# The Decoupling of the CDS and Bond Markets: An Empirical Study of the CDS-Bond Basis of the Credit Crisis

Fredrik Sundelin* Tommy Torwald†

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**Abstract**

We examine determinants of the credit default swap (CDS) prices, bond credit spreads and the CDS-bond basis of 62 U.S. firms during the period 2007 to 2009. We try to explain the basis by employing credit risk factors from structural models and by introducing a control for market liquidity as well as a funding liquidity factor. We find no evidence of credit risk factors affecting the basis; instead we find liquidity and funding liquidity to be the dominant factors. We also examine the basis within broader credit rating groups, and two findings emerge: First, the credit spread of firms with lower ratings is more sensitive to changes in credit risk factors and funding liquidity. Second, the basis of firms with lower ratings is more sensitive to funding liquidity.

Keywords: Corporate Bonds, Credit Default Swaps, Credit Crisis, Basis

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Discussants: Henrik Bark and David Boxi Hu

*Email address: 21358@student.hhs.se

†Email address: 21231@student.hhs.se

# Contents

# 1 Introduction

The Law of One Price asserts that identical goods should have the same price. Nevertheless, during the credit crisis of 2007 to 2009, a persistent pricing error between the credit default swap (CDS) market and the bond market was observed. This thesis investigates the so called decoupling of the CDS and bond markets by studying structural model determinants of credit risk, market liquidity and funding liquidity. Using data from the period April 2, 2007 to December 31, 2009, we show that the decoupling was not caused by differing pricing of credit risk, and suggest that the basis depended on limited funding at hand for investors, which in practice restricted the possibility to the exploit the arbitrage. Our results are in line with recent suggestions by Gârleanu and Pedersen (2009), who show that the price of an asset must depend on the funding costs, and that two securities with identical cash flows will trade at a basis if they have different margin requirements. We further produce results comparable to empirical studies such as Collin-Dufresne et al. (2001), Blanco et al. (2005), Zhu (2004), De Wit (2006) and Alexopoulou et al. (2009), and find that the credit crisis might have brought about a change in the CDS and bond markets' sensitivity to liquidity factors.

We thus extend the current literature in the following way:

I. *Pricing of credit risk.* We show that credit risk is priced similarly in the CDS and bond markets, in our time period, and that the basis does not seem to be caused by differing pricing of credit risk between the CDS and bond markets.

II. *Market liquidity and funding liquidity.* We find that bond-specific liquidity plays a major role in the development of the basis. More importantly, we are, to the best of our knowledge, among the first to empirically evaluate the role of funding constraints for investors in relation to the CDS-bond basis. Our findings show that funding constraints was a significant cause of the basis during the financial crisis.

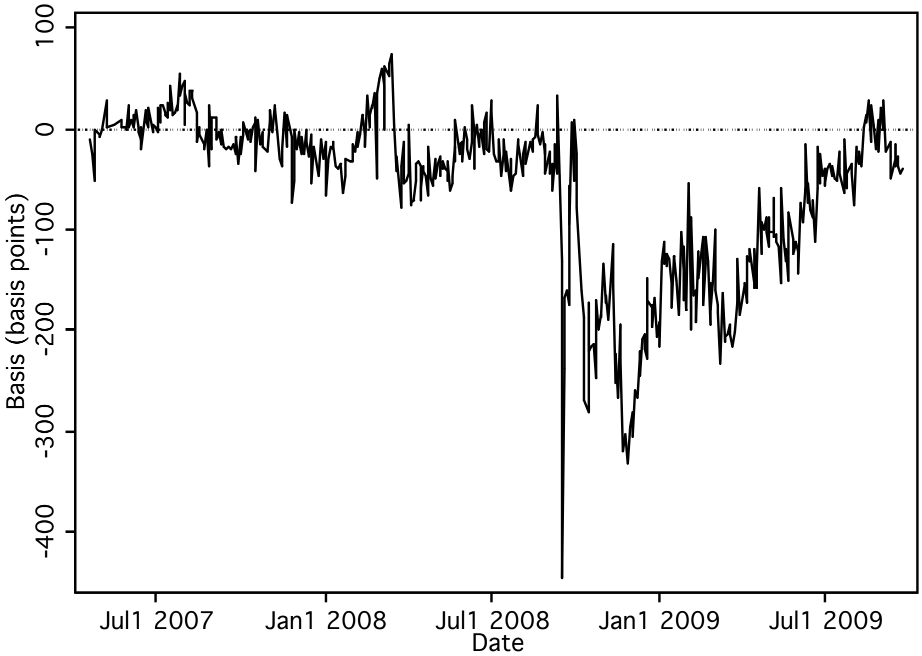
A CDS is a contract in which the protection against the default of a reference entity is exchanged for a series of payments called a CDS premium, or CDS spread. The seller of the CDS pledges to buy the defaulted bond at par, and the buyer, in exchange for this protection, makes regular payments expressed as a percentage of the insured notional amount. Since the innovation in the early 1990's, the CDS has developed into the most common form of credit protection, and is now a building block of most credit derivative products (Batterman et al., 2008). CDS contracts are of great use for many market participants, because it allows them to hedge specific cash market exposures, or incorporate other strategies such as taking long or short positions to speculate on changing credit quality of firms.

The pattern with which the bond and CDS markets co-move used to be predictable (Leland, 2008), but that relationship weakened during the crisis, causing significant losses for many investment banks and hedge funds. The difference between the price of a CDS contract and the bond credit spread is known as the CDS-bond basis. To avoid arbitrage, the basis should be close to zero. Figure 1.1 below illustrates how the basis developed during the financial crisis for the investment bank Goldman Sachs.

A large basis is supposedly easy to exploit, and the process of doing so is called basis trade. Exploiting a negative basis (when CDS spreads are lower than bond spreads) involves a long position in the bond, and a long position in protection on the same bond. At maturity, the basis must be zero, and so a basis trade yields a positive carry return over the holding period. A positive basis is somewhat more complicated to exploit, primarily because of the limited supply of bonds in the repo market and the limited number of market participants that can sell CDS contracts (Leland, 2008). Nevertheless, active basis trading has traditionally kept basis levels very low.

**Figure 1.1**

This figure illustrates how the basis, defined as the CDS premium less the bond credit spread, developed during the financial crisis 2007 to 2009 for the investment bank Goldman Sachs. The sustained negative basis observed after July-August 2008 illustrates the main motivation of this paper.




The persistent negative basis illustrated in Figure 1.1 is therefore puzzling; what changes brought about such a fundamental decoupling of the credit markets? Brunnermeier and Pedersen (2009) and Gârleanu and Pedersen (2009) propose that the basis depends on the availability of funds to investors.

The number of empirical studies in this area is, however, limited; especially in relation to the credit crisis. The focus of this paper is therefore to investigate the causes of the persistent negative basis observed during the credit crisis. Given that liquidity severely worsened and capital became increasingly scarce during the credit crisis (Brunnermeier, 2009, Kim et al., 2009), our main hypothesis is that the basis was largely driven by liquidity differences between the markets and limited availability of funds. Furthermore, because credit risk and liquidity risk might be positively correlated (Bühler and Trapp, 2008), we also expect credit risk factors to play a significant role in the explanation of the basis. Specifically, the aim is to study whether:

1. the decoupling can be explained by differing pricing of credit risk in the CDS and bond markets, or whether
2. the decoupling can be explained by liquidity changes in the bond market, or whether
3. the decoupling can be explained by investors' funding constraints.

We limit the scope to a largely non-dynamic approach, and do not evaluate the supposed lead-lag relationship or price-discovery between the markets.

The remainder of this paper is structured as follows: In section 2, we describe the theoretical framework underlying our methodology, beginning with an explanation of the details about the CDS-bond basis, followed by a review of relevant literature. In section 3, we present the details of our model and the proxies we employ and in section 4 we explain our methodology and describe our data. In section 5, we present our results, and section 6 contains some concluding remarks and suggestions for further research.

# 2 Theoretical Framework

## 2.1 The CDS-bond basis

The notion of a zero basis between the CDS and bond market rests on the idea that both markets should price approximately the same risks. For example, a holder of a fixed-rate bond receives steady cash flows until the maturity of the bond, provided the bond issuer does not default. If the issuer defaults, the value of the bond drops to the recovery value. Similarly, a CDS seller receives premium payments until maturity, unless a credit event occurs. If the reference entity defaults, the loss to the CDS seller is the par value minus the recovery value of the delivered bond. Therefore, the bond holder and CDS seller are exposed to the same risks. If the bond is benchmarked against a risk-free reference rate, then the difference between this benchmark and the bond's yield to maturity – the credit spread – should approximately equal the CDS spread. The word "spread" for the CDS price emanates from the fact that the periodic payments are expressed as a fraction of the insured nominal value. A CDS spread of 20 basis points on a nominal of 10 million dollars is hence equivalent to a yearly insurance premium of 20 000 dollars.

We define the basis as the difference between the CDS spread and the bond spread:

$$Basis = CDS\,spread - Bond\,spread \tag{2.1}$$

Specifically, Duffie (1999) and Francis et al. (2003) show that the cash flow profile of a CDS is more readily comparable to a par floating rate bond funded at Libor[1], or with an asset swapped fixed-rate bond funded in the repo market. Francis et al. (2003) and De Wit (2006) demonstrate that the relationship should be such that there exists an approximate arbitrage relationship between the asset swap spread (ASW) and the CDS spread.

An asset swap is a package consisting of two trades: a purchase of a bond and a fixed-for-floating interest rate swap agreement. The fixed leg payer of the swap pays cash flows that are identical in size and timing to the coupons of the bond, and the floating rate payer in return pays the Libor rate plus an additional rate called the ASW. The ASW is usually the rate such that the present value of the swap is zero when entering into the agreement, and the ASW is hence a function of the credit risk of the bond over the interbank credit risk (Libor). The value of the asset swap is zero when the present value of the fixed leg payments equals the value of the floating leg payments which, at initiation, are the present value of the Libor and ASW payments of the relevant time period. As such, the ASW is a measure of the credit spread of the bond.

The arbitrage relationship demonstrated by Francis et al. (2003) and De Wit (2006) can be illustrated as follows: For an investor who funds himself at Libor, a combined position of buying protection in a CDS and entering into an asset swap where the fixed coupon payments are swapped for a stream of floating rates is fully hedged in any state of the world. Before maturity, there are two possible states of the world: no default of the reference entity or default of the reference entity. The combined position is always risk-free, assuming unwinding of the interest rate swap in the case of default[2]. Any deviation from the equality of the CDS spread and ASW would constitute an arbitrage opportunity.

While the ASW provides a useful insight into the arbitrage relationship between the CDS and bond markets, the argument has some problematic weaknesses. It is significantly more difficult

[1] The Libor is a reference interest rate corresponding to interbank borrowing costs. It is the rate at which financial institutions believe that they can borrow funds from other institutions for a certain time-period.

[2] In a practical setting, it is not always possible to unwind a position in an interest rate swap, because the payments of the fixed leg is not linked to the actual coupons and the cost of unwinding is paid by the swap buyer (O'Kane and Sen, 2004).

to exploit a situation where the CDS spread is higher than the ASW, for example, and the setup implicitly assumes that it is possible to borrow against the full value of the bond in the repo market. Furthermore, the ASW tends to underestimate risk as bond prices fall, and overestimate risk as prices rise (Francis et al., 2003). When prices move far below par, such as during a financial crisis, it implies that the compensation from the ASW will be much lower than the cost of the CDS, yielding this type of trading less beneficial. In fact, the term structure of asset swap spreads deviate significantly from that of the CDS spreads even for discounts or premiums as low as 400 basis points, as illustrated by Duffie (1999).

So far, we have explained how the CDS and bond markets are expected to co-move. Due to some elements that are specific to the nature of the CDS market, it is sometimes difficult to determine the expected size and direction of the basis. CDS spreads are affected by some additional risks that are not present in the bond market. For example, not all credit events are defaults, and a CDS is often required to pay out even if the bond issuer does not experience a full default. Another well-known risk is the delivery option inherent in CDS contracts. This option allows CDS buyers to, in the event of default, deliver any bond out of a range of bonds, because the specific reference asset is often not specified. Other factors, that aggregate to usually make the CDS-bond basis *positive*, include funding cost differences, counter-party risk and demand for CDS contracts. We summarize and discuss the most important factors in Appendix, Table A.8. Because most of these factors expose the CDS seller to a larger risk than a bond holder, it is unlikely that any of these factors is the cause of the large negative basis observed during the credit crisis.

## 2.2 Determinants of credit risk

While there is an active debate regarding theory and assumptions behind models aiming to explain credit risk, it lies beyond the scope of this paper to evaluate the validity of existing models. This section, instead, aims to briefly outline the different approaches[3] to valuing credit instruments, because they form the ground on which we chose the variables included in the empirical model.

There are two primary categories of credit risk models: structural models and reduced-form models. The former draw on the work of Black and Scholes (1973) and Merton (1974). Structural models assume that a firm defaults when the value of the firm's assets drops below a certain threshold. The default threshold is in turn a function of the amount of outstanding debt. Collin-Dufresne et al. (2001) explain that, in structural models, holding a risky debt claim is analogous to holding a risk-free debt claim and having sold a put option at the value of the risk-free claim to the firm's equity holders. By put-call parity, holding a debt claim is also equivalent to holding the total firm and having sold to the equity holders a call option on the firm with strike price equal to the value of the outstanding risk-free debt claim. The value of the debt, then, is calculated as the risk-neutral present value of expected future cash flows. Structural models hence assert that the default risk is associated with the size of the debt claim (i.e. the amount of leverage), the cash flows to the debt holders and the risk-free rate. In addition, most models include a set of state variables, capturing for example the term-structure of interest rates (Merton (1974) assumes that they are constant), non-deterministic (stochastic) volatility of assets, bankruptcy costs or time-varying recovery rates.

