e.g. Expected Default Frequencies, equity prices, etc.) to arrive at an accurate assessment.

Third, CDS market liquidity appears to play a role both before and after the start of the crisis in explaining euro area bank CDS spread changes, as evidenced by the rolling regressions. This finding suggests that the role of CDS market liquidity should explicitly be taken into account when analyzing CDS spreads. Most existing studies still treat liquidity as being part of the regression residual.

Finally, the fact that our model’s explanatory power vanishes around May 2006 is in line with the analysis produced by the IMF in its 2007 Global Financial Stability Report (see IMF, 2007). The IMF noticed several manifestations of strong risk appetite which may have led to severe underestimation of economic risks or overestimation of liquidity in levered instruments in the second part of 2006. The fact that our credit spread model starts losing any explanatory power around the same period simply corresponds to the lack of credit risk pricing.
6. References


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