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Liquidity and CDS premiums on European companies around the Subprime crisis

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Abstract This paper sheds new light on the liquidity dynamics of the credit default swaps (CDS) market in Europe around the Subprime crisis. Based on an original dataset of 94 European companies from 2005 to 2009, we use a panel regression analysis to study the relationship between CDS premiums and liquidity. We measure the level of liquidity, look at liquidity risk, and study the liquidity spillovers from the bond and equity markets to the CDS market. We show that the effect of liquidity on CDS premiums is dominated by the influence of worsening credit conditions and deteriorating investors' expectations about default risk. Controlling for credit risk, we also find that liquidity risk is priced in the European CDS market and that liquidity spillovers from the bond market matter in determining CDS premiums.

Keywords CDS · Liquidity · Subprime crisis

JEL Classification C58 · G1

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1 Introduction

Liquidity is an important topic in capital markets. There are two main advantages provided by a liquid market: improved allocation and information efficiency. Liquidity implies that investors are able to quickly buy or sell a financial product whenever they want and at a fair price. A liquid market also provides more accurate prices as it better reflects the expectations and perceptions of many different investors. It allows investors to better conduct their investment strategy and manage their risk.

Liquidity is not only important by itself, but also because of the comovements in liquidity across assets. Seminal studies by Chordia et al. (2000) and Hasbrouck and Seppi (2001) have indeed provided evidence of significant commonality in liquidity. Amihud (2002) and Pastor and Stambaugh (2003) made the link between expected stock excess return and changes in market liquidity, suggesting an "illiquidity premium", thus showing that systematic liquidity is important for asset pricing. This set of studies has led Acharya and Pedersen (2005) to propose the first liquidity-adjusted capital asset pricing model (LCAPM), where a security's required return depends on its expected liquidity as well as on the co-variances of its own return and liquidity with the market return and liquidity.

Commonality in liquidity is of particular concern in stressful market conditions. The last financial crisis has indeed shown that dramatic shifts in liquidity across assets (and asset classes) can occur at a very rapid pace. Liquidity can dry very quickly and take a long time to recover.

This paper focuses on liquidity on the credit default swaps (CDS) market, using data that partially cover the recent Subprime crisis. The CDS market is often considered as being rather illiquid; compared to the equity markets, CDS bid-ask spreads are indeed usually higher. The CDS market OTC nature also makes it a non-continuous market where investors have to wait for the next trader if they want to close their deal.

Market liquidity can drop very quickly in stressful market conditions, especially for financial instruments, such as CDS, of which trading is over-the-counter and heavily depends on the degree of confidence between counterparties. As CDSs have been used by a growing pool of investors around the world, they have become increasingly scrutinized by regulatory bodies which must now face the need to better understand the dynamics of credit derivatives in general. Much still needs to be done. The liquidity of CDSs has been scarcely studied in the recent past and it comes as no surprise that the consequence of the Subprime crisis on this market has not been fully understood yet.

The liquidity of CDSs and its impact on prices has been studied in a few papers only. The most comprehensive study has been performed by Tang and Yan (2006, 2008). The objective of this paper is to carry out a similar analysis on the European market by exploiting a unique dataset of 94 European corporate CDSs during the period 2005–2009. In particular, we aim to shed new light on the dynamics of CDS liquidity in stressful market conditions.

Our empirical study based on panel data regressions is divided in three sections. First, we study the relationship between CDS premiums and liquidity levels, controlling for credit risk. Two liquidity proxies are used: the proportional quoted bid-ask spread and the frequency of quote updates. Consistent with previous papers, we find that illiquidity increases CDS premiums, using either one or the other proxy.

Second, we focus on the relationship between CDS premiums and liquidity risk, which is proxied by the betas of the Acharya and Pedersen (2005) liquidity-adjusted capital asset pricing model (LCAPM). Our results show that liquidity risk is priced in the CDS market, and is even more important than the traditional CAPM beta. Third, we look at liquidity spillovers from the bond and equity markets to the CDS market. While we find a positive spillover from bond illiquidity to CDS premiums, there is no significant relationship between liquidity on the equity market and CDS premiums. All in all, those results show that the relationships between CDS liquidity and CDS premiums that has been documented for US markets during tranquil periods also show up in Europe both at tranquil and turbulent times.

This paper is structured as follows. In Sect. 2, we provide a review of the literature on CDS premiums. We cover the role of CDS versus bonds as credit measures, the relationship between liquidity and CDS premiums and the importance of liquidity in financial crisis periods. Section 3 presents the data on CDS premiums and liquidity proxies and provides descriptive statistics for our sample. Section 4 presents the selected control variables for credit risk, describes the methodology and details the empirical results on the influence of liquidity level, liquidity risk and liquidity spillover on CDS premiums. Concluding remarks are given in Sect. 5.

2 Literature review

Credit risk is the risk that a reference entity might default and fail to reimburse its debts. When CDS did not exist, bonds were the only financial products which provided a measure of credit risk through their spread over the risk free-rate. However, bonds were not good proxies of credit risk as their spreads were also subject to interest rate risk, liquidity risk and taxes. For example, Collin-Dufresne et al. (2001) find that credit risk variables, extracted from structural models, could only explain one quarter of the variation in bond spreads. They show that other factors, unrelated to credit risk, are also impacting the bond spread.

When the CDS market became more liquid, researchers and practitioners started using CDS premiums as a pure measure of credit risk based on the no-arbitrage theory and on the fact that CDS premiums are not influenced by interest rate risk as bonds are. The assumption that CDS premiums are a pure measure of credit risk has been used by researchers to address several issues. Aunon-Nerin et al. (2002) aim at analyzing the factors influencing credit risk. By regressing their premiums on credit risk factors extracted from structural form models, they can explain 82 % of the variation in CDS premium which is much better than the results obtained by Collin-Dufresne et al. (2001) for the bond market. Houweling and Vorst (2005) assess the performance of reduced-form models to calculate credit risk. They use reduced-form models to price CDS using parameters from the bond market and obtain more efficient results than simply comparing bond's credit spreads to CDS premiums.

Longstaff et al. (2005) find that the credit risk implied from the CDS market is lower than the one implied from the bond market. They conclude that bond spreads include other factors than credit risk such as tax and illiquidity. They also show that the CDS market reacts faster to changes in credit risk than the bond market. Blanco et al. (2005) support the view that bond spreads and CDS premiums are closely interlinked.

When they are not, CDSs are found to be more efficient in the short-run, as credit risk variables better explain their premium than the bond spread. Using a panel data technique to explain the price difference between the two markets, Zhu (2006) finds that CDS premiums lead the bond market in the short-run.

Even though there is ample evidence that CDS premiums are a cleaner measure of credit risk than bond spreads, some studies show that those premiums are plagued by liquidity issues and might not be such a perfect measure of credit risk. For example, Berndt et al. (2005) find that an average of 33 basis points in CDS premiums are not explained by credit risk, as measured by Moody's KMV's EDF indicator, which is a widely used measure of forward default probabilities.

The first direct analysis of CDS liquidity has been conducted by Chen et al. (2011) who use the frequency of price updates as liquidity proxy. Using a term structure approach to estimate the impact of various factors on CDS premiums, they find that the liquidity premium for the protection buyer can be significant and that liquidity risk is priced in the CDS market.