One of the central messages of Merton's model is that two investors who have quite different utility functions and different expectations for a firm's future but who agree on the volatility of the firm's value will, for a given risk-free interest rate and current firm value, agree on the value of a security of the firm. This simple intuition means that the parameters are quite easily testable, because both interest rates and volatility (or relevant proxies and estimations for them) are observable in the market.

[3]Because this section aims to outline the general thought of structural models rather than in detail review all relevant studies, we cannot cover all relevant literature. Some notable contributions to the field that are not covered here are for example Leland (1994) and Collin-Dufresne and Goldstein (2001).

Despite the appealing intuition of Merton's structural model, it suffers from some weaknesses. For example, interest rates are assumed to be constant, and defaults are assumed to occur only when assets are completely exhausted. In reality, interest rates are neither constant nor deterministic – especially not for corporate bonds – and firms default long before assets are exhausted. The promising outlook of the structural models are further questioned by Jones et al. (1983), who show that structural models predict credit spreads that are much lower than those observed in the market (sometimes several percentage points). These results are confirmed by Ogden (1987), who further notes that firm size seem to be an important factor and that constant interest rates is an important misspecification.

In an extended framework, Black and Cox (1976) relax the assumption of complete exhaustion of assets by introducing a default barrier, or a lower threshold. Longstaff and Schwartz (1995) develop the Black-Cox framework, and incorporates both default-risk and interest-rate risk.

Lyden and Saraniti (2000) find that both the Merton and the Longstaff-Schwartz models underpredict spreads. Using a more practical approach, KMV (now Moody's KMV) develops the Vasicek-Kealhofer model, which builds on the Merton and Black-Cox framework. The Vasicek-Kealhofer model incorporates a measure of default probability called Expected Default Frequency. It is essentially similar to the Merton model, but it translates the model-implied probability of default a EDF measure using historical default rates of firm's with similar characteristics and default probabilities[4].

The other approach of modeling research focuses on so called reduced-form models[5]. In a reduced-form approach, default is an exogenously driven process which is often represented by a random "stopping time" which has an arrival intensity (or hazard rate) that is either deterministic or stochastic. The risk associated with default is assumed to be affected by the expected recovery rate, which in turn is usually assumed to be constant. Litterman and Iben (1991) were first to model credit risk in a reduced-form model. The model is simpler than many successors, in that it assumes constant 0 % recovery rates (an assumption which is easily relaxed, however, as shown by Acharya and Schaefer, 2009).

The reduced-form modeling approach is attractive for example because of the comparable mathematical tractability. However, the underlying intuition is somewhat less appealing than that of the structural models, because reduced-form models lack a clear definition of the default process. Thus, it is difficult to identify the exogenous process that drives the default probability, and it is difficult to incorporate this approach in an empirical setting. Furthermore, Arora et al. (2005) note that reduced-form models make rather poor out-of-sample predictions.

Nevertheless, there is some empirical support of reduced-form models. For example, Houweling and Vorst (2005) find that a reduced-form model explains CDS spreads better than credit spreads of corporate bonds. Most empirical work, however, focus on estimating the parameters of the models rather than testing their empirical performance.

## 2.3 The role of liquidity

The fact that Merton-style structural models tend to underpredict credit spreads of corporate bonds is often referred to as the credit spread puzzle, although it is arguably not very puzzling anymore. One of the more popular explanations for the puzzle is the fact that structural models lack a liquidity factor. Much new research focus on the ability of liquidity to explain the cross-sectional as well as time-series variation of bond spreads and returns. For example, Driessen

[4] For a detailed discussion on this framework, refer to for example Crosbie and Bohn (2003) or Kealhofer (2003).

[5] It is beyond the scope of this paper to review the field of reduced-form modeling in any great detail. To the best of our knowledge, prominent contributions are for example made by Jarrow and Turnbull (1995) and subsequently Jarrow et al. (1997), Duffie and Singleton (1999), Hull and White (2000) and Hull and White (2001).

(2005) decomposes corporate bond returns into default, liquidity and tax factors using the Duffie and Singleton (1999) reduced-form approach, and Liu et al. (2006) study how default and liquidity risks are incorporated in interest rate swaps and find that the credit premium for all but for very short maturities compensate for liquidity risk.

Traditionally, the notion of liquidity refers to the ability to perform transactions in large quantities quickly with limited impact on the price of the security (Covitz and Downing, 2007). More recent studies, however, further distinguish between market liquidity and funding liquidity. Market liquidity is what is typically associated with the term liquidity in that it refers to the ease of finding somebody who takes the other side of a trade (Brunnermeier, 2009). Kyle (1985) outlines three forms of market liquidity. Firstly, the bid-ask spread, which captures how much a trader loses on selling an asset and immediately repurchasing it. Secondly, the market depth, which measures how many units can be traded at the current bid or ask price without affecting the price. Lastly, the market resiliency captures how fast prices bounce back after temporarily having fallen.

Funding liquidity refers to the ease with which investors and traders can obtain funding from financiers. When it is high, raising funds is easy. Brunnermeier and Pedersen (2009) provide a useful case study on the funding requirements of hedge funds, banks and market makers, and they explain that levered traders typically use purchased assets as short-term collateral and borrow against them. However, it is normally not possible to borrow against the full value of the asset, because the financier is exposed to counter-party risk and thus has to make sure the collateral can be sold to cover the position if the borrower defaults. This gives rise to a haircut, which is the difference between the value of the collateral and the cash obtained from borrowing against it. In essence, therefore, the capital needed in a transaction where the purchased asset is borrowed against is represented by the margin, or haircut (Francis et al., 2003). This illustrates the first form of funding liquidity risk, as outlined by Brunnermeier (2009).

The second form is linked to the short-term financing requirements more directly. As Brunnermeier (2009) explains, banks have become increasingly dependent on very short-term maturity financing during the period leading up to the crisis[6]. Assets, at the same time, often have long maturities. This leaves banks exposed to severe maturity-mismatching, and creates a dependency on being able to roll over short-term debt. If rolling over the debt is not possible, it is equivalent to margins increasing to 100%, because it renders the assets impossible to borrow against. Hence, this increases the capital requirements and thus the funding liquidity risk. Brunnermeier (2009) refers to this form of funding liquidity risk as rollover risk. Withdrawal of capital from an investment fund, similarly, has the same effect as a margin increase, and Brunnermeier (2009) calls this last form of funding liquidity risk redemption risk.

During the financial crisis, funding liquidity risk proved particularly important. Brunnermeier and Pedersen (2009) show, informally and in a general framework, how losses, funding problems and subsequently firesales and dropping prices lead to higher margins and more losses, which in turn lead to new funding problems and more firesales, etc. They extend the idea of margin risk into a complete framework where investors' scarcity (or "shadow") cost of capital is linked directly to funding liquidity. The model further provides an explanation for the commonality of liquidity across assets, because funding constraints affect all securities (Garcia, 2009).

Gârleanu and Pedersen (2009) further extend the Brunnermeier and Pedersen (2009) framework and derive a model for margin-based asset-pricing. They explain that liquidity crises give rise to deviations from the Law of One Price and show that the model can be used to explain the CDS-bond basis of the credit crisis of 2007 to 2009. In particular, this is because a bond requires a larger margin than a CDS. A bond is a funded instrument which means that an investor needs cash to finance the position in the bond. A position in a CDS, on the other hand, is unfunded

[6] One reason for this, as noted by Brunnermeier (2009), is that long-term financing is more difficult and expensive to obtain when banks suffer from the debt-overhang problem discussed by Myers (1977). This, in turn, implies that it is usually not possible to to raise long-term debt to cover increasing margins, because collateralized lending enjoys seniority. Hence, to cover margins, traders must often unwind positions and sell part of the assets.

and does not require any initial cash outlay. Since an investor uses the bond as collateral and borrows against it in the repo market to finance the investment, a position in a bond uses more of a financier's capital than a position in a CDS, and this is reflected in the margin requirements. The margin requirement of a CDS is mostly a function of counter-party risk and does not include a premium for borrowed cash.

## 2.4 Empirical findings

The empirical research field on fixed-income securities is vast, so in this section we focus on empirical findings that are relevant to our purpose of investigating the causes of the CDS-bond basis. We first present various factors that have been shown to affect credit spreads or CDS spreads, and subsequently summarize research closely related to this study in Table 2.1.

Leverage is a central component of structural models, and has hence been used in a wide range of studies. For example, Nashikkar et al. (2008) use leverage measured as book value of debt divided by the sum of the book value of debt and the average market value of equity during a quarter, and find that it significantly affects the CDS-bond basis. Alexopoulou et al. (2009) use stock returns as a proxy for firms' financial health and leverage, and find that it explains CDS and bond spreads. Similarly, since structural models use a "contingent claims" approach to value debt instruments, the probability of asset values dropping below the default barrier increases with volatility. Therefore, we typically expect credit spreads to be closely related to the volatility of the firm's assets. This is confirmed by Aussenegg and Goetz (2009), who find that CDS spreads are highly sensitive to equity market volatility, especially in periods of financial crises.

Besides credit risk, other important determinants of credit spreads are interest rates. Longstaff and Schwartz (1995) show that higher spot rates increase the risk-neutral drift of the firm value, which reduces the probability of default and thus reduces CDS and credit spreads. Duffee (1999) further finds that a default-free process adequately prices corporate bonds, and so we expect interest rates to be negatively correlated with credit spreads. Furthermore, since interest rate risk likely constitute a larger portion of the total credit spread for higher rated bonds, it is likely that lower rated bonds are relatively less sensitive to these factors.

Collin-Dufresne et al. (2001) and Alexopoulou et al. (2009) note that low long-term interest rates may suggest a weakening economy and thus, perhaps, lowering recovery rates, in which case we would expect spreads to widen. Indeed, Fama and French (1989) show that there is an important relationship between business cycles and returns of stocks and bonds and Collin-Dufresne et al. (2001), Blanco et al. (2005) and Alexopoulou et al. (2009) use market implied volatility and market equity returns to capture the business climate (though with different results). Acharya et al. (2007), Gagliardini and Gouriéoux (2003) and Duffie and Singleton (1999) show that both default probabilities and recovery rates may vary with the general business climate and Acharya et al. (2007) show that recovery rates are lower when firms are in distress. Altman and Kishore (1996) show that recovery rates are time-varying.

Elton et al. (2001) find that corporate bond returns are affected by risk factors common with the stock market. Specifically, they show that market excess return and the factors introduced by Fama and French (1993) explain the return on corporate bonds. As a possible explanation, they propose that the factors may proxy for default expectations. Surprisingly, they assert that the none of the alternative measures of credit risk they use contain any additional information about systematic risk beyond the information already captured by the Fama-French factors. Collin-Dufresne et al. (2001) find similar support, and confirm that the Fama-French factors are statistically significant across several rating-groups.

A wide range of studies show that market liquidity, as identified by for example bid-ask spread and trading volumes, affect corporate as well as sovereign bonds. Covitz and Downing (2007) (looking at very short-term maturities) find that, although credit risk plays an important role, liquidity is also a determinant of corporate bond spreads. Longstaff et al. (2005), assuming that CDS spreads capture the default component of bond yields, find evidence of a significant non-default component of bond yields. They measure bond liquidity as the bid-ask spread, outstanding debt amount and coupon rate, and show that these factors affect the non-default component of yields. de Jong and Driessen (2006) confirm a negative relationship between liquidity shocks and realized return and Acharya et al. (2009) find regime-switching effects of liquidity factors (very high sensitivity in periods of macroeconomic stress).

Fontaine and Garcia (2009) measure the value of funding liquidity, and find that funding liquidity explains the cross-section of bond returns.

To the best of our knowledge, the studies that in nature are similar to ours are summarized in table 2.1.

**Table 2.1**

**A comparison of recent empirical studies.** This table summarizes some recent empirical studies that address the determinants of credit spreads, the CDS-Bond basis or the lead-lag relationship (the co-integration) of the the CDS and bond markets. To the best of our knowledge, they form a good representation of recent empirical findings related to our study.

| | Description of study | | |
|---|---|---|---|
| Authors | Central purpose of study | Data time period | Conclusion |
| Alexopoulou et al. (2009) | Study determinants of CDS spreads and credit spreads and examine their long-run relationship. | 2004–2008 | Systematic factors play an important role in explaining CDS spreads. Credit spreads are more sensitive to firm-specific factors and liquidity factors. Confirms co-integration of markets (CDS leads bond market), but weaker relationship during the credit crisis. |
| Zhu (2004) | Compares the pricing of credit risk in the CDS and bond markets and examines the dynamic linkages betweem them. | 1999–2002 | Confirms co-movement in the long run, but finds short-run deviations due to various short-run dynamics. Further confirms leading price-discovery in the CDS market, and that liquidity matters for price discovery. |
| De Wit (2006) | Examines co-integration of CDS spreads and asset swap spreads. | 2004–2005 | Finds co-integration for 88 of 144 firms. Detects fourteen basis drivers. Observes positive basis in 2004–2005. |
| Blanco et al. (2005) | Study determinants of CDS spreads and credit spreads and examine the dynamic linkages betweem them. | 2001–2002 | Find that in some cases, basis is caused by imperfections in contract specifications and measurement errors in the credit spread. Otherwise, basis is caused by faster price discovery in the CDS market than in the bond market. Macroeconomic variables have a larger impact on credit spreads than on CDS spreads. Find stable long-run co-integration. |
| Collin-Dufresne et al. (2001) | Investigate the determinants of credit spreads. | 1988–1997 | Theoretical determinants have limited explanatory power. Principal components analysis shows that spreads are mostly driven by a single common factor; neither macroeconomic nor financial variables is able to explain the systematic component. Suggest that credit spread changes are driven by local supply and demand shocks that are independent of both credit risk factors and standard proxies for liquidity. |
| Norden and Weber (2004) | Study the relationship between CDS, bond and stock markets by examining lead-lag relationships in a VAR model. | 2000–2002 | Find that stock returns lead CDS and bond spread changes. Find co-integration for 36 of 58 firms and that the CDS market is more sensitive to the stock market than the bond market and that the magnitude of this sensitivity increases when credit quality worsens. |
| Aussenegg and Goetz (2009) | Investigate determinants of credit spreads measured by asset swap spreads. | 2006–2009 | Credit spreads exhibit varying dynamics depending on macroeconomic market conditions. In periods of distress, credit spreads are more sensitive to equity market volatility, while in tranquil periods stock returns provide better explanations of spreads. Interest rates are important determinants of spread levels. Find evidence of autocorrelation of asset swap spread changes. |
| Nashikkar et al. (2008) | Investigate the role of liquidity in the CDS and bond markets. | 2002–2006 | Find that bonds with high ”latent liquidity” (turnover of funds holding the bond) are more expensive relative to their CDS counterpart. Further find that leverage and other firm-specific measures affect the CDS-bond basis. |
| Trapp (2009) | Studies trading opportunities that arise from the CDS-bond basis. | 2001–2007 | Confirms co-integration relationship for 82 of 116 firms. Shows that the magnitude of the basis is related to measures of idiosyncratic credit risk and liquidity, and to market conditions. |

# 3 The model

To formalize our aim to investigate the cause of the suspended negative basis observed during the credit crisis, we formulate a model that incorporates our expectations. We want to study if credit risk pricing differed in the CDS and bond markets, and if liquidity and funding constraints can help explain the large deviation from the historical pattern. Taking into account the theoretical framework on which our analysis is built, we are interested in the naïve model:

$$basis_{i,t} = \beta_{0,i} + \beta_1 Credit\ risk_{i,t} + \beta_2 Interest\ rate\ risk_{i,t} + \beta_3 Liquidity\ risk_{i,t} + \beta_4 Funding\ risk_{i,t} + u_{i,t} \tag{3.1}$$

We now proceed to specify the components of the model more carefully.

