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Complications in CDS-Bond Basis Analysis and Modeling

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Abstract
In our study, we begin by introducing the historical aspects of the Credit Default Swap and the CDS bond basis. Then, the document introduce the arbitrage relationship between the CDS spread, the corporate bond yield and the risk free rate. Some factors that contribute to the failure of this relationship are addressed in addition to a discussion of the potential arbitrage opportunities. Numerical analysis was conducted on the basis of thirty firms for different term structures. Analysis included Vasicek modeling, time-series tests, and simple and logistic regression.

Contents

1. Introduction

1.1 Historical Overview of the Credit Default Swap

A Credit Default Swap (CDS) is a bilateral contract that enables the protection buyer to acquire insurance against a specific corporation referred to as reference entity from defaulting (Hull, 2012). As such, the holder of the CDS contract pays the seller a pre-determined premium called a CDS spread which is calculated on the basis of the notional principal. In turn, the seller stands as insurer in case of a credit event. Thus, in case of a credit event the holder of a CDS contract has the right to sell a bond issued by the reference entity at its face value to the protection seller. A credit event is defined by the International Swaps and Derivatives Association (ISDA) as the failure of the reference entity to pay its obligations, bankruptcy of the reference entity, ”obligation and acceleration default” or the event of a restructuring. Generally, credit default swaps are structured with quarterly payments over a five-year period, but there are several different maturities and payment structures available on the over the counter market. The underlying credit asset of the CDS is typically mortage backed securities (MBS), municipal bonds and as mentioned above, corporate donds.

The CDS is referred to as the most utilized credit derivative today (Hull, 2012), but how did this financial instrument become so popular, and what triggered its creation? The first case of a credit default swap can be traced to the early 1990s. At the time, commercial banks were prone to finding a way of reducing their exposure towards interest rate counterparty risk, the result was the creation of the credit default swap (Morgan Stanley, 2006). The creation of the CDS was truly revolutionary giving rise to a financial instrument that could facilitate credit risk transfer. A specific case which often is mentioned as the triggering effect for the CDS in the 1990s, is the classic case when JPMorgan Chase created a CDS in order to circumvent regulatory requirement when providing a credit line for their client Exxon (Bloomberg BNA, 2014). At the end of the 1990s a lot had changed in the market for credit default swaps. The main difference was that ISDA had established a standard contract for the CDS that were to be traded on the OTC market (Hull, 2012). This launched a momentum of growth in the market for CDS and in the late 90’s the estimated size of the CDS market was around three hundred billion dollars (Tett, Gillian, 2009).

The OTC market for credit default swaps continued to grow, and in the period 2004 to 2007 the CDS notionals outstanding increased by approximately a hundred percent per year, and later peaked in 2007 (BIS, 2013). A contribution to this increase was a CDS engineered with subprime mortgage securities acting as the underlying credit asset (Sounders et al, 2011). When the underlying mortages began to default in the midst of 2008 the value of the subprime mortage securities plummeted. This triggered a large scale of credit events for this type of CDS. The insurance company AIG (American International Group) was a major holder of short CDS contracts, which led them to an $18 billion loss (Sounders et al, 2011). The loss set off a downgrade in credit rating, which forced AIG to post an additional $14.5 billion in collateral. AIG was later bailed out by the Federal Reserve as the default of AIG would have jeopardized the operation of several financial institutions (mainly investment banks and other insurance companies).

The financial crisis motivated the regulatory system all over the world to invoke several new regulations concerning OTC traded derivatives (Sounders et al, 2011). Today, derivative dealers and derivative contracts are under supervision, and regulators have imposed regulations that are to improve market efficiency and transparency and regulations that act against manipulation of these types of financial instruments. These regulations have altered the structure of the CDS market and the way in which credit default swaps are traded today. The total amount of CDS that are notional outstanding has decreased over the last years. The decrease is said to be a result of so called trade-tear- ups (ISDA, 2013). Trade tear ups are a tool that is used to reduce transactions and decrease risks. However, ISDA found that the number of transactions had increased from 2011-2013 (CDS Market Summary: Market Risk Transaction Activity, 2013).

Thus far, the report has presented a historical overview of the credit default swap, the document will now introduce the CDS-Bond Basis and how the CDS market can be influenced by arbitrage activities.