Tang and Yan (2008) provide a more systematic study of the liquidity effect on CDS premiums. Performing different types of regressions (including control variables for credit risk), they show that the impact of liquidity is significant, regardless of the different liquidity proxies used. Applying the liquidity-adjusted CAPM to CDS quotes, they find the effect of liquidity risk to be significant. Finally, they identify a liquidity spillover from the bond, stock and stock options markets to the CDS market.

Another line of studies is based on reduced-form models to model default time. Buhler and Trapp (2006) use a reduced-form model of credit risk which takes into account liquidity factors for the corporate bond and CDS markets. They find that bonds and CDS have the same credit risk but different liquidity premiums. They later extended their model to a reduced-form model incorporating correlation between bond and CDS liquidities, on the one hand, and between default and bond/CDS liquidity, on the other hand (Buhler and Trapp 2008). Their results demonstrate that credit risk bears on bond and CDS liquidity: when credit risk increases, liquidity decreases. They also find, as in Tang and Yan (2006), evidence of a liquidity spillover between the bond and CDS market. All in all, credit risk and liquidity components represent 95 and 4 % of the CDS premium respectively. For bonds, the values are 60 and 35 %. Correlation between credit risk and liquidity on the CDS and bond markets also has an impact of respectively 1 and 5 %.

In Chen et al. (2010), bid-ask spreads are found to be 'too large' in the CDS market for the CDS premium to be considered as a pure measure of credit risk. Using a similar method to Buhler and Trapp (2006), they use hazard rates to calculate bond spreads, incorporating CDS liquidity factors. When the liquidity effect in CDS premiums is appropriately taken into account, they find that CDS premiums can be used as a reliable guide to analyze corporate bond spreads: once liquidity is taken into account, the bond and CDS markets exhibit the same value for credit risk.

Bongaerts et al. (2011) do not rely on reduced-form models, but instead use a modified version of the Acharya and Pedersen (2005) LCAPM to analyze the liquidity impact. This model includes the effects of expected liquidity and liquidity risk. Using CDS data, they find that both are priced in CDS premiums and that the effect of expected liquidity is stronger than the effect of liquidity risk.

Finally, Pu (2009) focuses on the commonality in liquidity across the bond and CDS markets. He applies a factor decomposition analysis for different measures of CDS and bond liquidities in order to check whether there is a common liquidity factor that affects credit spreads. Strong evidence of commonality across the two markets is found, which could explain the non-default component of CDS premiums.

Little has been written on the liquidity of CDSs during the Subprime crisis. Predescu et al. (2009) have presented some preliminary results based on Fitch CDS liquidity scores. These are aggregates of different liquidity proxies, such as inactivity and staleness of quotes, dispersion of mid-quotes across contributors, and scaled bid-ask spread.

The Subprime crisis has led to severe liquidity drops in the OTC markets. The CDS market itself has been strongly affected by liquidity shocks. CDS premiums increased substantially in all sectors during 2008 and 2009. Bid-ask spreads were also under pressure. Bongaerts et al. (2011) note that market participants were extremely reluctant to take on positions in CDS contracts. Protection sellers were hard to find despite the relatively high premiums that were offered.[1] They also add that the lack of resilience of OTC markets has been attributed to inadequate regulation, as well as to the absence of designated market makers or dealers. Lax regulation is argued to have led dealers to commit too little market making capital (Lagos et al. 2009).

Those issues have led to the release of new guidelines by regulatory bodies with respect to liquidity risk management. For example, such guidelines can be found in ‘Principles of Sound Liquidity risk Management and Supervision’ by the Basel Committee (September 2008) and ‘Strengthening Liquidity Standards’ by the Financial Services Authority in the UK (December 2008). In the former, the Basel Committee argues that many institutions have “failed to take account of a number of basic principles of liquidity risk management when liquidity was plentiful. Many did not have an adequate framework that satisfactorily accounted for the liquidity risks posed by individual products and business lines […] Many firms viewed severe and prolonged liquidity disruptions as implausible and did not conduct stress tests that factored in the possibility of market wide strain or the severity or duration of the disruptions.” The Basel Committee thus provides guidance for managing liquidity risk. They focus on “the necessity of allocating liquidity costs, benefits, and risks to all significant business activities; the identification and measurement of the full range of liquidity risks, including contingent liquidity risks, the management of intraday liquidity risk and collateral.”

In this paper, special attention is given to liquidity risk within the CDS market as well as liquidity spillover between markets. This is of particular relevance since the financial crisis has emphasized the highly correlated nature of illiquidity. Our study contributes to the existing literature by characterizing CDS liquidity dynamics on European companies in periods of financial trouble. The key questions addressed in this paper are: To what extent does liquidity bear on European corporate CDS premiums in stressful market conditions? Are there significant liquidity spillovers between the CDS, bond, and equity markets in these circumstances?

[1] There are no rules regulating liquidity provision in OTC markets, contrary to some exchange-traded markets where market makers have to propose firm prices at both bid and offer sides. In OTC markets, liquidity provision is done on a voluntary basis.

3 Data and descriptive statistics

3.1 CDS data

The dataset includes corporate and sovereign CDSs that were traded by a major European Investment Fund since 2006. Before 2006, the Fund did not use this kind of product to hedge their debt portfolio. The corporate and sovereign CDSs included in the portfolio refer to 371 different underlying bonds. We use the ISIN of bonds which are unique, instead of the multiple CDS codes. There can be up to 100 different CDS codes for the same product. We focus on euro-denominated CDSs. We strictly focus on corporate CDSs since the dynamics of sovereign CDSs may be argued to be different. The set is now composed of 257 different fixed-income securities. From those, the name of the company is extracted.

We then collect the codes for both the company's 5-year senior CDS and equity from Bloomberg. CDS daily prices since 2005 are downloaded. If there are missing data either for the CDS, the equity, or other variables (such as equity volatility or leverage), the company is eliminated from the dataset. The number of relevant CDSs falls down to 94. For each of these 94 CDSs, the daily closing premium, last bid quote, and last ask quote are retrieved over the period January 2005 to December 2009. Prices are given in basis points.

CDS liquidity is not easily measured because CDSs are not traded on centralized exchanges (yet). Data about trades and volume are often proprietary or incomplete which makes it hard to find relevant information. Among the scarce literature attempting to measure CDS liquidity, different proxies have been used. Those are quote updating frequency (Chen et al. 2011), volatility-to-volume ratio, number of contracts outstanding, trade-to-quote ratio (Tang and Yan 2008), half the quoted spread (Bongaerts et al. 2011), number of trades, and proportional quoted bid-ask spread (Chen et al. 2010),

Based on the data we have at hand, three liquidity proxies can be computed: the absolute quoted bid-ask spread, the proportional quoted bid-ask spread and the quote updating frequency. The absolute quoted bid-ask spread is computed as $\text{Ask}_{\text{quote}} - \text{Bid}_{\text{quote}}$, while the proportional quoted bid-ask spread is calculated as:

$$\text{Prop}_{\text{spread}} = \frac{\text{Ask}_{\text{quote}} - \text{Bid}_{\text{quote}}}{\frac{\text{Ask}_{\text{quote}} + \text{Bid}_{\text{quote}}}{2}}$$

Quote updating frequency is calculated as the number of days that have non-zero daily quote differences per month (Chen et al. 2011). This number is divided by the total number of days in a month to have standardized measures. When the quote updating frequency is equal to 1, it means that liquidity is maximal for that month. If it is equal to 0, it means perfect illiquidity.