1. *Credit spreads and basis.* We define the basis as the difference between the CDS spread and the credit spread for a CDS and a bond of the same maturity.

2. *Leverage.* Following Collin-Dufresne et al. (2001), Blanco et al. (2005), Zhu (2004) and Alexopoulou et al. (2009), we consider stock returns as a proxy for leverage and firms' financial health. Using leverage derived from book values is problematic, because it is infrequently sampled, and is often affected by accounting principles. Instead, we apply the reasoning that, all else equal, negative stock returns reduce the market value of equity and thus increase leverage. Increasing leverage induces uncertainty of repayment capacity, which should be reflected in bond and CDS spreads. Furthermore, we argue that this proxy is especially relevant in crisis periods, when the premonition of default becomes more real. Equity holders in heavily leveraged firms will expect to recover less from default than those of less leveraged firms, and this should be reflected in the stock price as the firm approaches distress. We denote this factor by $ret_{i,t}$.

3. *Volatility.* In structural models, increased asset volatility increases the risk of the firm value falling below the default barrier. Higher volatility signals a deterioration of repayment capacity, which increases the probability of default. We capture this effect by a rolling ten-period realized volatility of firm-specific stock returns. While this represents neither the instantaneous volatility in the models nor the volatility of the firms total assets, we deem that it is sufficient to capture at least some degree of the asset volatility. Most studies use the Black and Scholes (1973) option-implied volatility (see for example the studies referenced above), because of its forward-looking nature (Cremers et al., 2008). However, this data is not available to us for more than a sub-sample of the period. As a reference, we perform some comparative regressions on a sub-sample of our dataset, and we find that the rolling realized volatility measure produces materially similar results[7]. We denote the volatility factor by $vol_{i,t}$.

4. *Interest rates and yield curve slope.* As pointed out by Longstaff and Schwartz (1995), higher spot rates increase the risk-neutral drift of the firm value, which reduces the probability of default and thus spreads. As a proxy for long-term spot rates, we use ten-year swap rates. Many studies, such as Alexopoulou et al. (2009) and Collin-Dufresne et al. (2001), focus on Treasury rates with longer maturities to capture benchmark spot rate changes, and some studies, for example De Wit (2006), use both Treasury and swap rates to compare their effects. To control for differences in interest rate sensitivity and convexity between the bonds, we use the difference between the ten and two-year swap rate as well as the square of the

[7]The coefficients are more significant and of larger magnitude when we use implied volatility for the shorter time period where data is available, and Cao et al. (2009) find that option-implied volatility explains CDS spreads better than realized volatility in a time series. However, our main results remain the same regardless of volatility measure.

ten-year swap rate. This approach is similar to that used by Collin-Dufresne et al. (2001), who interpret their slope factor as an indication of expectations of future short rates as well as an indication of economic health. In our case, we also intend these variables to capture interest rate sensitivity. As a notation for the ten-year swap rate, we use $r_t^{10}$. The slope, given by $r_t^{10} - r_t^2$ is denoted $slope_t$. Since we will use the first difference of $r_t^{10}$, the convexity control becomes the square of the first differenced ten-year swap rate, denoted $\left(\Delta r^{10}\right)_t^2$.

5. *Market liquidity.* To capture the supposed market liquidity effect on bond prices, we include a proxy intended to capture bond-specific market liquidity. While there is a range of possible proxies for market liquidity, we consider a measure used by Han and Zhou (2006) and Wang (2009), which is proposed by Downing and Xing (2005). We refer to the measure as $liq_{i,t}$, and it is defined as the daily price volatility divided by the average price as a proportion of daily dollar trading volume. Specifically, it is specified as:

$$liq_{i,t} = \frac{\frac{P_{i,t}^{max} - P_{i,t}^{min}}{\bar{P}_{i,t}} \times 100}{\sum_{j=1}^{N} Q_{i,t}^{j}} \tag{3.2}$$

where $P_{i,t}^{max}$ and $P_{i,t}^{min}$ are the maximum and minimum price of bond $i$ a particular trading day $t$, $\bar{P}_{i,t}$ is the average price of bond $i$ in day $t$, and the denominator is the sum of the dollar value of all trades $j = 1, \ldots, N$ the same day.

The intuition, as explained by Wang (2009), is that trading of less liquid bonds move prices more for a given volume. By definition, this measure is only available for days when there are at least two trades.

For the sake of robustness, we also consider other proxies for market liquidity, namely the logarithm of the age of the bond (Wang, 2009) and the logarithm of cumulative trading volume (Elton and Green, 1998).

6. *Funding liquidity.* As a proxy for investors' funding constraints, we use the spread between the three-month Libor and the three-month overnight indexed swap (the Libor-OIS spread). While it would have been desirable to use a direct measure of funding costs for investors, such data is not available to us. Gorton and Metrick (2009a) illustrate that haircuts on corporate bonds in the repo market rose sharply during the credit crisis, across all rating groups. Likewise, Brunnermeier (2009) exemplifies how haircuts on S&P 500 futures rose in a similar manner. Data on margins and haircuts for corporate bonds is, however, proprietary, and we have not been able to gain access to such data. Instead, we argue that the Libor-OIS spread proxy for changing counter-party risk in the interbank market.

An OIS is a fixed-for-floating interest rate swap in which the floating leg is equal to the geometric average of an overnight reference interest rate of the payment period. In the United States, the reference rate is the Federal Funds rate. The Federal Funds rate is an unsecured interbank overnight rate. It is the rate paid by banks that borrow and lend reserves to each other through the Federal Reserve.

The Federal Funds rate is thus materially similar to the Libor, and, actually, the spread between the two should theoretically be close to zero[8]. The discrepancy is that in an OIS, there is no exchange of principal. The OIS rate is set at the initiation of the contract and reflects the market's expectation of the overnight Federal Funds rate over the term of the contract (Thornton, 2003). At the end of the contract, the net obligation is settled. As an effect, the counter-party risk in an OIS contract is minimal (Griffoli and Ranaldo, 2009).

[8]Since an interbank lending position can be hedged by financing the loan in the overnight Federal Funds market and entering into an OIS for the same term as the first loan, the spread between the Libor and the OIS should be zero by no arbitrage. When there are transaction costs or counter-party risk, this does not hold. For a detailed discussion, see Gorton and Metrick (2009b), who also point out the no-arbitrage condition has kept the Libor-OIS spread below 10 basis points historically.

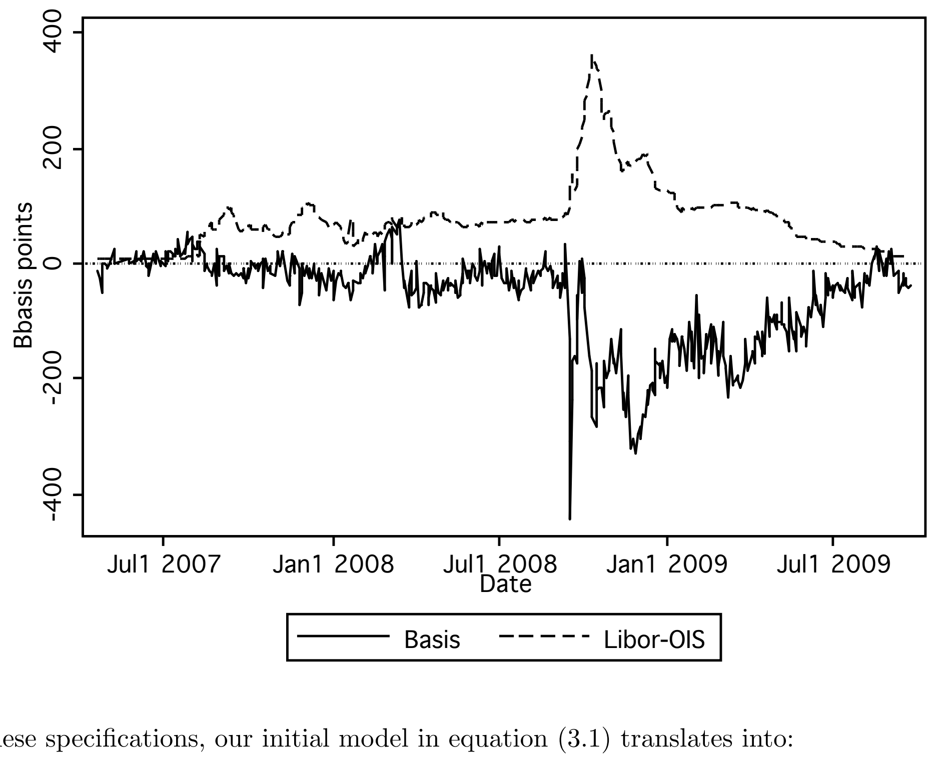
The spread between the Libor and OIS, then, reflects the difference between interbank lending *with* counter-party risk (Libor) and interbank lending which is virtually *free* from counter-party risk, and it proxies for counter-party risk in the interbank market (Gorton and Metrick, 2009a). Hui et al. (2009) and Gorton and Metrick (2009a) also use the Libor-OIS spread as a proxy for funding liquidity. Figure 3.1 below illustrates graphically how the basis evolved relative to the Libor-OIS spread for the investment bank Goldman Sachs. Summary statistics over the correlation between the basis and the Libor-OIS spread are available in Appendix, figure A.7.

Other proxies we consider are the TED spread, which is the difference between Libor and equal-maturity Treasury bills, and the spread between Libor and the repo general collateral rate. The former captures funding liquidity since interbank financing costs (Libor) increase in uncertain times when counter-party risk is perceived as high. This increases the demand for high-rate collateral, making Treasury bonds more attractive to hold, pushing down the Treasury rates and thus increasing the TED spread (Brunnermeier, 2009). Similarly, as explained by Gârleanu and Pedersen (2009), the Libor-repo general collateral spread captures the differing costs between uncollateralized borrowing such as the Libor and collateralized borrowing such as a repo.

In the model, we refer to the Libor-OIS spread as $liborois_{i,t}$

**Figure 3.1**

This figure illustrates how the CDS-bond basis evolved relative to the Libor-OIS spread during the financial crisis for the investment bank Goldman Sachs. The basis and the Libor-OIS seem to co-move, indicating that the Libor-OIS spread captures some change that caused the basis.




Using these specifications, our initial model in equation (3.1) translates into:

$$basis_{i,t} = \beta_{0,i} + \beta_1 ret_{i,t} + \beta_2 vol_{i,t} + \beta_3 r_t^{10} + \beta_4 slope_t + \beta_5 \left(r^2\right)_t^2 + \beta_6 liq_{i,t} + \beta_7 liborois_t + u_{i,t} \tag{3.3}$$

Next, because most firms are heavily affected by the general business climate, and because recovery rates tend to be lower in recessions (Blanco et al., 2005), we also consider factors reflecting the business climate.

7. *The business climate.* In line with Collin-Dufresne et al. (2001) and Alexopoulou et al. (2009), we use market equity returns as captured by the returns of the S&P 500, denoted $S\&P_t$ in the model. Similar to our argument about individual stock returns, we assume that market equity returns captures the market's expectations about economic activity. Furthermore, we use the VIX index[9], denoted $VIX_t$, which – besides reflecting market volatility and capturing some sort of market unease – provides a support to the firm-specific realized volatility measure.