1.2 Arbitrage Activities and the CDS-Bond Basis

If one assumes a theoretically frictionless market then there exists a no-arbitrage relationship between the CDS of a specific reference entity, the underlying bond, and the risk free rate (e.g., LIBOR). This contingency is linked via the CDS-Bond Basis and can be expressed in the following way:

$$\begin{aligned} Basis_t &= CDS_t - (y_t - r_{ft}) \\ &= CDS_t - ASW_t \end{aligned}$$

where y_t is the corporate bond yield, r_{ft} is the risk free rate, and ASW_t is the asset swap spread.

From observing the above relationship we can infer that the CDS-Bond Basis is equivalent to the difference in the CDS spread and the credit spread. Furthermore, the credit spread reflects the risk premium related to the bond yield. Thus, as long as the default risk is equivalently priced in the bond and the CDS, one would in theory expect that any deviations from a zero CDS-Bond Basis would facilitate arbitrage opportunities (Augustin, 2012). Moreover, in a frictionless market the Asset Swap Spread (on the same reference entity) should reflect the same spread as that of the credit spread. This relationship is portrayed in Figure 1. Hence, short sell a corporate bond investing the proceeds at the risk free rate (in this case the LIBOR). At the same time, undertaking an asset swap, exchanging the corporate bond coupon for LIBOR plus an Asset Swap Spread. This offsetting strategy should in a frictionless market reflect the same exposure as a short CDS position.

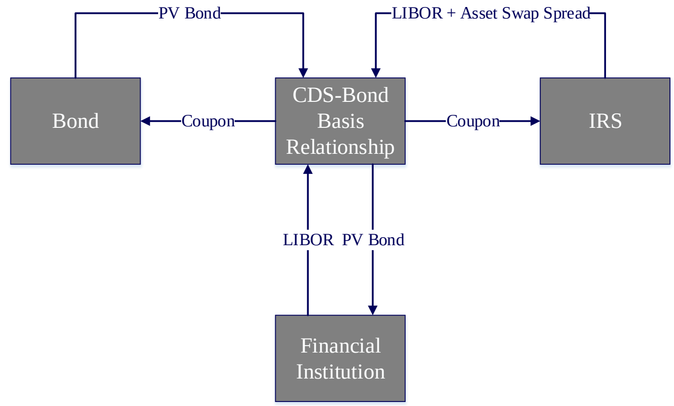

Figure 1. The CDS-Bond Basis Relationship

However, although the zero CDS-Bond Basis relationship may seem reasonable in a frictionless market, it has historically deviated from zero reflecting both negative and positive values. Furthermore, according to Oehmke and Zawadowski (2014), there is actually a high activity of arbitrage activities in via the CDS-Bond Basis. So why has the average CDS-Bond Basis deviated from zero? There are several reasons for this phenomenon, according to Emmanuelle Ollèon-Assouan of Banque de France the main reasons for a positive CDS-Bond Basis is due to structural and market-related factors.

It is difficult to determine the factors that has the most significant impact on the CDS-Bond Basis. When we observe a positive CDS-Bond Basis, it is often related to the 'cheapest-to-deliver bond option', the management of larger portfolios, and to the asset swap spread. First, in the case of a credit-event the protection buyer has the option to choose the least valued bond from a specific selection of the reference entity (De Wit, 2006). Hence, the seller of the CDS is exposed to the so called 'cheapest-to-deliver bond option' and will therefore claim a premium in the form of a higher spread, which in turn increases the CDS-Bond Basis. Second, for firms with strong credit ratings the asset swap spread may be lower than that of the LIBOR (London Interbank Offered Rate). Thus, as the CDS spread can not be negative, the CDS-Bond Basis for this specific reference entity will reflect a positive value. In the management of larger portfolios with several different types of financial instruments one are constantly exposed to credit risk. Therefore, banks, hedge funds, and asset management firms often try to hedge their credit risk exposure. As it is difficult to obtain outright short position in the cash market these market players tend to hedge their risk through going long in CDS contracts instead (De Wit, 2006). The abnormal demand in the CDS market inflates the CDS spread, which in turn increases the CDS-Bond Basis.