3.2 Other data

Based on the equity ticker, we download different information related to the company from Bloomberg. Those are related to historical performance of the company.

The daily measures are the daily closing prices, bid and ask quotes, daily volume of transaction, number of shares outstanding, total shareholder equity, historical option-implied volatility, 30-day volatility, book value per share, total of all short and long term debts, and market capitalization. As described more precisely in Sect. 5, these data are used as equity liquidity proxies and control variables.

The ratings related to the company's bonds are extracted from Thomson Reuters. We select the senior bonds with no embedded option and with issue dates and maturities close to January 2005 and December 2009 respectively. The issue and maturity dates are used to calculate two bond liquidity proxies: age and time-to-maturity. In addition, Reuters provides ratings from Moody's, Standard and Poor's, Fitch Ratings and Dominion Bond Rating Services. We keep all of them as these companies change their ratings at different times and each change may have an impact on the way investors judge a company's ability to reimburse its debts. We use the Bank of International Settlements' Rating Scales Comparison to harmonize the four different ratings into only one scale.

3.3 Descriptive statistics

Table 1 shows the dispersion of quotes according to the different ratings. Most of the companies in our sample are rated BBB (35 %) and A (32 %). By splitting the sample into two time periods (before and after July 2007), we see that the percentage of companies rated below BBB has increased from 4 to 11 % and the companies rated above BBB has decreased from 48 to 41 %. As the companies are identical in the two samples, this indicates that many companies have seen their rating downgraded after July 2007.

Table 2 presents the average CDS premiums in our sample by groups of rating. As expected, CDS premium rises as the rating declines. For example, the average premium is 54.93 basis points for the AAA-rated group and 1250.38 basis points for the C-rated group. If ratings and CDS premiums are measures of risk, their relationship is expected to be close.

Splitting the sample in two periods, we see in Table 2 that the average premium for all rating categories increases after July 2007. In the second subsample, the premium of AAA-rated companies is higher than for AA-rated companies. One likely explanation is that CDS premiums may react to news more promptly than credit ratings. As suggested by Hull et al. (2004), the CDS market would anticipate rating announcements, especially negative rating events. The only possible rating change for AAA bonds is downgrading. So, for this class of highly rated bonds, the market would particularly succeed in incorporating information into CDS premiums before rating agencies could adjust the ratings of the corresponding reference entities.

Figure 1 shows the evolution of the average CDS transaction prices between January 2005 and December 2009. Premiums started rising slowly around the summer of 2007 before reaching a peak in May 2009. The average premium first raised to a maximum of 192.01 basis points in March 2008, then decreased until 133.72 before rising again after September 2008, which corresponds to Lehman's bankruptcy and

Table 1 Distribution of the number of CDS quotes by rating group

	ALL		Before July 2007		After July 2007	
AAA	985	0.8 %	688	1.1 %	299	0.5 %
AA	14, 688	12.0 %	7, 179	11.8 %	7, 509	12.3 %
A	39, 599	32.4 %	21, 772	35.6 %	17, 827	29.1 %
BBB	43, 210	35.3 %	19, 309	31.6 %	23, 901	39.0 %
BB	5, 943	4.9 %	2, 080	3.4 %	3, 863	6.3 %
B	1, 884	1.5 %	303	0.5 %	1, 581	2.6 %
C	1, 692	1.4 %	251	0.4 %	1, 441	2.4 %
NR	14, 353	11.7 %	9, 511	15.6 %	4, 848	7.9 %
Total	122, 354	100 %	61, 093	100 %	61, 269	100 %

Note The first two columns give results for the entire time sample (value and percentage), the third and fourth columns give results between January 2005 and July 2007 and the last two columns give results between July 2007 and December 2009. Ratings go from AAA to C, AAA being the highest and C the lowest. *NR* non-rated

Table 2 Distribution of average CDS premium in basis points by rating group

Rating	All	Before	After
AAA	54.93	9.39	159.70
AA	53.09	12.11	92.27
A	58.33	24.08	100.06
BBB	104.62	49.81	148.82
BB	322.85	127.63	427.78
B	850.04	262.66	961.84
C	1250.38	379.70	1401.48
NR	105.17	89.90	146.90

Note The first column give results for the entire time sample, the second column give results between January 2005 and July 2007 and the last column give results between July 2007 and December 2009. Ratings range from AAA to C, AAA being the highest and C the lowest. *NR* non-rated

AIG's bailout. The highest point was hit in March 2009 with an average premium of 414.70 bps. Since then, premiums have been slowly decreasing.

Table 3 shows that the average absolute quoted bid-ask spread represents 8 basis points on average for the whole sample. It increases as the rating deteriorates, from 5 basis points for A-rated CDSs to 72 basis points for C-rated CDSs. Houweling and Vorst (2005) find similar results for US-denominated CDSs, from May 1999 to January 2001. We also observe that after July 2007, both the CDS premium and the bid-ask spread widen, the latter increasing from 4 basis points to 12 basis points on average.

To have a better evaluation of the dynamics of the bid-ask spread for each rating group, we can compare it to the mid-quote. Table 4 shows that the proportional bid-ask spread is declining with the rating, demonstrating the improvement of liquidity as ratings decline, for both time periods in the sample. For AAA-rated contracts, the bid-ask spread amounts to 24 % of the quote whereas for C-rated contracts, the bid-ask spread

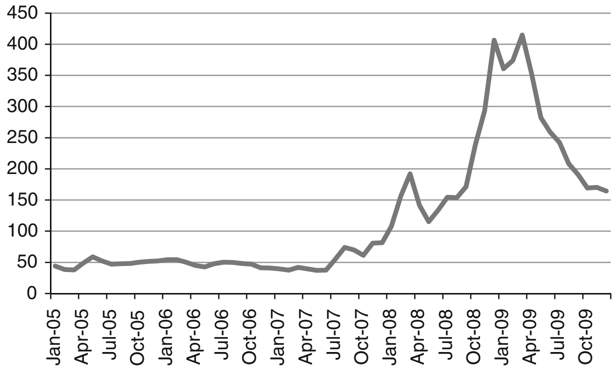

Fig. 1 Market average CDS premium (in basis points) between January 2005 and December 2009. *Note* The sample includes 94 euro-denominated CDS for European contracts with reference issues being senior unsecured bonds

Table 3 Distribution of CDS average absolute quoted bid-ask spread by rating group

Quoted bid-ask spread	All	Before	After
AAA	5.01	2.74	10.25
AA	5.04	2.82	7.15
A	5.19	3.61	7.10
BBB	6.90	4.15	9.12
BB	17.97	7.51	23.60
B	44.34	11.59	50.57
C	72.66	10.60	83.42
NR	8.87	7.52	11.54
Average	8.36	4.48	12.23

Note Results for the entire time sample are reported in the first column; results between January 2005 and July 2007 are reported in the second column, while the last column includes results between July 2007 and December 2009. Ratings range from AAA to C, AAA being the highest and C the lowest. *NR* non-rated

only amounts to 5 % of the quote. This can be explained by the fact that investors are more willing to seek protection against companies that are low-rated and hence more likely to default, which contributes to the improvement of liquidity for this group of ratings. After July 2007, the average proportional bid-ask spread seems lower for all rating groups, except for B and C-rated groups. For AAA-rated group, the bid-ask spread after July 2007 amounts only to 10 % of the quote, instead of 30 % before the start of the crisis. For C-rated group, the bid-ask spread represents 5 % instead of 3 % before. This could be explained by the fact that since the crisis, investors are less keen on trading lower rated companies: They would instead focus on CDSs related to highly rated companies, which exhibit lower risks. Interestingly, even though B and C-rated groups become slightly more illiquid after July 2007, all the other groups become much more liquid. In general for all ratings, liquidity has improved from 15 to 7.7 %.