Lastly, we consider three separate models to more readily compare the effect of the factors on CDS and credit spreads ("CS"). We use the first difference of the variables $CDS$, $CS$, $basis_{i,t}$, $vol_{i,t}$, $r_t^{10}$, $slope_t$, $liborois_{i,t}$ and $VIX_t$ because we find that they are non-stationary processes[10]. This leads to the final specification of:

$$\Delta CDS_{i,t} = \beta_{0,i} + \beta_1 ret_{i,t} + \beta_2 \Delta vol_{i,t} + \beta_3 \Delta r_t^{10} + \beta_4 \Delta slope_t + \beta_5 \left(\Delta r^{10}\right)_t^2 + \beta_6 liq_{i,t} + \beta_7 \Delta liborois_t + \beta_8 S\&P_t + \beta_9 \Delta VIX_t + u_{i,t} \tag{3.4}$$

$$\Delta CS_{i,t} = \beta_{0,i} + \beta_1 ret_{i,t} + \beta_2 \Delta vol_{i,t} + \beta_3 \Delta r_t^{10} + \beta_4 \Delta slope_t + \beta_5 \left(\Delta r^{10}\right)_t^2 + \beta_6 liq_{i,t} + \beta_7 \Delta liborois_t + \beta_8 S\&P_t + \beta_9 \Delta VIX_t + u_{i,t} \tag{3.5}$$

$$\Delta basis_{i,t} = \beta_{0,i} + \beta_1 ret_{i,t} + \beta_2 \Delta vol_{i,t} + \beta_3 \Delta r_t^{10} + \beta_4 \Delta slope_t + \beta_5 \left(\Delta r^{10}\right)_t^2 + \beta_6 liq_{i,t} + \beta_7 \Delta liborois_t + \beta_8 S\&P_t + \beta_9 \Delta VIX_t + u_{i,t} \tag{3.6}$$

where $CDS_{i,t}$, $CS_{i,t}$ and $basis_{i,t}$ are the CDS spread, credit spread and basis respectively for firm $i$ in day $t$.

Table 3.1 below summarizes our hypothesized signs. The signs on the basis variable derives from the following reasoning: If liquidity risk and default risk are correlated in such way that poor liquidity can be associated with increased sensitivity to credit risk, then the credit risk component of a spread will also reflect part of the liquidity risk. Consequently, the credit risk component in the bond market is possibly larger than that of the CDS market. Therefore, we should observe a significant effect of credit risk factors on the basis.

[9]The VIX, or CBOE Volatility Index, is constructed using the implied volatility of a range of S&P 500 index options.

[10]We perform an Augmented Dickey-Fuller unit root test for each time series in the panel dataset. When the majority of the time series for a particular variable are found to be unit roots, we conclude that it is non-stationary. The basis does not have unit roots, in most cases, but we use the first difference to simplify the comparison of the regression results.

**Table 3.1**

**Explanatory variables of the regression model**. This table outlines our predicted signs on the explanatory variables in the regression model $\Delta CDS_{i,t}\,(\Delta CS_{i,t})\,(\Delta basis_{i,t}) = \beta_{0,i} + \beta_1 ret_{i,t} + \beta_2 \Delta vol_{i,t} + \beta_3 \Delta r_t^{10} + \beta_4 \Delta slope_t + \beta_5 \left(\Delta r^{10}\right)_t^2 + \beta_6 liq_{i,t} + \beta_7 \Delta liborois_t + \beta_8 S\&P_t + \beta_9 \Delta VIX_t + u_{i,t}$. We use two different measures of credit spread, Asset Swap Spread and Z-spread, but the predictions are the same regardless of measure. A plus or minus sign means we expect a positive or negative coefficient respectively, and "Insig." means that we do not expect the coefficient to be significantly different from zero.

| | | Predicted sign | | |
|---|---|---|---|---|
| Variable | Description | $\Delta CDS_{i,t}$ | $\Delta CS_{i,t}$ | $\Delta basis_{i,t}$ |
| $ret_{i,t}$ | Stock return | − | − | + |
| $\Delta vol_{i,t}$ | Firm-specific volatility | + | + | − |
| $\Delta r_t^{10}$ | Change in long interest rate | − | − | Insig. |
| $\Delta slope_t$ | Change in slope of yield curve | − | − | Insig. |
| $\left(\Delta r^{10}\right)_t^2$ | Change in convexity | + | + | Insig. |
| $liq_{i,t}$ | Liquidity measure | + | + | − |
| $\Delta liborois_t$ | Libor-OIS spread | + | + | − |
| $S\&P_t$ | Return on the S&P 500 | − | − | + |
| $\Delta VIX_t$ | Market implied volatility volatility | + | + | − |

# 4 Data and methodology

## 4.1 Data description

The data we use for the study consist primarily of CDS data, bond data, reference interest rates and equity market data. CDS data is obtained from Datastream[11]. The spreads are composites aggregated from spreads reported by major market makers, and we do not know whether a certain spread is an indicative quote or a spread reported from an actual transaction. Furthermore, no firm has CDS quotes time series without gaps, and we do not have information on whether quotes are left out because the data is unavailable or because no trading occurred. We download data on 624 firms that have traded CDS contracts during our time period, which we use to compose a dataset of CDS contracts matched with corresponding bonds. We limit the CDS data to five-year maturities, because this is the most traded maturity (Blanco et al., 2005). We do not include an explicit control for liquidity in the CDS market, but we believe that choosing a liquid maturity is sufficient, seeing for example that Bühler and Trapp (2008) state that only about 4% of the CDS spread is attributable to liquidity, compared to about 35% for corporate bonds (Bühler and Trapp, 2008).

Price, volume and the yield to maturity data for a large amount of transactions carried out in the U.S. corporate bond market during our time period are obtained from TRACE[12], accessed through WRDS[13]. The total sample contains 23 165 691 transactions and 31 245 corporate bonds. The transaction frequency varies between bonds, and for most bonds there are quite large gaps in the time series. Issue dates, maturity dates and coupon rates are obtained from the CUSIP Service Bureau[14], accessed through WRDS, and credit rating for bonds are obtained from Fidelity Investments Fixed Income Center.

A quite large proportion of the bonds we use in the final dataset are callable, which means that the issuer can redeem the bond before maturity. This makes the bonds extra sensitive to interest rate changes, since the value of the embedded call option increases as it becomes closer to "in the money", i.e. as interest rates drop. We acknowledge that this will likely affect our measure of the basis to some degree, but controlling for fixed effects and interest rate changes as well as yield curve slope and convexity will most likely capture the main part of the callability effect.

We consistently use swap rates as reference rates in our calculations and regressions. Daily data on swap rates for maturities between one and thirty years are obtained from the Federal Reserve Board. Other reference rates are obtained from Datastream, including Libor rates for all maturities from overnight to twelve months, three-month Treasury rates, OIS rates and repo overnight general collateral rates. Lastly, we use Eudodollar futures supplied by Datastream to determine the future Libor quotes for any given day during our sample period.

The swap rates are not bootstrapped to zero rates. This means that there is an embedded "coupon effect" in the swap rates we use, because they represent the rate paid in the fixed leg in an fixed-for-floating interest rates swap. Our swap rates are thus either higher or lower than the actual zero rates, depending on the slope of the yield curve. Compared to using Treasury rates, which

[11]Datastream is a large financial statistics database provided by Thomson Reuters.

[12]Trade Reporting and Compliance Engine (TRACE) is the corporate bond market price service of the Financial Industry Regulatory Authority, a self-regulatory organization. TRACE was introduced in 2002, and consolidates transaction data of almost the complete U.S. corporate bond market.

[13]Wharton Research Data Services (WRDS) of Wharton School at the University of Pennsylvania provides access to a variety of databases.

[14]The CUSIP Service Bureau, operated by Standard & Poor's for the American Bankers Association, provides attributes for over 5 million corporate, municipal and government securities in North America.

are often artificially low[15], we deem that the effect will not be crucial for our results.

Daily stock prices and levels of the S&P 500 index and are obtained from CRSP[16] accessed through WRDS. For the main model, we calculate the volatility from the realized stock returns, but for a robustness test performed on only the latter half of our time period, we use one month implied volatility data from Datastream. Daily data on the CBOE Volatility Index (VIX) are obtained from the Chicago Board Options Exchange, accessed through WRDS.

Lastly, for robustness tests we use data on the Fama and French (1993) factors, which is provided by Kenneth French and accessed through WRDS.

## 4.2 Construction of the dataset

To enable an apples-to-apples comparison between the CDS spread and the credit spread, we construct a five-year credit spread that matches the maturity of the five-year CDS spread. We follow the methodology of Blanco et al. (2005) and Houweling and Vorst (2005), and search for a pair of bonds for each firm. The first bond should have three to five years left to maturity at the beginning of our time period. The second bond should have at least five years left to maturity at the end of our period. With such a pair of bonds, it is always possible to combine the two bonds to form a five-year credit spreads.

We proceed in the following manner: First, from our bond data we remove trades with prices reported inclusive of commission, with prices reported as a weighted average price for multiple trades, or otherwise non-regular trades. Then, we keep only the last price of the day as a closing price. Doing so, we create somewhat of an intra-day timing mismatch between the bond and CDS quotes. However, the impact of such a mismatch is likely to be trivial, because bond prices tend not to fluctuate much intra-day.

Next, we consider how it is possible to find an "optimal" set of firms given the look of our dataset. To interpolate a five-year credit spread for a certain day, we need the price for both bonds in the pair. Furthermore, to calculate the basis we also need the spread for the CDS that day. Since there are gaps in both the CDS and bond time series, observations do not necessarily match on all days in the sample, so the number of final observations we can achieve depends on which two bonds we combine together. Consequently, we examine every combination possible of the 31 245 bonds and 624 CDS contracts. We then select those bond combinations where we can find at least 300 days with prices for both bonds and CDS spreads. We deem 300 observations to be acceptable since there are approximately 690 trading days in our time period.

Lastly, we manually inspect each chosen firms. We remove firms that experienced credit events during our time period and firms that were acquired by another firm. We also replace bond pairs where the credit rating of each bond differs by more than two rating steps and bonds rated lower than Highly Speculative (corresponding to a S&P rating of B+ to B-). We then assign a credit rating to each bond pair. In general, we take into account the rating from both Moody's and Standard & Poor's for each bond and weigh them together into a reasonable composite rating for

[15]Treasury bills and bonds must be purchased by financial institutions to fulfill regulatory requirements (Hull, 2009), which increases the demand, driving the yields down. In addition, the capital reserve a bank is required to carry as collateral for a Treasury instrument investment is substantially smaller than for virtually all other investments, including instruments with very low risk. This further increases demand, and pushes the yields down. Lastly, in the United States, Treasury instruments are given a favorable tax treatment compared to other fixed-income investments, because they are not taxed at the state level (Elton et al., 2001). Hence, because of tax and regulatory issues, Treasury rates are often artificially low. Other problems with Treasury rates include the existence of "humps" in on-the-run Treasury bond prices, following the on-the-run premium of about 15-25 basis points. For a detailed discussion on special repo rates and this effect, see for example Fisher (2002) or Duffie (1996).

[16]The Center for Research in Security Prices (CRSP) at Booth School of Business of the University of Chicago collects data from NYSE, AMEX and NASDAQ stock markets.

the pair. We also divide the ratings into broader rating groups. The assumptions underlying these conversions are detailed in Table A.1.

In total we obtain a dataset comprising of 62 firms. Table A.6 summarizes the main characteristics of each firm with regard to credit spread, CDS spread, basis and credit rating.

## 4.3 Determining the credit spread

The credit spread is the difference between the bond's yield to maturity and the risk-free rate, and thus reflects the credit risk of the bond. However, there are other components inherent in the bond yield, such as liquidity risk, interest rate risk and funding risk. Measuring the credit spread is not always straightforward; especially not if it is supposed to be comparable to the CDS spread.

A conventional measure of credit spread is the interpolated spread or I-spread. It is simply calculated as the yield to maturity of the bond less the yield of a risk-free benchmark of the same maturity (Francis et al., 2003). While methodologically tractable, it does not take into account the term structure of interest rates. For example, when the yield curve is hump-shaped, the I-spread would overstate the credit spread.

A more refined measure is the zero volatility spread, or the Z-spread. The Z-spread is defined as the spread that must be added to the yield curve at every point in time so that the sum of the discounted cash flows of the bond equals its price. For each bond and day, we calculate the Z-spread in the following way:

$$P = \sum_{t=1}^{T} \left( \frac{C_t}{(1 + r_t + Z)^t} + \frac{FV}{(1 + r_t + Z)^T} \right), \; t = 1, 2, ..., T \tag{4.1}$$

Where $P$ is the dirty price[17] of the bond, $C_t$ is the coupon payment at time $t$, $r_t$ is the risk-free benchmark with maturity $T$, $FV$ is the face value of the bond, and $Z$ is the Z-spread which is found iteratively.

As mentioned, we use the swap rate as a risk-free benchmark. However, the swap rate is only available for certain maturities. To construct a complete yield curve, we use the Nelson and Siegel (1987) interpolation method. The approach is common (see for example Elton et al., 2001), and the efficiency of the rather simple model is confirmed by for example Dahlquist and Svensson (1996). Essentially, we fit a polynomial function with least squares minimization to the swap rate data, and use the model parameters to obtain interpolated swap rates for any date. For detailed discussion on the Nelson-Siegel method, refer to Nelson and Siegel (1987).

While the Z-spread offers an intuitive interpretation, it is not a tradable spread. A measure that is in fact tradable is the previously discussed Asset Swap Spread (ASW), which, for this reason, is often the focus of empirical studies (for example De Wit, 2006). For each bond and day, we calculate the ASW in the following way:

$$0 = 100 - P + \sum_{t=1}^{T} \frac{C_t}{(1 + r_t)^t} - \sum_{t=1}^{T} \frac{(L_t + ASW) \times \alpha_t}{(1 + r_t)^t}, \; t = 1, 2, ..., T \tag{4.2}$$

where $P$ is the dirty price of the bond at initiation, $C_t$ is the coupon payment at time $t$, $r_t$ is the risk-free benchmark with maturity $t$, $L_t$ is the forward three-month Libor rate at time $t$, $\alpha_i$ is the accrual factor, and $ASW$ is the Asset Swap Spread.

[17] Bond quotes are usually referred to as "clean" prices, because they do not include accrued interest. The clean price of the bond plus the interest accrued since the last coupon payment equals the bond's dirty price.