As with the positive CDS-Bond Basis, a negative basis can also stem from several different factors. This document will present some of the main sources for a negative CDS-Bond Basis. These factors are related to acquiring funding, counterparty default risk and contractual differences between the bond and the CDS contract. First, many market players can only obtain funding at a rate that exceeds the interbank offered rate (typically the LIBOR). These financial institutions are therefore prone to shorting CDS contracts achieving a higher spread then they would obtain if they undertook the asset swap spread strategy (described above, also see Figure 1). Secondly, when going long in a CDS contract one is exposed to the fact that the protection seller might default. An example of this is the case of AIG during the subprime mortgage crisis of 2007 to 2009. As mentioned above, if AIG had not been bailed out by the Federal Reserve they would have left several protection buyers without coverage. As such the financial institutions that had bought protection from AIG were very much exposed to counterparty default risk. The default of AIG would have resulted in vast amount of losses for several financial institutions (mainly investment banks).

Until now, this report has presented several of what practitioners and academics regard as main reasons for alterations in the CDS-Bond Basis. However, it must be mentioned that there are many other potential reasons for observing changes in the CDS-Bond Basis, some of which can affect the basis in both directions. This document will now present and discuss the historical fluctuations of the average CDS-Bond Basis.

1.3 Historical Fluctuations of the CDS-Bond Basis

Before the financial crisis, in the period from 2000 to 2006, the average CDS-Bond Basis had been positive. In contrast, the average CDS-Bond Basis was highly negative during the subprime mortgage crisis (from 2007 to 2009). This report begins by discussing of the pre- crisis period.

There are several research reports that indicate a positive average CDS-Bond Basis during the period of 2000 to 2005. Examining the comparison completed by Jan De Wit (2006) we clearly see that five out of six relevant papers during this time period indicate a positive basis (De Wit 2006). The report also showed a median positive basis of 7.5 basis points in the period from 2004 to 2005. Another study made by Zhu (2004) reflects a basis of 13 basis points from 1999 to 2002, other studies using different techniques of cointegration obtained similar results. Thus, this clearly demonstrates a strong indication of a positive average CDS-Bond Basis during this period. Furthermore, the findings of Jan De Wit (2006) also conclude that there exists a long- run equilibrium between the CDS premium and the (par) asset swap spread of the same reference entity, and that the basis move with the general market conditions.

However, as we can see from Figure 2, the average CDS-Bond Basis was highly negative from 2007 to 2009. We can also infer that the CDS- spread and bond spread increased in a similar manner. Hence, as the default risk of companies increased the bond spread increased, similarly as the default risk increased the CDS Spread increased. Nevertheless, here it is important to divide between different industries and different levels of credit ratings (Augustin, 2012). It is especially important to examine the difference between financials and non-financials because of their very different exposures during the crisis of 2007-2009. As we can see from Figure 3 the credit rating of different companies had a great impact on the basis. AAA- rated companies even demonstrate an overall positive change in the basis whereas A and BB rated companies had a highly negative change in the CDS-Bond Basis. Furthermore, financials demonstrated higher bases than non-financials that where exposed to a high level of counterparty risk. Patrick Augustin (2012) also found that when the market liquidity dried up, companies that had higher asset liquidity had lower CDS-Bond Basis. Conversely companies with low asset liquidity had a greater spread. Finally, the results of Augustin (2008) implies that there might have been a demand effect that was the main driver in the alteration in the CDS-Bond Basis.

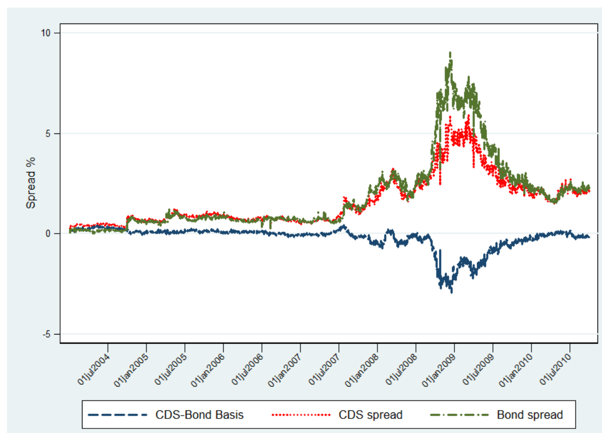

Figure 2. Mean CDS-Bond basis as well as the mean CDS and Bond spreads from January 2004 to September 2010. Source: CMA, Mergent FISD, Federal Reserve Bank, TRACE

2. Previous Research

There are numerous amounts of literature studying the relationship between CDS and bound spreads. Chan-Lau et al. (2004), Norden and Weber (2004), Blanco et al. (2005), De Wit (2006) and Fontana (2010) tested the long run cointegration relationship of the two markets. Although during the normal period, namely before the 2007/08 financial crisis, such parity relationship holds well, institutional frictions, market liquidity and other markets factors cause the short term deviation from its equilibrium (Augustin, (2012)). Meanwhile, there are some other approach to study the determinants of the CDS-Bond basis taken by Mahanti et al. (2010) and Bai and Collin-Dufresne (2011).