Figure 2 shows the evolution of the average CDS quoted bid-ask spread which increases from July 2007 to January 2009, pointing to worsening liquidity conditions

Table 4 Distribution of CDS average proportional quoted bid-ask spread by rating group

Proportional quoted bid-ask spread (in %)	All (%)	Before (%)	After (%)
AAA	23.6	29.5	9.8
AA	17.9	27.1	9.1
A	14.0	18.6	8.5
BBB	8.1	9.0	7.1
BB	6.1	6.3	6.0
B	5.3	4.6	5.4
C	5.1	2.9	5.6
NR	12.4	14.1	8.9
Average	11.0	15.0	7.7

Note The first column give results for the entire time sample, the second column give results between January 2005 and July 2007 and the last column give results between July 2007 and December 2009. Ratings range from AAA to C, AAA being the highest and C the lowest. *NR* non-rated

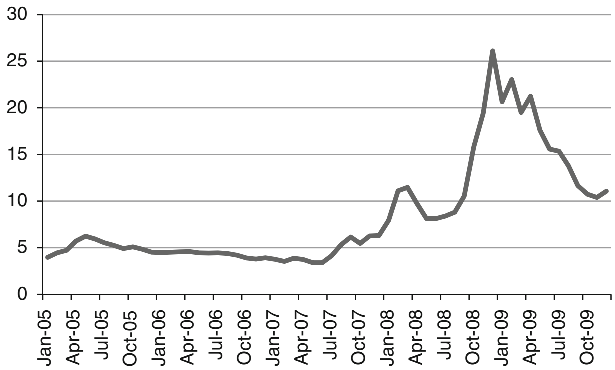

Fig. 2 Evolution of CDS market quoted bid-ask spread between January 2005 and December 2009. *Note* The sample is the same as in Fig. 1

in absolute terms. However, when adjusting this measure to the mid-quote, it can be seen that the proportional measure of the bid-ask spread falls down (Fig. 3). From January 2009, the absolute spread decreases while the proportional spread stabilizes.

The frequency of quote updates follows the same pattern as the proportional bid-ask spread (Fig. 4). Compared to 2006, quotes are updated more frequently in 2007. The frequency of quote updates points to improved liquidity in the few months preceding the crisis. The market has nevertheless been through several illiquidity peaks since the summer of 2007 (December 2007, August 2008 and December 2008).

The preceding figures reveal interesting features about the state of liquidity in the European corporate CDS market. When rumors of a housing market meltdown in the US crisis started to spread around the world, investors' perception of default probabilities deteriorated. This had a significant impact on the absolute level of the bid-ask spread on the CDS market. However, the proportional bid-ask-spread is a better measure of the cost of liquidity per contract (in euros), as it is measured against the cost of

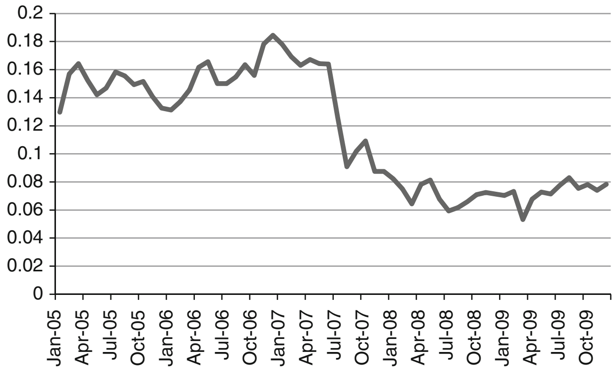

Fig. 3 Evolution of the CDS market proportional quoted bid-ask spread between January 2005 and December 2009. *Note* The sample is the same as in Fig. 1. When the proportional quoted bid-ask spread increases, liquidity decreases

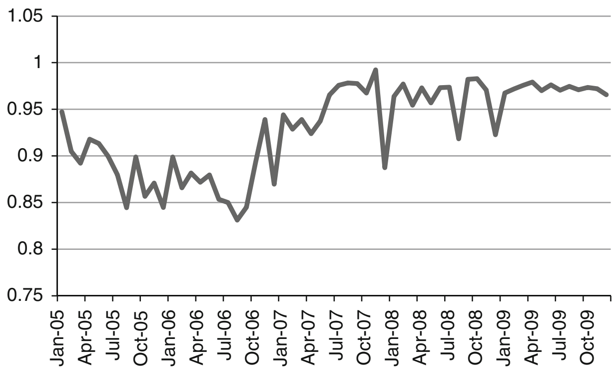

Fig. 4 Evolution of CDS market frequency of quote updates per month between January 2005 and December 2009. *Note* The sample is the same as in Fig. 1. When the frequency of quote updates increases, liquidity increases

buying a protection against default (in euros). Interestingly, the proportional bid-ask spread decreases after July 2007 and slightly widens from September 2008 onwards.

4 Empirical analysis

In this section, we first describe the proxies for credit risk that we use as control variables in the analysis of CDS premiums. We then turn to the empirical analysis itself, which is divided in three parts: the analysis of liquidity levels, the role of liquidity risk and the potential liquidity spillover from the bond and stock markets to the CDS market.

4.1 Control variables

Different factors can be directly related to the credit risk component of the CDS premiums. A good understanding of those factors is important in order to extract the default risk component of the spreads and better examine the liquidity risk component. Those factors should be sufficient to efficiently characterize the credit risk component.

Many authors have studied credit risk and the variables influencing it, either using bond spreads or CDS premiums. Collin-Dufresne et al. (2001) use spot rate, the slope of the yield curve, leverage, option-implied volatility, and business climate (S&P500 returns) to study the influence of credit risk on bond spreads. Aunon-Nerin et al. (2002) use factors extracted from structural models to study the CDS premium. Those factors are credit ratings, interest rate, slope of the yield curve, time-to-maturity, stock returns, variance of the firm's assets, leverage, index returns and idiosyncratic factors (sovereign/corporate, US/non-US).

Based on the literature as well as on data availability, we select the following variables as controls for credit risk: credit ratings of related senior unsecured bonds, stock returns, option-implied volatility, leverage, firm's size proxied by market capitalization, and book-to-market ratio. More details for each of those variables are provided below.

4.1.1 Credit rating

Ratings are attributed to companies and governments by rating agencies, such as Fitch, Moody's, and Standard and Poor's. The rating represents the ability of the reference entity to reimburse its debts in the future. It is an estimate of the default probability of the reference entity. A lower rating implies a higher risk of default. As such, a lower rating will also imply a higher CDS premium as it typically widens when default risk increases. The relationship is expected to be strong: in Aunon-Nerin et al. (2002), credit rating is the most important factor influencing the premium of CDSs. In theory, both measures represent the pure credit risk of a firm and hence should be strongly related. Moreover, Daniels and Jensen (2005) note that the CDS market seems to react faster and more significantly than the bond market to changes in credit rating. However, ratings are not frequently revised and it may be argued that market participants anticipate changes in ratings, which could consequently reduce their explanatory power.