As a risk-free benchmark, we use the same interpolated swap rates as in the calculation of the Z-spread. We estimate Libor forward rates using Eurodollar futures contracts, which in essence give us Libor futures rates. A Eurodollar future allows an investor to lock in a Libor rate for a period of time in the future, and thus represents the market's prediction of what the Libor rate will be at that time. We linearly interpolate between Eurodollar futures to obtain a rate for each payment date.

Lastly, for each firm and day, we linearly interpolate between the two selected bonds to obtain a five-year Z-spread and a five-year ASW. See Table A.6 for summary statistics.

# 5 Results

## 5.1 Basic setup

Table 5.1 reports the results from regressions (3.4), (3.5) and (3.6)[18]. The results show that, out of the credit risk factors derived from the Merton (1974) framework, only leverage significantly explains spread changes in the bond market and the CDS market. Credit risk factors do not seem to affect the basis. The main factors affecting the basis are instead related to market liquidity and funding liquidity.

As explained in section 3, we use the first difference of several variables. It is necessary for statistical reasons, but introduces some problems with respect to the interpretation of the coefficients. Therefore, we also include a regression performed with a non-differenced basis (CDS spread minus Z-spread) as the dependent variable. Throughout the analysis, we will refer to this regression when commenting significance levels, but the signs on the coefficients may not be as expected.

Looking at the summary statistics in Table A.6, we first note that the ASW is consistently below the Z-spread. Throughout our time period, most bonds trade at prices well below par, so the ASW will underestimate the credit spread, as discussed in section 2.1. For the rest of the this section, will use the Z-spread as a measure of the credit spread.

Stock returns affect both credit spreads and CDS spreads in the expected direction, and the coefficient is highly significant. In line with our predictions, higher stock returns reduce spreads, but the sensitivity to stock returns seems to be similar for both CDS and credit spreads. Consequently, stock returns does not seem to be a significant determinant of the basis.

The market return is a significant determinant of credit spreads, but is incorrectly signed according to our predictions. Since we consider the market return to proxy for overall changes in recovery rates, this is surprising. Positive market return should be associated with lower credit spreads.

Firm volatility is correctly signed but insignificant for all variables. Judging from the size of the coefficients, the bond market seems to be more sensitive to volatility than the CDS market, but no coefficients are significant. The market volatility is correctly signed for credit spreads, but is not significant in any regression. Though insignificant, we note that the firm-specific volatility measure plays a more important role than market implied volatility, because the coefficients on firm-specific volatility are consistently larger (firm-specific volatility and market implied volatility are measured in the same unit).

The liquidity measure seems to accurately capture what we intended it to do. As expected, worsening liquidity (higher values of the liquidity measure) translates into higher credit spreads and a significant basis. For the CDS spread, the coefficient is insignificant, which we take to mean that the measure succeeds in capturing the bond-specific liquidity. Even though the coefficient in the CDS spread regression is small and insignificant, we note that the sign is positive. It is possible that this is an example of the correlation between liquidity risk and credit risk that we discussed earlier, so that some of the liquidity risk in the bond market spills over to the CDS market. For example, the delivery option risk in CDS contracts should be positively correlated with bond liquidity, since there is a possibility that an illiquid bond will be delivered – especially if the probability of delivery is high. Consequently, lower liquidity in the bond market can lead to higher CDS premiums, explaining the positive sign.

Funding liquidity is a highly significant determinant for both CDS and credit spreads, and all signs are in line with our expectations. Higher Libor-OIS spreads are associated with scarcer availability

[18] The regressions are estimated using OLS with Huber-White heteroskedasticity robust standard errors.

of funds, which should affect credit spreads more than CDS spreads since bonds require larger margins, as discussed in section 2.3 (Gârleanu and Pedersen, 2009). As seen, this leads to negative changes in the basis. Looking at the non-differenced basis variable, we see that the coefficient is very large in magnitude and highly significant, indicating that there is a strong relationship between the funding constraints to investors and the CDS-bond basis. The reason for the positive coefficient is related to the first differencing discussed above. Clearly, we would expect a negative relationship, and Table A.7 shows that the correlation between the basis and the Libor-OIS spread is indeed highly negative for almost all firms in the sample. The only exceptions are Medtronic, which is negatively correlated in the second half of the sample, and American Express, which has an average basis close to zero.

The long-term interest rate and the yield curve slope are highly significant for both CDS and credit spreads most of the time. The coefficient for the long-term interest rate is negative for both CDS and credit spreads. This is in line with our predictions, since we expect an increase in risk-free rates to increase the drift of the firm and to decrease CDS and credit spreads. However, we expect the effect to be similar for both CDS and credit spreads so that it does not give rise to a basis. On the contrary, the effect of the ten-year swap rate is notably larger for credit spreads than for CDS spreads. Even though we control for the yield curve slope and convexity, this seem to be an important determinant of the basis, driving the basis negative when interest rates rise.

As explained in section 4.1, we are forced to include many callable bonds in the dataset, and the bonds therefore likely have high convexity, which would explain the strong sensitivity to the ten-year swap rate and the convexity control. The convexity in a CDS arises primarily because the expected profit or loss for either party does not change linearly with spread changes; an increase in the spread level follows from an increase in the probability of default. As the probability of default increases, so does the probability of an early termination of the contract, and hence it arises a convexity issue[19]. As evident, neither the duration nor the convexity are the same in CDS contracts and bonds, and this effect becomes especially prominent for callable bonds. Therefore, the different sensitivities to convexity might be a reason for the effect on the basis.

For robustness, we try our model with a variety of different specifications. We use the TED spread and the Libor-repo general collateral spread instead of the Libor-OIS spread, both of which prove to be a less significant determinants of the basis. We also use age and trading volume as alternatives to the liquidity measure, and this does not change our conclusions. Our findings also remain unchanged after considering the Fama and French (1993) risk factors, which do not seem to capture the changes in the CDS-bond basis.

In relation to other studies, we believe some specifications are less suitable for stressed time periods like the credit crisis, because the focus is often heavily leaned towards capturing market liquidity and not funding liquidity. Instead, most authors control for a so called mean-reverting nature of the basis by including a lagged basis term. We argue that such studies may incorporate only the effect of a pricing error rather than controlling for its cause. The notion of a mean-reverting basis rests on the assumption that the markets price risk equally in the long run, but because of market frictions there might be a short-run basis. For this reason, we believe, it is common that the focus of empirical work is on the co-integration of the markets, and not on the pricing errors themselves. If funding constraints provide a natural explanation for the CDS-bond basis, then a lagged basis term should cancel out the effect of the Libor-OIS spread. We find that this is indeed true. We run regressions analogous to those of Zhu (2004), Blanco et al. (2005) and Alexopoulou et al. (2009). We first run our standard specification with a lagged first differenced basis term, and find that the coefficient on the lagged basis term is significant and signed as expected (price correction is faster in CDS market). Next, we run the same regression but without taking the first difference on the dependent variable, in the same manner as Zhu (2004). Our results show that about 9% of the errors are corrected to the next period, compared to 7-9% as found by Zhu (2004).

[19]Because future survival is conditional on previous survival, the cumulative survival probability is more affected than that of the current period. For a detailed discussion on duration and convexity of credit derivatives, refer to Beinstein and Scott (2006).

Lastly, we apply the same Granger two-step approach as Alexopoulou et al. (2009), and estimate an error correction term from the regression $CDS_{i,t} = CS_{i,t} + \epsilon_{i,t}$, and substitute $\hat{\epsilon}_{i,t}$ in place of the lagged basis term. Doing so, we find significant results with the same signs as with our lagged basis terms, with coefficients of the same magnitude. Overall, the results are very similar to those of Alexopoulou et al. (2009). Seeing that the effect of the Libor-OIS factor seems to diminish with the inclusion of error correction terms, we interpret this as funding requirements playing an important role in determining the CDS-bond basis.

**Table 5.1**

**Regression results, main specification.** This table shows the outcome of running the regressions $\Delta CDS_{i,t}\,(\Delta CS_{i,t})\,(\Delta basis_{i,t})\,(basis_{i,t}) = \beta_{0,i} + \beta_1 ret_{i,t} + \beta_2 \Delta vol_{i,t} + \beta_3 \Delta r_t^{10} + \beta_4 \Delta slope_t + \beta_5 \left(\Delta r^{10}\right)_t^2 + \beta_6 liq_{i,t} + \beta_7 \Delta liborois_t + \beta_8 S\&P_t + \beta_9 \Delta VIX_t + u_{i,t}$. We use stock returns, $ret_{i,t}$, as a proxy for leverage and financial health of the firms, and $\Delta vol_{i,t}$ is the changes in firm-specific ten-period realized volatility. We use three factors to control for interest rate changes: changes in the ten-year swap rate, $r_t^{10}$, changes in the slope of the yield curve, $slope_t$, which is calculated as the difference between the ten-year and the two-year swap rates, and finally we use changes in the ten-year swap rate squared, $\left(\Delta r^{10}\right)^2$, to control for convexity issues. Bond-specific market liquidity is captured by a measure of price volatility to trading volume, $liq_{i,t}$, and changes in the Libor-OIS spread, $liborois_t$, proxy for funding liquidity by capturing interbank counter-party risk. Lastly, we include returns of the S&P500 index and changes in the VIX volatility index to capture changes in the business climate and varying general recovery rates. The regression is performed on the complete dataset consisting of 62 firms.

| | $\Delta CDS_{i,t}$ | $\Delta CS_{i,t}$ | $\Delta basis_{i,t}$ | $basis_{i,t}$ |
|---|---|---|---|---|
| $ret_{i,t}$ | -2.107*** | -2.655*** | 0.0579 | -0.433 |
| | (0.000) | (0.000) | (0.890) | (0.455) |
| $\Delta vol_{i,t}$ | 0.769 | 1.570 | -1.281 | 0.728 |
| | (0.256) | (0.204) | (0.339) | (0.744) |
| $\Delta r_t^{10}$ | -0.0904*** | -0.675*** | 0.583*** | 0.263** |
| | (0.004) | (0.000) | (0.000) | (0.037) |
| $\Delta slope_t$ | -20.89*** | 15.10 | -32.48*** | -54.13** |
| | (0.001) | (0.168) | (0.003) | (0.011) |
| $\left(\Delta r^{10}\right)_t^2$ | -12.07 | 44.67 | -51.42 | -650.0*** |
| | (0.586) | (0.167) | (0.105) | (0.000) |
| $liq_{i,t}$ | 1.047 | 10.39*** | -9.184** | -37.30*** |
| | (0.339) | (0.007) | (0.015) | (0.000) |
| $\Delta liborois_t$ | 0.307*** | 0.530*** | -0.178 | 1.116*** |
| | (0.000) | (0.000) | (0.184) | (0.000) |
| $S\&P_t$ | 0.511 | 2.273*** | -1.079 | 1.407 |
| | (0.387) | (0.006) | (0.119) | (0.290) |
| $\Delta VIX_t$ | -0.0754 | 0.425 | -0.384 | 1.328 |
| | (0.706) | (0.341) | (0.402) | (0.156) |
| Constant | 0.0000166 | -0.000220*** | 0.000246*** | -0.00636*** |
| | (0.589) | (0.000) | (0.000) | (0.000) |
| $N$ | 17489 | 19550 | 17489 | 18258 |
| adj. $R^2$ | 0.084 | 0.050 | 0.009 | 0.025 |

$p$-values in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## 5.2 Cross-sectional variations

So far we have assumed homogeneity among firms; an assumption implicit in the panel regression approach. Assuming that each firm is equally sensitive to the credit risk factors is clearly inappropriate. For example, we expect firms with high leverage to be more sensitive to increased volatility than firms with low leverage. Consequently, the coefficients in our first regressions are unable to fully capture the effects of changes in credit risk and liquidity factors.

To shed some light on the cross-sectional variations, we perform the same regressions as earlier (equations (3.4), (3.5) and (3.6)) on subsamples divided according to credit rating groups. The credit rating groups are outlined in Table A.1.

Tables A.2, A.3, A.4 and A.5 report the results of the regressions within rating groups. The results reveal two main findings. First, the credit spreads for firms with lower ratings are more sensitive to changes in credit risk factors and changes in funding liquidity. Second, the basis for firms with lower ratings is more sensitive to funding liquidity.

The coefficient for stock return is correctly signed for both CDS and credit spreads, and its significance and size increases as the credit rating decreases. For high grade bonds, stock return is insignificant, while it is highly significant for the other rating groups. This is in line with our predictions, since we expect CDS and credit spreads for firms with lower rating to be more sensitive to changes in leverage. Comparing the sensitivities for each rating group, we see that the sensitivity of the CDS and the credit spread are of similar magnitude. This translates into an insignificant coefficient for the basis, as was the case using the full sample.

Liquidity is a somewhat significant determinant of the credit spread. Looking at the significance of the non-differenced basis in the regression, we see that liquidity is significantly associated with basis for all but the highest rating.

The slope of the yield curve proves significant for determining the credit spread for higher rating groups, and the size of the coefficient decreases with higher rating. This result is related to the definition of the Z-spread. Firms with higher ratings have lower Z-spreads, and thus a large part of their yields consists of a risk-free rate. Consequently, the credit spread of a firm with a high rating becomes relatively more sensitive to changes in the slope of the yield curve. Because the effect is not similar for the CDS, the yield curve slope becomes significant for the basis for all rating groups except the lowest. The ten-year swap rate is highly significant and correctly signed for the credit spread and for all ratings. The size of the coefficient is generally larger for lower ratings, which is in line with the findings for the full sample. Bonds with lower credit quality have a higher probability of default, and the marginal effect of an increase in the risk-free rate is hence larger for low-rated firms than high-rated firms. Similar to our findings above, the swap rate also seems to be a determinant of the basis.