Ratings appear in an alphabetical form (A-B-C) which is not convenient for regressions. Thus they are transformed here into a numerical scale from 1 for the AAA-rating to 17 for C-rating.[2] This methodology was used by Aunon-Nerin et al. (2002).

4.1.2 Stock returns

Stock returns are indicators of the firm value. Credit spreads are expected to decrease with the firm's equity return, *all else equal* (Collin-Dufresne et al. 2001).

[2] The correspondence between numerical and alphabetical scale for ratings is as follows: AAA = 1; AA+ = 2; AA = 3; AA- = 4; A+ = 5; A = 6; A- = 7; BBB+ = 8; BBB = 9; BBB- = 10; BB+ = 11; BB = 12; BB- = 13; B+ = 14; B = 15; B- = 16; C = 17.

Table 5 Results of the regression of CDS premiums on 30-day equity volatility (Vol_30d) using a two-way fixed effects model

	Coefficient	t-statistic
Constant	36.89	28.78
Vol_30d	2.66	72.64
N	122.354	
R^2	0.491	
Adj.R^2	0.485	

Note The dependent variable is the CDS premium. The sample consists of 1,303 days and 94 companies. Both cross-section and period dummy variables are used

Table 6 Results of the regression of CDS premiums on option implied volatility (opt_imp_vol) using a two-way fixed effects model

	Coefficient	t-statistic
Constant	−1.98	−1.38
Opt_imp_vol	3.74	90.35
N	120.040	
R^2	0.599	
Adj.R^2	0.595	

Note The dependent variable is the CDS premium. The sample consists of 1,303 days and 94 companies. Both cross-section and period dummy variables are used

4.1.3 Option-implied volatility

Volatility of the firm value has a direct influence on the probability of default because if idiosyncratic volatility rises, the possibility that the firm value hits the default barrier increases. Campbell and Taskler (2003) find that equity volatility can explain bond spreads as much as credit ratings. Zhang et al. (2009) also find that equity volatility alone can explain 48 % of variation in CDS premiums.

In Bloomberg, there are two available proxies for volatility: the 30-day equity volatility or the option-implied volatility. We perform OLS regressions with time and cross-section dummies and find that the explanatory power of option-implied volatility on CDS premiums is much higher (Tables 5 , 6). Henceforth, this proxy will be used in the subsequent multiple panel regressions.

4.1.4 Leverage

Leverage is expected to have an impact on credit spread as higher leverage raises the probability of default of a firm, due to increased fixed interest payments on debts. In fact, structural models predict that default is triggered when the leverage ratio approaches unity (Collin-Dufresne et al. 2001). We follow Tang and Yan (2008) and compute leverage as follows:

Table 7 Correlation matrix for all control variables

	ln(mkt_cap)	Leverage	B/M ratio	Rating	Eq	Opt_imp volatility	Bidask spread
ln(mkt_cap)	1						
Leverage	0.128	1					
B/M ratio	−0.278	0.275	1				
Rating	−0.540	−0.260	0.030	1			
Eq	−0.050	−0.431	−0.118	0.063	1		
Opt_imp_vol	−0.326	0.193	0.609	0.103	−0.062	1	
Bidask_spread	0.308	0.219	−0.155	−0.472	0.018	−0.313	1

Note Ln(market_cap) is the market capitalization in ln form; B/M ratio is the book-to-market ratio; rating is the rating of the underlying entity; Eq is equity returns; opt_imp volatility is option-implied volatility; bid-ask spread is the CDS proportional quoted bid-ask spread

Table 8 Results of likelihood ratio test and F-test

Effects test	Statistic	d.f.	Prob.
Redundant fixed effects tests			
Test cross-section and period fixed effects			
Cross-section F	762.07	−89.1	0
Cross-section Chi-square	52992.00	89	0
Period F	4.25	−1302.1	0
Period Chi-square	5464.94	1302	0
Cross-section/period F	52.97	−1391.1	0
Cross-section/period Chi-square	56531.57	1391	0

Note The dataset includes 94 euro-denominated CDS on European companies between January 2005 and December 2009

$$\text{Leverage} = \frac{\text{Book value of debt}}{\text{Market value of equity} + \text{book value of debt}}$$

Book value of debt is extracted from Bloomberg as the sum of short- and long-term debts.

4.1.5 Firm size and book-to-market ratio

According to Fama and French (1995), both variables are associated with the probability of default and the level of distress of a firm. Low book-to-market ratio (i.e. a high stock price relative to book value) is typical of firms with high average returns on capital, whereas high book-to-market ratio is typical of firms that are relatively distressed. All else equal, the impact of book-to-market ratio should thus be positive as a higher ratio implies a higher spread. Small-size firms are also more likely to experience default than big companies. Book-to-market ratio is computed as follows:

$$\text{Book-to-market ratio} = \frac{\text{Book value per share} \times \text{number of shares outstanding}}{\text{Current market capitalization}}$$

Table 9 Results of the regression of CDS premiums on control variables and a liquidity proxy using issuer clustering and time fixed-effects

	Specification 1		Specification 2	
	Coefficient	t-statistic	Coefficient	t-statistic
Constant	−470.29	−12.31	−344.66	−2.64
Rating	53.84	24.91	49.54	5.41
Opt_imp_vol	4.25	10.92	4.48	2.50
Leverage	143.92	9.50	175.59	3.04
Ln(market_cap)	−10.11	−5.34	−9.38	−1.07
Eq	0.056	8.08	0.08	1.91
B/M ratio	37.28	1.54	33.01	0.43
Bid-ask spread ($\times 10^2$)	5.17	7.42		
Quote_update ($\times 10^2$)			−0.65	−2.95
N	105.992		4.910	
R^2	0.710		0.615	
Adj.R^2	0.706		0.606	

Note The sample consists of 1,303 days and 94 entities. The dependent variable is the CDS premium. The liquidity proxy is the CDS proportional bid-ask spread (Bid-ask spread) in specification 1 and the frequency of quote updates (quote_update) in specification 2. The control variables for credit risk are: rating (rating), equity returns (eq), option implied volatility (opt_imp_vol), leverage (leverage), market capitalization in ln form (ln(market_cap), and book-to-market ratio (B/M ratio)

The size of the firm is proxied by its market capitalization. Tang and Yan (2008) use market capitalization in logarithmic form in their regressions. In simple two-way fixed-effects OLS panel regressions, we indeed find that the explanatory power of this specification is higher.

4.1.6 Correlation matrix

Table 7 Shows the correlation matrix between the different control variables used in this paper to capture the effect of credit risk. Interestingly, variables seem to be weakly correlated. The highest value equals 0.609 between option-implied volatility and the book-to-market ratio, and the second highest correlation (in absolute value) is −0.54 between rating and market capitalization. Interestingly, there is not much correlation between any of the control variables and the proportional spread.

4.2 Liquidity level and CDS premiums

To assess the effect of liquidity characteristics on CDS premiums, controlling for other credit risk measures, we use the following regression specification:

$$\text{CDS}(i,t) = \alpha + \beta 1 \times \text{CDSLiquidity}(i,t) + \text{Controls}(i,t) + \varepsilon(i,t),$$

Table 10 Results of the regression of CDS premiums on control variables, the CDS proportional bid-ask spread, and the four betas of the LCAPM

	Specification 1		Specification 2		Specification 3		Specification 4	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	−507.253	−3.183	−538.997	−3.188	−647.778	−3.640	−640.079	−3.563
Rating	40.444	2.921	48.342	4.648	53.897	5.455	52.674	4.917
Opt_imp_vol	4.061	2.122	4.508	2.428	4.128	2.195	4.136	2.198
Leverage	90.830	1.662	141.806	2.698	93.223	1.558	97.682	1.718
Ln(Market_cap)	3.111	0.285	−3.155	−0.324	2.736	0.249	2.747	0.249
Eq	0.030	1.098	0.0154	0.581	−0.001	−0.027	−0.004	−0.100
B/M ratio	2.603	0.053	22.808	0.348	11.907	0.208	11.807	0.206
Bid-ask spread ($\times 10^2$)	4.388	2.415	5.776	3.040	3.188	1.649	3.428	1.928
Beta1	13.402	1.47	23.080	2.215			4.474	0.774
Beta2	0.502	1.330						
Beta3	−3.661	−2.600						
Beta4	4.575	0.445						
Bnet					1.967	3.172	1.786	3.030
N	4.910		4.910		4.910		4.910	
Adj.R^2	0.606		0.567		0.590		0.590	

Note The sample consists of 1,303 days and 94 entities. The dependent variable is the CDS premium. The liquidity proxy is the CDS proportional bid-ask spread (Bid-ask spread). The control variables for credit risk are: rating (rating), equity returns (eq), option implied volatility (opt_imp_vol), leverage (leverage), market capitalization in ln form (ln(market_cap), and book-to-market ratio (B/M ratio). Betas 1–4 are the LCAPM's betas. $\beta_{\text{net}} = \beta^1 + \beta^2 - \beta^3 - \beta^4$. The estimation uses a period fixed-effect and issuer-clustered standard errors

where CDS(i, t) is the CDS premium for company i at time t, CDSLiquidity(i, t) is the proxy for CDS liquidity for company i at time t, and Controls are the credit risk control variables for company i at time t, as described in the previous section.

We consider two specifications depending on the liquidity proxy. When using the proportional bid-ask spread, data are computed at the daily frequency. Monthly frequency is applied when we make use of the frequency of quote updates per month as our second liquidity proxy.

Our dataset is a large time-series and cross-section panel, with 1,303 daily observations on 94 entities. The simplest way to estimate the above-mentioned model consists in performing a single pooled OLS regression. However, simple pooled OLS regressions often lead to biased estimators because panel dataset typically exhibit unobserved firm-specific effects, unobserved time-specific effects, or even both. Unobserved firm-specific effects mean that the regression residuals of a firm are correlated across time. Time-specific effects mean that regression residuals for a given time period may be correlated across different firms (Petersen 2009). If the effects are present and ignored, the OLS standard errors would be biased and the residuals would not be independent and identically distributed.

Table 11 Liquidity Spillover from the bond market to the CDS market

	Specification 1		Specification 2		Specification 3	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
Constant	953.38	34.57	1030.46	40.80	980.39	35.79
Rating	63.02	124.3	62.62	124.30	63.94	129.24
Opt_imp_vol	2.81	65.50	2.81	65.49	2.96	75.83
Leverage	132.19	16.71	122.02	15.69	132.70	16.77
Ln(Market_cap)	−171.72	−67.37	−168.11	−67.36	−163.35	−69.92
Eq	0.28	29.47	0.28	29.77	0.28	30.07
B/M ratio	−13.62	−13.24	−13.38	−13.02	−13.35	−12.98
Bid-ask spread ($\times 10^2$)	2.45	29.75	2.58	32.42	2.35	28.88
Age($\times 10$)	0.66	8.20	0.46	6.08		
Time_to_maturity($\times 10$)	0.44	6.94			0.25	4.24
N	105.995		105.992		105.992	
Adj.R^2	0.695		0.695		0.695	

Note The sample consists of 1,303 days and 94 entities. The dependent variable is the CDS premium. The CDS liquidity proxy is the CDS proportional bid-ask spread (Bid-ask spread). The control variables for credit risk are identical to Table 11. The liquidity proxies for the bond market are the average age and average time to maturity. Period and issuer fixed-effects are used in the estimation

Table 12 Liquidity Spillover from the equity market to the CDS market

	Specification 1		Specification 2		Specification 3	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
Constant	660.98	5.13	657.40	5.09	654.42	5.06
Rating	69.13	29.37	69.16	29.15	69.13	29.13
Opt_imp_vol	3.31	12.23	3.35	12.41	3.32	12.27
Leverage	155.20	4.25	154.48	4.23	155.36	4.25
Ln(market_cap)	−128.91	−10.97	−129.30	−11.01	−128.98	−10.97
B/M ratio	−21.59	−4.08	−21.04	−3.98	−21.53	−4.07
Bid-ask spread ($\times 10^2$)	3.54	8.20	3.53	8.24	3.54	8.26
EQ_BAS ($\times 10^2$)	54.08	1.47			4.29	1.30
AMIHUD($\times 10^3$)			19.99	0.66	19.88	0.67
N	4.910		4.910		4.910	
Adj.R^2	0.709		0.709		0.709	

Note The sample, the dependent variable, the CDS liquidity proxy, and the control variables for credit risk are identical to Table 11. The liquidity proxies for the equity market are the proportional quoted bid-ask spread and Amihud's measure of illiquidity, respectively. A two-way fixed effects panel data model is estimated

One way to avoid this issue would be to perform separate cross-sectional or time series regressions and average the results obtained. Nevertheless, this technique assumes perfect heterogeneity across time or across cross-sections, which may be very restrictive.

Table 13 Liquidity Spillover from the equity market to the CDS market

	Specification 1		Specification 2		Specification 3	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Constant	−497.25	−3.01	−501.07	−3.01	−499.32	−3.01
Rating	55.16	5.34	55.29	5.32	55.17	5.34
Opt_imp_vol	4.73	2.65	4.76	2.67	4.73	2.64
Leverage	115.59	2.39	116.49	2.42	115.62	2.39
Ln(market_cap)	−9.13	−1.06	−9.02	−1.05	−9.12	−1.06
B/M ratio	32.96	0.44	33.63	0.45	32.95	0.44
Bid-ask spread ($\times 10^2$)	6.19	3.08	6.16	3.09	6.19	3.08
EQ_BAS ($\times 10^2$)	7.37	0.62			7.37	0.62
Amihud($\times 10^3$)			5.43	0.24	5.56	0.25
N	4.910		4.910		4.910	
Adj.R^2	0.532		0.532		0.532	

Note Table 13 is based on the same model as in Table 11, except that period fixed-effects and issuer-clustered standard errors are used in the estimation

To deal with the fact that residuals may be correlated across firms or across time in panel data, we can employ fixed- or random-effects models. We conduct both an F-test and a likelihood-ratio test to determine whether the fixed-effects model (time and cross-section) is a better fit than the pooled OLS regression. Table 8 shows the results of these tests.