The Libor-OIS is not significant for the credit spread except for the upper medium rating. For the CDS spread, the Libor-OIS is highly significant for all ratings. In line with our hypothesis, the coefficients are much smaller for the unfunded CDS position than for the credit spread. Therefore, the Libor-OIS should affect the basis. Indeed, the Libor-OIS spread significantly affects the basis across all rating groups, and the size of the coefficient is largest for the lowest rating, indicating that lower rating groups are more sensitive to funding liquidity than higher rating groups.

Evidently, there is a cross-sectional variation among firms in their sensitivity to the factors determining the basis. This section has illustrated that bonds of different credit quality have different sensitivity to credit risk, liquidity risk and funding risk.

# 6 Concluding remarks

In this thesis we examine the CDS and credit spreads and the resulting CDS-bond basis of 62 U.S. firms during the period 2007 to 2009. We try to explain CDS and credit spreads and the CDS-bond basis by employing credit risk factors, a market liquidity factor and by introducing a funding liquidity factor. The credit risk factors leverage, firm volatility and recovery rates are derived from the structural models of credit risk, and we proxy for them by using stock returns, realized volatility and controls for the business climate (market returns and the VIX volatility index) respectively. In addition, we add variables that proxy for market liquidity and funding liquidity. We use a measure of price volatility to trading volume to control for market liquidity, and based on recent research, we use the Libor-OIS spread as a proxy for funding liquidity. To the best of our knowledge, this one of the first studies that use a funding liquidity factor to study the determinants of the CDS-bond basis.

We find scarce evidence of credit risk factors affecting the basis. Stock return and firm volatility are rarely significant determinants of the basis, and market return is more often than not incorrectly signed. Liquidity, on the other hand, is highly significant for the basis, so that increased liquidity in the bond market lowers the basis. The funding liquidity factor is highly significant for both CDS and bond spreads as well as for the basis.

We also have reason to believe that there may be large differences between firms with regards to their sensitivity to the determinants of the CDS and bond spreads and the basis. For example, we expect firms with high leverage to be more sensitive to increased volatility than firms with low leverage. Consequently, the coefficients in our first regressions are unable to fully capture the effects of changes in credit risk and liquidity factors. To examine this notion, we divide the dataset into subsamples according to the credit rating of the firms. We create four broad credit rating groups, and run the same regressions within the groups. We conclude that there are indeed large differences in sensitivity to factors explaining both CDS and bond spreads and the basis, and two findings emerge: First, the credit spread of firms with lower ratings is more sensitive to changes in credit risk factors and funding liquidity. Second, the basis of firms with lower ratings is more sensitive to funding liquidity.

We draw a simple yet intuitively appealing conclusion: The large discrepancies that were observed 2007 to 2009 between the CDS and bond markets were not mainly caused by any fundamental change in the pricing of credit risk in the markets. Instead, the pricing discrepancies may not have been traded away for the reason that the funding needed for the trades was unavailable.

For future research, we would like to point to the time variability of the sensitivities to basis determinants. We have found indications for that the sensitivities to credit risk, market liquidity and funding liquidity vary over time, and we suspect that there is a possibility that a permanent shift in the sensitivity to certain factors occurred some time during the financial crisis. This could for example mean that certain rating groups experienced a permanent increase in the sensitivity to some of the factors. To be able to make more accurate interpretations of the information content of the credit markets, future research needs to assess the possible occurrences of shifts in the sensitivity to credit risk and liquidity risk for certain rating groups or firms with other special characteristics.

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# A Tables

**Table A.1**

**Assumptions of credit rating conversion and rating band assignment.** This table outlines our assumption of credit rating conversion between Moody's and Standard & Poor's long-term credit rating. It also show how we assume that the particular ratings are divided into larger groups.

| | Credit rating by institute | |
|---|---|---|
| Rating group | Moody's | Standard & Poor |
| High grade | Aaa | AAA |
| | Aa1 | AA+ |
| | Aa2 | AA |
| | Aa3 | AA- |
| Upper Medium grade | A1 | A+ |
| | A2 | A |
| | A3 | A- |
| Lower Medium grade | Baa1 | BBB+ |
| | Baa2 | BBB |
| | Baa3 | BBB- |
| Low grade | Ba1 | BB+ |
| | Ba2 | BB |
| | Ba3 | BB- |
| | B1 | B+ |

**Table A.2**

**Regression results, divided by credit rating (CDS spread).** This table shows the outcome of the regression $\Delta CDS_{i,t} = \beta_{0,i} + \beta_1 ret_{i,t} + \beta_2 \Delta vol_{i,t} + \beta_3 \Delta r_t^{10} + \beta_4 \Delta slope_t + \beta_5 \left(\Delta r^{10}\right)_t^2 + \beta_6 liq_{i,t} + \beta_7 \Delta liborois_t + \beta_8 S\&P_t + \beta_9 \Delta VIX_t + u_{i,t}$, when the total sample is split into four rating groups. We use stock returns, $ret_{i,t}$, as a proxy for leverage and financial health of the firms, and $\Delta vol_{i,t}$ is the change in firm-specific ten-period realized volatility. We use three factors to control for interest rate changes: changes in the ten-year swap rate, $r_t^{10}$, changes in the slope of the yield curve, $slope_t$, which is calculated as the difference between the ten-year and the two-year swap rates, and finally we use changes in the ten-year swap rate squared, $\left(\Delta r^{10}\right)^2$, to control for convexity issues. Bond-specific market liquidity is captured by a measure of price volatility to trading volume, $liq_{i,t}$, and changes in the Libor-OIS spread, $liborois_t$, proxy for funding liquidity by capturing interbank counter-party risk. Lastly, we include returns of the S&P500 index and changes in the VIX volatility index to capture changes in the business climate and varying general recovery rates. In total, there are 62 firms in the dataset.

| Variable | High grade $\Delta CDS$ | Upper Medium grade $\Delta CDS$ | Lower Medium grade $\Delta CDS$ | Low grade $\Delta CDS$ |
|---|---|---|---|---|
| $ret_{i,t}$ | -0.0136 | -1.225*** | -2.676*** | -2.549*** |
| | (0.857) | (0.000) | (0.006) | (0.000) |
| $\Delta vol_{i,t}$ | 0.0905 | 0.915 | -0.153 | 4.169* |
| | (0.788) | (0.164) | (0.885) | (0.083) |
| $\Delta r_t^{10}$ | -0.0449*** | -0.0834** | -0.0908 | -0.109 |
| | (0.000) | (0.021) | (0.141) | (0.315) |
| $\Delta slope_t$ | 3.965** | -12.53** | -20.40* | -57.06** |
| | (0.033) | (0.030) | (0.077) | (0.031) |
| $\left(\Delta r^{10}\right)_t^2$ | -9.397** | -10.49 | -66.59** | 97.51 |
| | (0.020) | (0.436) | (0.048) | (0.249) |
| $liq_{i,t}$ | -0.428 | 0.804 | 2.197 | -2.946 |
| | (0.292) | (0.230) | (0.287) | (0.123) |
| $\Delta liborois_t$ | 0.0456*** | 0.213*** | 0.375*** | 0.485*** |
| | (0.006) | (0.000) | (0.001) | (0.003) |
| $S\&P_t$ | -0.138 | 0.220 | 0.441 | -0.0871 |
| | (0.104) | (0.607) | (0.705) | (0.946) |
| $\Delta VIX_t$ | 0.112 | 0.318 | -0.659* | 0.176 |
| | (0.104) | (0.184) | (0.057) | (0.852) |
| Constant | 0.0000115 | 0.00000375 | 0.0000758 | -0.0000278 |
| | (0.172) | (0.912) | (0.196) | (0.782) |
| $N$ | 1334 | 7589 | 6676 | 1890 |
| adj. $R^2$ | 0.099 | 0.048 | 0.102 | 0.179 |

$p$-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table A.3**

**Regression results, divided by credit rating (credit spread).** This table shows the outcome of the regression $\Delta CS_{i,t} = \beta_{0,i} + \beta_1 ret_{i,t} + \beta_2 \Delta vol_{i,t} + \beta_3 \Delta r_t^{10} + \beta_4 \Delta slope_t + \beta_5 \left(\Delta r^{10}\right)_t^2 + \beta_6 liq_{i,t} + \beta_7 \Delta liborois_t + \beta_8 S\&P_t + \beta_9 \Delta VIX_t + u_{i,t}$, when the total sample is split into four rating groups. We use stock returns, $ret_{i,t}$, as a proxy for leverage and financial health of the firms, and $\Delta vol_{i,t}$ is the change in firm-specific ten-period realized volatility. We use three factors to control for interest rate changes: changes in the ten-year swap rate, $r_t^{10}$, changes in the slope of the yield curve, $slope_t$, which is calculated as the difference between the ten-year and the two-year swap rates, and finally we use changes in the ten-year swap rate squared, $\left(\Delta r^{10}\right)^2$, to control for convexity issues. Bond-specific market liquidity is captured by a measure of price volatility to trading volume, $liq_{i,t}$, and changes in the Libor-OIS spread, $liborois_t$, proxy for funding liquidity by capturing interbank counter-party risk. Lastly, we include returns of the S&P500 index and changes in the VIX volatility index to capture changes in the business climate and varying general recovery rates. In total, there are 62 firms in the dataset.

| Variable | High grade $\Delta CS$ | Upper Medium grade $\Delta CS$ | Lower Medium grade $\Delta CS$ | Low grade $\Delta CS$ |
|---|---|---|---|---|
| $ret_{i,t}$ | -0.520 | -2.558** | -2.658*** | -3.322*** |
| | (0.447) | (0.014) | (0.001) | (0.008) |
| $\Delta vol_{i,t}$ | 1.343 | -0.0388 | 1.150 | 11.28 |
| | (0.775) | (0.967) | (0.550) | (0.137) |
| $\Delta r_t^{10}$ | -0.573*** | -0.527*** | -0.738*** | -0.974*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| $\Delta slope_t$ | 46.12*** | 22.12* | 16.06 | -23.86 |
| | (0.007) | (0.081) | (0.370) | (0.652) |
| $\left(\Delta r^{10}\right)_t^2$ | 15.88 | 56.04* | 31.25 | 58.86 |
| | (0.769) | (0.094) | (0.535) | (0.649) |
| $liq_{i,t}$ | 13.67** | 16.93*** | 5.429 | 13.14 |
| | (0.013) | (0.000) | (0.316) | (0.192) |
| $\Delta liborois_t$ | 0.134 | 0.555*** | 0.528 | 0.671 |
| | (0.239) | (0.000) | (0.105) | (0.153) |
| $S\&P_t$ | 0.310 | 3.877*** | -0.158 | 4.326 |
| | (0.742) | (0.009) | (0.898) | (0.128) |
| $\Delta VIX_t$ | 0.275 | 1.056** | -0.682 | 1.753 |
| | (0.694) | (0.027) | (0.406) | (0.441) |
| Constant | -0.000175* | -0.000244*** | -0.000236** | -0.000177 |
| | (0.065) | (0.000) | (0.029) | (0.452) |
| $N$ | 1642 | 8643 | 7253 | 2012 |
| adj. $R^2$ | 0.026 | 0.062 | 0.053 | 0.051 |

$p$-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table A.4**

**Regression results, divided by credit rating (first differenced basis).** This table shows the outcome of the regression $\Delta basis_{i,t} = \beta_{0,i} + \beta_1 ret_{i,t} + \beta_2 \Delta vol_{i,t} + \beta_3 \Delta r_t^{10} + \beta_4 \Delta slope_t + \beta_5 \left(\Delta r^{10}\right)_t^2 + \beta_6 liq_{i,t} + \beta_7 \Delta liborois_t + \beta_8 S\&P_t + \beta_9 \Delta VIX_t + u_{i,t}$, when the total sample is split into four rating groups. We use stock returns, $ret_{i,t}$, as a proxy for leverage and financial health of the firms, and $\Delta vol_{i,t}$ is the change in firm-specific ten-period realized volatility. We use three factors to control for interest rate changes: changes in the ten-year swap rate, $r_t^{10}$, changes in the slope of the yield curve, $slope_t$, which is calculated as the difference between the ten-year and the two-year swap rates, and finally we use changes in the ten-year swap rate squared, $\left(\Delta r^{10}\right)^2$, to control for convexity issues. Bond-specific market liquidity is captured by a measure of price volatility to trading volume, $liq_{i,t}$, and changes in the Libor-OIS spread, $liborois_t$, proxy for funding liquidity by capturing interbank counter-party risk. Lastly, we include returns of the S&P500 index and changes in the VIX volatility index to capture changes in the business climate and varying general recovery rates. In total, there are 62 firms in the dataset.

| Variable | High grade $\Delta basis$ | Upper Medium grade $\Delta basis$ | Lower Medium grade $\Delta basis$ | Low grade $\Delta basis$ |
|---|---|---|---|---|
| $ret_{i,t}$ | 0.809 | -0.121 | 0.0360 | 0.834 |
| | (0.270) | (0.743) | (0.963) | (0.341) |
| $\Delta vol_{i,t}$ | -1.323 | 0.725 | -1.592 | -6.978 |
| | (0.808) | (0.523) | (0.426) | (0.290) |
| $\Delta r_t^{10}$ | 0.517*** | 0.411*** | 0.696*** | 0.829*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| $\Delta slope_t$ | -41.41** | -32.46** | -36.58** | -22.79 |
| | (0.033) | (0.013) | (0.047) | (0.625) |
| $\left(\Delta r^{10}\right)_t^2$ | -36.21 | -51.84 | -89.69* | 39.16 |
| | (0.561) | (0.133) | (0.065) | (0.747) |
| $liq_{i,t}$ | -11.25** | -16.40*** | -2.596 | -17.89 |
| | (0.022) | (0.000) | (0.598) | (0.108) |
| $\Delta liborois_t$ | -0.0948 | -0.208 | -0.156 | -0.165 |
| | (0.486) | (0.118) | (0.572) | (0.707) |
| $S\&P_t$ | -0.224 | -1.763** | 0.539 | -4.462 |
| | (0.822) | (0.029) | (0.654) | (0.120) |
| $\Delta VIX_t$ | -0.152 | -0.688 | 0.345 | -1.798 |
| | (0.844) | (0.172) | (0.661) | (0.428) |
| Constant | 0.000222** | 0.000241*** | 0.000313*** | 0.000207 |
| | (0.041) | (0.001) | (0.004) | (0.397) |
| $N$ | 1334 | 7589 | 6676 | 1890 |
| adj. $R^2$ | 0.021 | 0.013 | 0.010 | 0.013 |