Both test statistics strongly reject the null of no time effect and no cross-section effects as p values are close to zero. We conclude that both effects are present in our dataset and that they should be taken into account when specifying the model. We also test for the presence of random-effects versus fixed-effects through the Hausman test, and conclude in favor of the latter.[3]

The different tests thus indicate that the best specification is a two-way fixed-effects model. As Petersen (2009) pointed out, most of the different methods used in the literature to deal with panel datasets (i.e. OLS, clustered standard errors, Fama-MacBeth standard errors, fixed-effects and adjusted Fama-MacBeth standard errors) may still bring biased results. Petersen (2009) recommends using both time dummies and issuer-clustered standard errors when both effects are present. Issuer-clustered standard errors are White standard errors to account for possible correlation within a cluster. We follow Pedersen's recommendation and apply time-dummies with issuer-clustered standard errors as a robustness check to the standard panel two-way fixed effects model.

Table 9 shows the results of the regression of CDS premiums on control variables and liquidity proxies, using issuer-clustering and time fixed-effects.[4] It allows us to identify whether liquidity has a significant impact on CDS premiums after accounting

[3] The test results are available upon request.

[4] Results with time- and issuer-fixed effects are qualitatively similar. They are not shown here but are available from the authors upon request.

for other credit-related variables. The first specification uses proportional bid-ask spread as a liquidity proxy while the second uses the frequency of quote updates.

More than 70 % of CDS premiums can be explained by our explanatory variables. Control variables typically display the expected sign and most of them are significant. Two exceptions are book-to-market, which is insignificant, and equity return, that has a positive impact on CDS premiums while we expected a negative relationship. However, let us note that, in their analysis of bond credit spreads, Collin-Dufresne et al. (2001) find that the impact of equity returns may go in opposite directions depending on the leverage and the rating category.

Most interestingly, both liquidity proxies are significant. The coefficient estimate of the bid-ask spread is positive: as the bid-ask spread widens (and liquidity decreases), the CDS premium increases. The second proxy confirms the nature of the liquidity-premium relationship. The coefficient estimate of the frequency of quote updates is negative, which means that as the frequency (and liquidity) rises, the CDS premium decreases.

4.3 Liquidity risk and CDS premiums

As explained before, liquidity risk is an important component in asset pricing models. The importance of liquidity risk can be assessed by using the liquidity adjusted capital asset pricing model (LCAPM) put forward by Acharya and Pedersen (2005). In this framework, a security's required return depends on its expected liquidity as well as on the co-variances of its own return and liquidity with the market return and liquidity. Acharya and Pedersen review the different means through which liquidity risk affects asset prices: commonality in liquidity with the market liquidity, return sensitivity to market liquidity and liquidity sensitivity to market returns.

Tang and Yan (2008) have adapted the method to CDS. As liquidity proxy, we use the proportional quoted bid-ask spread since it has been found to be the most statistically significant variable out of our two available liquidity proxies.

The liquidity adjusted CAPM can be written as:

$$E\left(r_t - r_t^f\right) = E(c_t) + \lambda\beta^1 + \lambda\beta^2 - \lambda\beta^3 - \lambda\beta^4$$

where $E(r_t - r_t^f)$ is the expected excess return, $E(c_t)$ is the expected level of liquidity, $\lambda = E(\lambda_t) = E(r_t^M - c_t^M - r^f)$ is the market risk premium, with r_t^M and c_t^M being respectively the market return and the market proportional bid-ask spread at time t.

We compute monthly averages from our daily data to retrieve more efficient results. For each time period, we calculate the illiquidity innovation. This innovation is obtained through the use of an ARIMA process:

$$c_t = \alpha + \beta_1 c_{t-1} + \beta_2 c_{t-2} + u_t$$

where c_t is the proportional quoted bid-ask spread at time t. We define the residuals of the previous regression as $c_t^i - E_{t-1}(c_t^i)$.

The same is done to calculate the innovation in CDS premiums:

$$r_t = \alpha + \beta_1 r_{t-1} + \beta_2 r_{t-2} + u_t$$

The residuals are computed as follows: $r - E_{\mathrm{t}} - 1(r_{\mathrm{t}}^{\mathrm{i}})$.

Both innovations are also calculated for an equal-weighted aggregate of all entities in our sample by time period. This gives: $c_t^M - E_{t-1}(c_t^M)$ and $r_t^M - E_{t-1}(r_t^M)$. We can then compute the betas for each CDS as:

$$\beta^{1i} = \frac{\operatorname{cov}\left[r_t^i, r_t^M - E_{t-1}\left(r_t^M\right)\right]}{\operatorname{var}\left(r_t^M - E_{t-1}\left(r_t^M\right) - \left[c_t^M - E_{t-1}\left(c_t^M\right)\right]\right)}$$

$$\beta^{2i} = \frac{\operatorname{cov}\left(c_t^i - E_{t-1}\left(c_t^i\right), c_t^M - E_{t-1}\left(c_t^M\right)\right)}{\operatorname{var}\left(r_t^M - E_{t-1}\left(r_t^M\right) - \left[c_t^M - E_{t-1}\left(c_t^M\right)\right]\right)}$$

$$\beta^{3i} = \frac{\operatorname{cov}\left(r_t^i, c_t^M - E_{t-1}\left(c_t^M\right)\right)}{\operatorname{var}\left(r_t^M - E_{t-1}\left(r_t^M\right) - \left[c_t^M - E_{t-1}\left(c_t^M\right)\right]\right)}$$

$$\beta^{4i} = \frac{\operatorname{cov}\left(c_t^i - E_{t-1}\left(c_t^i\right), r_t^M - E_{t-1}\left(r_t^M\right)\right)}{\operatorname{var}\left(r_t^M - E_{t-1}\left(r_t^M\right) - \left[c_t^M - E_{t-1}\left(c_t^M\right)\right]\right)}$$

β_1 relates to the commonality of individual return to market return, which is the usual CAPM beta. β_2 refers to the commonality of individual liquidity and market liquidity, and should have a positive impact on expected return. β_3 measures the commonality of individual return and market illiquidity and should negatively affect the expected return as investors will accept a lower return on securities that have high return in times of high market illiquidity (Brigo et al. 2011). Finally, β_4 measures the covariance between asset's illiquidity and the market return. This expected effect is also negative. Investors will accept a lower return on securities that are liquid in times of market downturns.

We run panel regressions of average CDS premiums on their respective betas, the above-mentioned control variables and the CDS bid-ask spread. Both period dummies and issuer-clustered standard errors are used. Cross-section fixed effects could not be used as the betas are constant over time. A composite liquidity beta, called β_{net}, is also included. It is computed as follows:

$$\beta_{\mathrm{net}} = \beta^1 + \beta^2 - \beta^3 - \beta^4$$

In Table 10, we report the regression results of CDS premiums on the LCAPM betas, the liquidity proxy as well as the control variables for credit risk.

The first specification includes all the different betas to separate their effects. β^2 is weakly significant and positive. It represents the sensitivity of individual liquidity shocks to market-wide liquidity shocks, also called commonality in liquidity. It means that individual CDS liquidity could be potentially affected by liquidity issues in the market. Our coefficient is stronger than the one obtained by Tang and Yan (2008). β^3 is significant and negative as expected. It represents the sensitivity of individual CDS premiums to market-wide liquidity shocks. Its significance suggests that investors are willing to accept low returns on an asset that provides high returns during periods of market illiquidity (Jacoby et al. 2007). Compared to Tang and Yan (2008), we obtain a higher level of statistical significance. Finally, β^4 is not significant. It measures the sensitivity of individual liquidity shocks to market-wide shocks on CDS premiums.