$p$-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table A.5**

**Regression results, divided by credit rating (basis).** This table shows the outcome of the regression $basis_{i,t} = \beta_{0,i} + \beta_1 ret_{i,t} + \beta_2 \Delta vol_{i,t} + \beta_3 \Delta r_t^{10} + \beta_4 \Delta slope_t + \beta_5 \left(\Delta r^{10}\right)_t^2 + \beta_6 liq_{i,t} + \beta_7 \Delta liborois_t + \beta_8 S\&P_t + \beta_9 \Delta VIX_t + u_{i,t}$, when the total sample is split into four rating groups. We use stock returns, $ret_{i,t}$, as a proxy for leverage and financial health of the firms, and $\Delta vol_{i,t}$ is the change in firm-specific ten-period realized volatility. We use three factors to control for interest rate changes: changes in the ten-year swap rate, $r_t^{10}$, changes in the slope of the yield curve, $slope_t$, which is calculated as the difference between the ten-year and the two-year swap rates, and finally we use changes in the ten-year swap rate squared, $\left(\Delta r^{10}\right)^2$, to control for convexity issues. Bond-specific market liquidity is captured by a measure of price volatility to trading volume, $liq_{i,t}$, and changes in the Libor-OIS spread, $liborois_t$, proxy for funding liquidity by capturing interbank counter-party risk. Lastly, we include returns of the S&P500 index and changes in the VIX volatility index to capture changes in the business climate and varying general recovery rates. In total, there are 62 firms in the dataset.

| Variable | High grade<br>*basis* | Upper Medium grade<br>*basis* | Lower Medium grade<br>*basis* | Low grade<br>*basis* |
|---|---|---|---|---|
| $ret_{i,t}$ | 2.754 | -1.624* | 0.504 | -0.839 |
| | (0.128) | (0.084) | (0.546) | (0.617) |
| $\Delta vol_{i,t}$ | -14.03* | 1.661 | -0.534 | 5.721 |
| | (0.087) | (0.669) | (0.846) | (0.519) |
| $\Delta r_t^{10}$ | 0.252 | 0.0733 | 0.431** | 0.566 |
| | (0.252) | (0.657) | (0.030) | (0.316) |
| $\Delta slope_t$ | -64.30 | -71.34** | -33.69 | -55.26 |
| | (0.102) | (0.016) | (0.286) | (0.555) |
| $\left(\Delta r^{10}\right)_t^2$ | -432.6*** | -449.6*** | -760.5*** | -921.1*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| $liq_{i,t}$ | -8.336 | -43.83*** | -13.50 | -113.1*** |
| | (0.727) | (0.000) | (0.186) | (0.000) |
| $\Delta liborois_t$ | 0.838** | 0.821*** | 1.131*** | 2.982*** |
| | (0.011) | (0.000) | (0.001) | (0.000) |
| $S\&P_t$ | -1.629 | 2.836 | 1.386 | -0.956 |
| | (0.416) | (0.144) | (0.490) | (0.871) |
| $\Delta VIX_t$ | 0.559 | 0.893 | 1.687 | 1.735 |
| | (0.716) | (0.473) | (0.256) | (0.679) |
| Constant | 0.000204 | -0.00317*** | -0.00927*** | -0.0140*** |
| | (0.427) | (0.000) | (0.000) | (0.000) |
| $N$ | 1468 | 7948 | 6899 | 1943 |
| adj. $R^2$ | 0.035 | 0.015 | 0.031 | 0.077 |

$p$-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table A.6**

**Summary statistics of dataset by firm.** This table provides summary statistics of the firms used in the study. The credit rating refers to an average rating of two bonds interpolated to a five-year maturity. ASW is the Asset Swap Spread, defined as the spread over Libor in the floating leg of an asset swap. The Z-spread is the Zero-volatility spread, defined as the amount of parallel shift of the swap curve needed for the present value of the bond's cash flows to equal the bond's price. CDS is the annualized premium for a five-year Credit Default Swap. The basis is defined as the difference between the CDS premium and the Z-spread.

| | | ASW (%) | | | Z-Spread (%) | | | CDS (basis points) | | | Basis (Z-spread, basis points) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Firm | Credit rating | Mean | Std. Dev | N | Mean | Std. Dev. | N | Mean | Std. Dev. | N | Mean | Std. Dev. | N |
| A T & T Inc | BBB- | 2.28 | 1.51 | 311 | 2.80 | 1.64 | 311 | 44.82 | 23.74 | 268 | -231.0 | 143.0 | 268 |
| Abbott Laboratories | AA | 0.32 | 0.52 | 549 | 0.78 | 0.55 | 549 | 48.91 | 29.48 | 485 | -32.5 | 36.0 | 485 |
| Aetna Inc New | BB+ | 1.39 | 1.29 | 273 | 1.83 | 1.52 | 273 | 73.11 | 38.41 | 252 | -117.7 | 123.1 | 252 |
| Alcoa Inc | A- | 2.72 | 2.65 | 459 | 3.41 | 2.87 | 459 | 308.43 | 278.15 | 440 | -42.9 | 65.4 | 440 |
| Allied Waste Industries Inc | BBB- | 2.31 | 1.26 | 203 | 2.92 | 1.48 | 203 | 316.37 | 102.90 | 196 | 28.9 | 184.0 | 196 |
| American Electric Power Co Inc | BBB | 1.62 | 1.05 | 252 | 2.16 | 1.15 | 252 | 60.84 | 18.83 | 242 | -157.9 | 101.1 | 242 |
| American Express Co | BBB+ | 1.47 | 1.52 | 427 | 2.07 | 1.72 | 427 | 219.25 | 164.96 | 411 | 5.1 | 70.4 | 411 |
| Anadarko Petroleum Corp | BBB | 1.98 | 1.55 | 321 | 2.61 | 1.70 | 321 | 126.59 | 87.35 | 307 | -140.5 | 97.7 | 307 |
| Anheuser Busch Inbev Sa Nv | A- | 0.50 | 0.92 | 276 | 0.98 | 1.05 | 276 | 61.37 | 41.97 | 246 | -40.4 | 68.4 | 246 |
| Autozone Inc | BBB- | 2.09 | 1.61 | 257 | 2.71 | 1.76 | 257 | 86.59 | 42.32 | 247 | -188.3 | 144.1 | 247 |
| Bank Of America Corp | BBB+ | 2.15 | 2.65 | 552 | 2.79 | 2.94 | 552 | 121.03 | 79.59 | 526 | -169.3 | 229.5 | 526 |
| Boston Scientific Corp | A | 2.91 | 1.58 | 257 | 3.65 | 1.82 | 257 | 165.17 | 69.08 | 252 | -200.1 | 166.6 | 252 |
| C V S Caremark Corp | A | 1.24 | 1.04 | 439 | 1.79 | 1.10 | 439 | 65.11 | 29.82 | 427 | -114.5 | 83.2 | 427 |
| Cablevision Systems Corp | BBB- | 4.56 | 1.95 | 325 | 5.50 | 2.14 | 325 | 533.51 | 156.28 | 291 | -26.3 | 137.5 | 291 |
| Capital One Financial Corp | BBB+ | 3.66 | 2.97 | 514 | 4.45 | 3.26 | 514 | 193.67 | 111.50 | 498 | -259.8 | 278.4 | 498 |
| Caterpillar Inc | BBB | 0.61 | 0.89 | 486 | 1.11 | 0.98 | 486 | 108.72 | 94.99 | 455 | -8.0 | 56.7 | 455 |
| Citigroup Inc | A+ | 2.84 | 3.06 | 557 | 3.53 | 3.44 | 557 | 199.82 | 157.19 | 527 | -166.7 | 208.8 | 527 |
| Citizens Communications Co | BB | 2.59 | 1.23 | 184 | 3.04 | 1.43 | 184 | 245.31 | 111.60 | 179 | -58.7 | 54.5 | 179 |
| Comcast Corp New | BBB+ | 1.56 | 1.28 | 480 | 2.10 | 1.39 | 480 | 120.15 | 72.59 | 375 | -104.7 | 84.5 | 375 |
| Consolidated Edison Inc | BB | 0.80 | 0.85 | 272 | 1.29 | 0.96 | 272 | 69.49 | 37.33 | 248 | -62.0 | 69.8 | 248 |
| Constellation Energy Group Inc | A- | 2.96 | 1.53 | 218 | 3.69 | 1.60 | 218 | 248.00 | 119.52 | 217 | -121.8 | 83.1 | 217 |
| Costco Wholesale Corp New | A | 0.36 | 0.57 | 561 | 0.81 | 0.61 | 561 | 52.08 | 28.22 | 507 | -29.6 | 38.2 | 507 |
| Deere & Co | A | 1.25 | 1.12 | 289 | 1.66 | 1.17 | 289 | 85.83 | 54.62 | 270 | -86.2 | 75.4 | 270 |
| Devon Energy Corp New | A | 1.16 | 1.16 | 347 | 1.54 | 1.27 | 347 | 52.42 | 27.03 | 330 | -102.5 | 104.6 | 330 |

*(continues)*

## Table A.6
(continued)

| Firm | Credit rating | ASW (%) Mean | ASW (%) Std. Dev | ASW (%) N | Z-Spread (%) Mean | Z-Spread (%) Std. Dev. | Z-Spread (%) N | CDS (basis points) Mean | CDS (basis points) Std. Dev. | CDS (basis points) N | Basis (basis points) Mean | Basis (basis points) Std. Dev. | Basis (basis points) N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Disney Walt Co | BBB- | 0.52 | 0.73 | 516 | 0.98 | 0.77 | 516 | 49.86 | 25.50 | 493 | -49.3 | 57.1 | 493 |
| Dominion Resources Inc Va New | BBB+ | 1.33 | 1.00 | 262 | 1.93 | 1.11 | 262 | 63.29 | 26.59 | 248 | -128.0 | 91.7 | 248 |
| Dow Chemical Co | A- | 2.02 | 1.88 | 450 | 2.50 | 2.06 | 450 | 178.18 | 173.92 | 439 | -73.1 | 72.7 | 439 |
| Du Pont E I De Nemours & Co | BBB+ | 0.46 | 0.67 | 538 | 0.90 | 0.72 | 538 | 62.07 | 43.57 | 504 | -28.3 | 46.0 | 504 |
| Firstenergy Corp | BBB- | 1.86 | 1.49 | 446 | 2.33 | 1.63 | 446 | 95.07 | 43.61 | 415 | -148.6 | 136.9 | 415 |
| Fortune Brands Inc | A | 2.00 | 1.44 | 431 | 2.62 | 1.59 | 431 | 152.42 | 62.06 | 413 | -116.5 | 111.0 | 413 |
| General Dynamics Corp | BBB+ | 0.28 | 0.63 | 339 | 0.72 | 0.65 | 339 | 46.86 | 27.18 | 310 | -27.5 | 44.0 | 310 |
| Goldman Sachs Group Inc | B+ | 1.57 | 1.60 | 552 | 2.12 | 1.74 | 552 | 155.78 | 103.04 | 537 | -59.5 | 79.7 | 537 |
| Goodyear Tire & Rubr Co | BBB+ | 5.05 | 3.42 | 472 | 5.97 | 3.84 | 472 | 550.36 | 347.54 | 464 | -50.0 | 96.6 | 464 |
| Hartford Financial Svcs Group I | BBB | 3.86 | 3.44 | 350 | 4.76 | 3.87 | 350 | 411.05 | 300.49 | 343 | -69.5 | 134.7 | 343 |
| Home Depot Inc | A | 1.61 | 1.36 | 555 | 2.17 | 1.47 | 555 | 132.24 | 75.39 | 525 | -91.7 | 80.4 | 525 |
| Honeywell International Inc | A+ | 0.63 | 0.80 | 378 | 0.76 | 0.90 | 378 | 53.67 | 31.92 | 345 | -23.6 | 75.5 | 345 |
| International Business Machs Co | BBB | 0.47 | 0.63 | 296 | 0.80 | 0.66 | 296 | 52.76 | 27.68 | 277 | -27.4 | 45.1 | 277 |
| Johnson Controls Inc | A | 2.14 | 2.25 | 466 | 2.78 | 2.42 | 466 | 245.61 | 242.31 | 437 | -43.7 | 71.9 | 437 |
| Jpmorgan Chase & Co | BBB+ | 1.11 | 1.13 | 567 | 1.63 | 1.25 | 567 | 92.52 | 46.24 | 533 | -75.7 | 87.1 | 533 |
| Kellogg Co | BBB- | 1.01 | 0.85 | 278 | 1.37 | 0.88 | 278 | 49.20 | 23.04 | 243 | -90.7 | 73.5 | 243 |
| Kraft Foods Inc | AA | 1.08 | 0.82 | 510 | 1.46 | 0.89 | 510 | 70.40 | 30.72 | 483 | -75.7 | 67.6 | 483 |
| Lilly Eli & Co | A | 0.25 | 0.58 | 415 | 0.71 | 0.61 | 415 | 36.67 | 21.01 | 371 | -37.6 | 42.6 | 371 |
| Mcdonalds Corp | AA- | 0.45 | 0.62 | 321 | 0.93 | 0.67 | 321 | 35.21 | 15.76 | 308 | -57.7 | 55.1 | 308 |
| Medtronic Inc | A- | -0.96 | 1.96 | 353 | -0.60 | 2.16 | 353 | 68.32 | 45.10 | 307 | 118.6 | 171.2 | 307 |
| Metlife Inc | BB+ | 1.73 | 1.24 | 358 | 2.22 | 1.39 | 358 | 340.73 | 243.70 | 345 | 118.2 | 140.0 | 345 |
| Motorola Inc | BBB+ | 3.70 | 2.92 | 452 | 4.40 | 3.35 | 452 | 235.12 | 160.74 | 436 | -211.2 | 206.5 | 436 |
| Progress Energy Inc | BB- | 1.07 | 1.04 | 265 | 1.59 | 1.12 | 265 | 48.39 | 16.93 | 244 | -115.8 | 98.4 | 244 |
| Royal Caribbean Cruises Ltd | BB- | 6.75 | 5.37 | 314 | 8.07 | 6.20 | 314 | 654.58 | 454.25 | 310 | -157.3 | 202.1 | 310 |
| S L M Corp | BB- | 6.59 | 4.65 | 412 | 7.85 | 5.45 | 412 | 715.56 | 494.62 | 407 | -75.8 | 155.8 | 407 |
| Sara Lee Corp | BBB | 1.54 | 1.20 | 369 | 1.97 | 1.29 | 369 | 53.29 | 18.79 | 354 | -145.9 | 119.8 | 354 |
| Sears Holdings Corp | BBB- | 8.87 | 7.76 | 194 | 10.80 | 9.56 | 194 | 554.15 | 392.46 | 192 | -534.1 | 638.4 | 192 |
| Simon Property Group Inc New | A- | 3.35 | 2.84 | 379 | 4.12 | 3.14 | 379 | 286.45 | 225.21 | 373 | -127.5 | 115.5 | 373 |
| Sprint Nextel Corp | A- | 5.62 | 3.60 | 435 | 6.79 | 4.17 | 435 | 472.53 | 310.44 | 429 | -204.6 | 160.8 | 429 |

*(continues)*

**Table A.6**
(continued)

| Firm | Credit rating | ASW (%) | | | Z-Spread (%) | | | CDS (basis points) | | | Basis (basis points) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | Std. Dev | N | Mean | Std. Dev. | N | Mean | Std. Dev. | N | Mean | Std. Dev. | N |
| Target Corp | A+ | 0.77 | 0.89 | 539 | 1.24 | 0.95 | 539 | 90.56 | 59.42 | 511 | -37.5 | 45.3 | 511 |
| United Technologies Corp | A- | 0.25 | 0.60 | 491 | 0.66 | 0.63 | 491 | 56.53 | 34.10 | 460 | -10.0 | 40.9 | 460 |
| Unitedhealth Group Inc | A | 1.68 | 1.41 | 528 | 2.26 | 1.55 | 528 | 149.65 | 98.45 | 496 | -80.0 | 72.8 | 496 |
| Wal Mart Stores Inc | A+ | 0.30 | 0.46 | 563 | 0.53 | 0.45 | 563 | 50.98 | 30.67 | 506 | -4.6 | 34.3 | 506 |
| Wellpoint Inc | A- | 1.70 | 1.20 | 342 | 2.31 | 1.32 | 342 | 163.21 | 94.70 | 322 | -69.6 | 59.3 | 322 |
| Wells Fargo & Co New | BB+ | 0.95 | 1.05 | 565 | 1.44 | 1.11 | 565 | 103.02 | 64.10 | 546 | -43.5 | 66.9 | 546 |
| Weyerhaeuser Co | AA | 2.74 | 2.18 | 456 | 3.35 | 2.41 | 456 | 167.73 | 70.77 | 444 | -170.0 | 193.3 | 444 |
| Williams Cos | BBB- | 2.87 | 2.11 | 250 | 3.49 | 2.36 | 250 | 154.39 | 82.69 | 239 | -198.6 | 167.8 | 239 |
| Xerox Corp | BBB- | 2.82 | 2.38 | 370 | 3.54 | 2.63 | 370 | 222.95 | 156.22 | 360 | -137.4 | 122.7 | 360 |
| Total | | 1.98 | 2.78 | 24841 | 2.58 | 3.16 | 24841 | 180.71 | 270.69 | 23418 | -85.0 | 165.3 | 23418 |

**Table A.7**

**Correlation between the CDS-bond basis and the Libor-OIS spread.** This table shows the correlation between the CDS-bond basis and the Libor-OIS spread. The CDS-bond basis is defined as the CDS spread less the Z-spread of a bond with the same maturity. The Libor-OIS spread is used as a proxy for counter-party risk in the interbank market, and is calculated as the three-month Libor less the three-month Overnight Indexed Swap rate. Only American Express Co and Medtronic Inc exhibit a weak positive correlation. The average values are shown as the first entry of the table.

| | Basis statistics | | | | | Basis statistics | | | |
|---|---|---|---|---|---|---|---|---|---|
| Firm | Credit rating | Mean | Std. Dev | Corr. Libor-OIS | Company | Credit rating | Mean | Std. Dev | Corr. Libor-OIS |
| **Mean** | | **-93,36** | **112,66** | **-0,55** | Goldman Sachs Group Inc | B+ | -59,48 | 79,68 | -0,15 |
| A T & T Inc | BBB- | -230,96 | 142,97 | -0,30 | Goodyear Tire & Rubr Co | BBB+ | -50,01 | 96,55 | -0,71 |
| Abbott Laboratories | AA | -32,50 | 36,00 | -0,80 | Hartford Financial Svcs Group In | BBB | -69,51 | 134,73 | -0,32 |
| Aetna Inc New | BB+ | -117,71 | 123,08 | -0,68 | Home Depot Inc | A | -91,72 | 80,37 | -0,51 |
| Alcoa Inc | A- | -42,87 | 65,37 | -0,76 | Honeywell International Inc | A+ | -23,62 | 75,52 | -0,63 |
| Allied Waste Industries Inc | BBB- | 28,85 | 184,05 | -0,59 | International Business Machs Cor | BBB | -27,39 | 45,06 | -0,18 |
| American Electric Power Co Inc | BBB | -157,87 | 101,12 | -0,78 | Johnson Controls Inc | A | -43,65 | 71,87 | -0,62 |
| American Express Co | BBB+ | 5,07 | 70,41 | 0,10 | Jpmorgan Chase & Co | BBB+ | -75,74 | 87,06 | -0,73 |
| Anadarko Petroleum Corp | BBB | -140,45 | 97,70 | -0,64 | Kellogg Co | BBB- | -90,72 | 73,52 | -0,73 |
| Anheuser Busch Inbev Sa Nv | A- | -40,43 | 68,38 | -0,39 | Kraft Foods Inc | AA | -75,71 | 67,56 | -0,50 |
| Autozone Inc | BBB- | -188,33 | 144,06 | -0,52 | Lilly Eli & Co | A | -37,60 | 42,61 | -0,76 |
| Bank Of America Corp | BBB+ | -169,34 | 229,48 | -0,80 | Mcdonalds Corp | AA- | -57,69 | 55,12 | -0,49 |
| Boston Scientific Corp | A | -200,08 | 166,63 | -0,47 | Medtronic Inc | A- | 118,58 | 171,22 | 0,12 |
| C V S Caremark Corp | A | -114,51 | 83,20 | -0,63 | Metlife Inc | BB+ | 118,23 | 139,97 | -0,52 |
| Cablevision Systems Corp | BBB- | -26,25 | 137,50 | -0,26 | Motorola Inc | BBB+ | -211,18 | 206,52 | -0,77 |
| Capital One Financial Corp | BBB+ | -259,80 | 278,38 | -0,83 | Progress Energy Inc | BB- | -115,81 | 98,42 | -0,45 |
| Caterpillar Inc | BBB | -7,98 | 56,70 | -0,61 | Royal Caribbean Cruises Ltd | BB- | -157,28 | 202,06 | -0,67 |
| Citigroup Inc | A+ | -166,71 | 208,84 | -0,71 | S L M Corp | BB- | -75,76 | 155,75 | -0,25 |
| Citizens Communications Co | BB | -58,65 | 54,53 | -0,22 | Sara Lee Corp | BBB | -145,92 | 119,76 | -0,70 |
| Comcast Corp New | BBB+ | -104,72 | 84,50 | -0,78 | Sears Holdings Corp | BBB- | -534,05 | 638,37 | -0,50 |
| Consolidated Edison Inc | BB | -62,04 | 69,77 | -0,62 | Simon Property Group Inc New | A- | -127,53 | 115,51 | -0,61 |
| Constellation Energy Group Inc | A- | -121,77 | 83,08 | -0,65 | Sprint Nextel Corp | A- | -204,63 | 160,77 | -0,66 |
| Costco Wholesale Corp New | A | -29,55 | 38,24 | -0,65 | Target Corp | A+ | -37,53 | 45,33 | -0,70 |
| Deere & Co | A | -86,19 | 75,41 | -0,72 | United Technologies Corp | A- | -10,04 | 40,94 | -0,72 |
| Devon Energy Corp New | A | -102,51 | 104,61 | -0,72 | Unitedhealth Group Inc | A | -80,03 | 72,78 | -0,73 |
| Disney Walt Co | BBB- | -49,27 | 57,14 | -0,43 | Wal Mart Stores Inc | A+ | -4,60 | 34,29 | -0,48 |
| Dominion Resources Inc Va New | BBB+ | -128,02 | 91,75 | -0,67 | Wellpoint Inc | A- | -69,56 | 59,27 | -0,63 |
| Dow Chemical Co | A- | -73,14 | 72,74 | -0,42 | Wells Fargo & Co New | BB+ | -43,49 | 66,90 | -0,59 |
| Du Pont E I De Nemours & Co | BBB+ | -28,34 | 45,98 | -0,67 | Weyerhaeuser Co | AA | -169,96 | 193,30 | -0,29 |
| Firstenergy Corp | BBB- | -148,59 | 136,87 | -0,58 | Williams Cos | BBB- | -198,58 | 167,84 | -0,47 |
| Fortune Brands Inc | A | -116,51 | 111,05 | -0,57 | Xerox Corp | BBB- | -137,42 | 122,72 | -0,51 |
| General Dynamics Corp | BBB+ | -27,49 | 43,96 | -0,04 | | | | | |

**Table A.8**

**Factors making basis deviate from zero.** This table provides a summary of some important factors that make the basis, defined as the CDS spread less the credit spread of a corporate bond, deviate from zero. A plus or minus sign means that the factor leads to positive basis (ceteris paribus), so that CDS spreads are higher than bond spreads, and vice versa. "+ or -" means that the factor affects the basis positively or negatively depending on the circumstances discussed in the description of the factor. These factors are discussed in detail by Francis et al. (2003), Choudhry (2004) and Choudhry (2006).

| Factor | Description | Basis |
|---|---|---|
| CDS spreads always larger than zero | Highly rated bonds may trade below Libor in the asset swap market, which reflects the market view of credit risk associated with these names being lower than the credit risk associated with banks. Insurance sellers (who finance themselves with Libor) on such bonds do, however, still expect a premium – a spread over Libor – for selling protection on the bond. | + |
| Not all credit events are defaults | CDS contracts have a higher risk of pay-out than the actual default risk of bonds. A CDS is often required to pay out on credit events that are not necessarily full defaults that would affect a bond holder. CDS sellers will demand a premium for this additional risk, which means that CDS spreads will be greater than credit spreads. | + |
| Delivery option of CDS contracts | CDS contracts that are settled physically often name a reference entity rather than a reference *asset*. If a credit event occurs, the buyer sometimes has an array of assets to choose from to deliver. The looser the definition of deliverable asset in the contract, the larger the potential basket to choose from. Hence, a CDS seller may potentially receive any bond from a basket of deliverable instruments, including a bond with a lower coupon, a convertible bond, a less liquid bond, an asset backed security or a long-dated bond, any of which might be cheaper to deliver than the actual bond held originally. In contrast, a long position in the cash bond market always means that the payments of a specific bond stand to be lost. The higher the probability of default, the higher is the value of the delivery option to the cash bond holder. The higher the value of the delivery option, the larger is the risk taken by the CDS seller, and the more positive the basis will be[20]. | + |
| Funding costs and arbitrage | Funding costs higher than or lower than Libor will drive the basis lower and higher respectively. A bond's "cost of carry" or funding cost is usually assumed to be its repo rate. For an investor to be indifferent between investing in a bond or selling a CDS, the alternatives must yield the same payoff. Since a CDS position is unfunded with an assumed funding cost of Libor, this demands a higher credit spread for bonds with repo rates higher than Libor. Conversely, repo rates below Libor will lead to lower credit spreads and a positive basis. | + or - |

*(continues)*

[20]For a detailed discussion on the delivery option in CDS contracts and expected recovery rates, see Jankowitsch et al. (2007)

**Table A.8**
(continued)

| Factor | Description | Basis |
|---|---|---|
| Counter-party risk | CDS buyers and sellers are exposed to counter-party risk. In the event of default, the buyer is dependent on the CDS seller being able to fulfill its obligation, making the CDS spread lower. On the other hand, the seller is exposed to counter-party risk of the buyer. Because the contract will terminate if the buyer defaults, there will be a mark-to-market gain or loss if the CDS spread has narrowed or widened since origination. | + or - |
| Market demand | Strong demand from CDS buyers (need for protection) will drive the basis wider. Strong demand from CDS sellers (over supply) will drive the basis tighter. For example, taking a short position in the cash bond market is often difficult, since the position in the repo has to be covered and there is a risk that the bond will go special (especially for high-quality credit names). These risks do not exist in the CDS market, and, other things being equal, increases the demand for protection and drives the basis wider. There are a wide range of determinants of the demand for protection, and the rapid growth of the market for synthetic collateralized debt obligations[21] has been one driver of the demand for CDS contracts.. | + or - |



[21] A synthetic collateralized debt obligation, or a synthetic CDO, is like a portfolio of CDS contracts which is tranched and sold to investors with varying degrees of risk appetite.