The second specification uses only β^1 which refers to the market (or default) risk only. It is significant, showing that some of the default component of CDS premiums is not completely captured by the control variables. Compared to Table 11, we also observe that three of our control variables (equity returns, market capitalization and book-to-market ratio) become insignificant when β^1 is included in the regressions.

In the last two specifications, the effect of β_{net} is significant, suggesting that the overall, net effect of liquidity risk on CDS premiums is positive. Although Tang and Yan (2008) obtain similar coefficient values, our results exhibit a higher level of significance. Interestingly, we observe in the last specification that the net beta effect mostly comes from the aggregate of the three liquidity betas, while the traditional CAPM beta is not significant.

4.4 Liquidity spillover and CDS premiums

How important are the liquidity spillovers from the bond and stock markets on CDS premiums?

Spillovers from the bond market can be explained by the fact that some investors may choose to trade CDS instead of bonds when the bond issue is not liquid enough. This could be particularly true in crisis periods, where liquidity in the bond market may dry up. Bondholders, who would like to short bonds but cannot because of liquidity shortage, could decide to buy CDS (which should be easier as liquidity has improved on the CDS market during the crisis, as we have seen above). As a consequence, illiquidity in the bond market could increase liquidity in the CDS market and, as such, affect CDS premiums.

Potential spillovers from the stock market can find its roots in capital structure arbitrage, a trading strategy that has become popular and which exploits potential relative price inefficiencies among equity and debt instruments of the same firm. In this respect, the development of the CDS market is helpful because it may provide a more efficient way to trade in credit risk than the corporate bond market. The importance of liquidity spillover might be even more relevant in times of financial distress. For example, if liquidity in the bond market drops sharply and very quickly, investors might seek another way of investing in (or hedging against) companies through the use of CDSs, which would consequently enjoy a higher level of liquidity.

In order to implement their strategies, credit traders often trade CDSs simultaneously with corresponding equity securities. So spillover from the stock market to the CDS market arises when equities and CDSs are traded together in speculative or arbitrage strategies. For example, if an investor wants to build a portfolio with both stocks and CDS contracts because of her private information, she may not trade CDS contracts at all if her stock or stock option positions are too costly to build. Therefore, liquidity in the equity market may help execute trades in the CDS market and thus reduce CDS premiums.

The methodology used to perform this analysis is based on Tang and Yan (2006). CDS premiums are regressed on several liquidity proxies for the bond and stock market, as well as on the control variables for credit risk used in the previous regressions. Significant coefficients for the bond and equity liquidity proxies would suggest that liquidity on those markets has an impact on the premiums of CDSs.

The liquidity proxies for the bond market are the average age and average time-to-maturity for all the senior unsecured bonds of each company in our sample. First, the age is a common liquidity proxy for bonds. When bonds get older, they are generally less traded and kept in buy-and-hold portfolio (Houweling et al. 2005). In other words, recently issued or new bonds may be more liquid because they attract more of investors' attention. Second, bonds with shorter maturity may be more liquid because investors for long bonds may prefer the cash flow from the coupon payments, therefore not trade the bonds (Bao et al. 2011).

The liquidity proxies for the equity market are the proportional quoted bid-ask spread and the Amihud measure of illiquidity which is also used by Tang and Yan (2006). The Amihud measure can be defined as the daily ratio of absolute stock return to its dollar volume, averaged over some period. It can be interpreted as the daily price response associated with one dollar of trading volume, thus serving as a rough measure of price impact (Amihud 2002). It is calculated as follows:

$$\mathrm{Illiquidity}_{\mathrm{im}} = \frac{1}{D_{\mathrm{im}}} \sum_{d=1}^{D_{\mathrm{im}}} \sqrt{\frac{|r_{\mathrm{id}}|}{\mathrm{Volume}_{\mathrm{id}}}}$$

where D is the number of days in month m for firm i, r is day d's return and Volume is day d's volume.

In Table 11, we focus on the spillovers from the bond market to the CDS market. In other words, we test whether the state of liquidity on the bond market is priced in CDS premiums. CDS premiums are therefore regressed on different control variables, the proportional quoted bid-ask CDS spread and at least one measure of bond liquidity.

The first specification includes the two liquidity proxies, while there is only one proxy in the second and third specifications: the age of the bond and time-to-maturity, respectively. Both liquidity proxies are significant, whatever the specification. CDS premiums increase as the maturity of bonds is longer and as the age of the bonds rises. As bonds become illiquid, investors willing to short bonds would prefer buying CDSs instead. This could have two potentially adverse effects on CDS premiums: on the one hand, liquidity improvement on the CDS market could lower the premiums, consistent with the relationship found in previous sections; on the other hand the arrival of more CDS buyers could alter the relative supply and demand balance in the CDS market and increase premiums. The second effect seems to dominate the first one, given that we find a positive coefficient for the bond illiquidity variables. Tang and Yan (2006) obtain the same results for the period 1998–2006 in the US, except that age is not significant. The coefficients are comparable in both studies.

The spillover effect from the equity market to the CDS market is analyzed in Table 12. A two-way fixed effects panel data model is used. The first and second specifications include one liquidity proxy used individually: the proportional quoted bid-ask spread and Amihud's measure of illiquidity, respectively. The third specification includes both. As a robustness check, we estimate the same regression using time period effects and issuer-clustered standard errors. The results are reported in Table 13.

In all specifications, no proxy for equity liquidity is significant. Liquidity spillover from the equity to the CDS market does not seem to matter between 2005 and 2009 for European companies. For the period 1998–2006 in the US, Tang and Yan (2006) find a significant coefficient for the Amihud measure of illiquidity. The absence of significance on the European market may indicate that the equity and CDS markets are less intertwined than in the US.

5 Conclusion

The objective of this paper was to study the liquidity dynamics of the CDS market in Europe between 2005 and 2009. Panel regressions have been performed on an original data set on European companies. Results show that the level, risk and spillover of liquidity are priced in the CDS market.

The level of liquidity in the European CDS market as measured by the proportional bid-ask spread does not seem to have significantly deteriorated around the Subprime crisis. Credit risk factors are the main drivers behind the rise in CDS premiums over the period, as liquidity around the subprime crisis shows evidence of significant resiliency.

Liquidity risk is nevertheless priced in CDS premiums. For example, we show that the sensitivity of individual CDS premiums to market-wide liquidity shocks is statistically significant, confirming that investors in CDS are willing to accept lower returns on a CDS if it provides higher returns during periods of market illiquidity

Liquidity spillover from the bond market to the CDS market is also undeniable and its impact is similar to Tang and Yan (2006) for the US. However, spillover from the equity market to the CDS market does not seem to matter, pointing to rather weak integration of the two markets around the subprime crisis.

This study only deals with CDS issued on European companies. It is possible that illiquidity affected the US market to a larger extent or in a different way. This is probably being covered in forthcoming papers. The impact of liquidity during the crisis can also be studied in the framework of a liquidity pricing model, as it has been done before. This is another avenue for further research.

The CDS market remains relatively opaque but the current (and gigantic) wave of regulation will help improve the transparency of the market in the coming few years. The liquidity of the CDS market will continue to improve only if the expected increase in standardization is thought to benefit investors to a larger extent than customization did in the past. However, the main argument behind the prolonged rise in liquidity on the CDS market in the coming years is the reduction in counterparty risk, thanks to the development of central clearing facilities.

CDSs will most probably become the purest measure of credit risk for European corporations, should liquidity continue to improve as it did in the past.

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