Currently there are three methods to construct the model

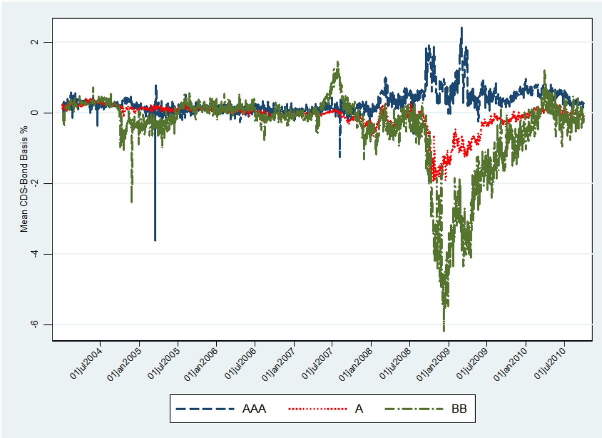

Figure 3. Illustrates the cross-sectional differences in the mean basis for the rating categories AAA, A and BB. Source: CMA, Mergent FISD, Federal Reserve Bank, TRACE

for CDS-Bond basis. The first is to use the par-equivalent spread approach (Elisade et al. (2009)), which based on a flat term structure and focus on the deviation of bonds from its par. However, this methodology fails partly due to its unrealistic assumption. The second methodology representing by Longstaff et.al (2005) is pricing the CDS and bond spread based on assuming credit risk models. The drawback of such methodology is that it relies heavily on the right choice of models (Huang and Huang (2003)). The last method used by most recent researches (Guo and Bhanot (2010), Fontana (2010)) is to estimate basis from observed CDS quotes and traction prices in credit markets.

2.1 Amihud Liquidity Measure

The next step is to discuss the choices of variables of the model for basis, which are asset-specific liquidity, market liquidity, funding liquidity, counterparty risk and control variables. To acquire the asset-specific liquidity Augustin (2012) modified Amihud's measure of illiquidity (Amihud (2002)) method to study CDS-Bond basis. The Amihud level of illiquidity for bond i on day t is computed as:

$$\text{Amihud}_t^i = \frac{1}{N_t}\sum_{j=1}^{N_t}\frac{|r_{j,t}^i|}{Q_{j,t}^i} = \frac{1}{N_t}\sum_{j=1}^{N_t}\frac{\left|\dfrac{P_{j,t}-P_{j,t-1}}{P_{j,t}}\right|}{Q_{j,t}^i}$$

Where N_t is the number of returns r_j on day, Q_j is the trading volume for a given trade in million of dollars. Although the Amihud method measures the illiquidity rather than liquidity characteristic, it serves to capture the of liquidity risk instead. In order to capture the market liquidity, Augustin (2012) used the approach of Lin et al. (2011). First, they define the scaled change in Amihud method by

$$\Delta\text{Amihud}_{M,t} = \frac{CAP_{t-1}}{CAP_1}(\text{Amihud}_{M,t} - \text{Amihud}_{M,t-1})$$

where CAP_t is the dollar value in the period between $t-1$ and t. Thus the market illiquidity can be obtained from the time series regression:

$$\Delta Amihud_{M,t} =$$
$$\phi_0 + d + \sum_{i=1}^{4}\phi_i\Delta Amihud_{M,t-i} + \phi_5\frac{CAP_{t-1}}{CAP_t}Amihud_{M,t-1} + \varepsilon_t +$$
$$\theta_1\varepsilon_{t-2} + \theta_2\varepsilon_{t-5} + \theta_3\varepsilon_{t-7} + \theta_4\varepsilon_{t-14}$$

To obtain funding liquidity, 3-month London interbank offered rate and the 3-month Overnight Index Swap (LIBOROIS) is used as the proxy (Augustin (2012)). Based on Amihud measure, the LIBOR-OIS spread is defined as:

$$LIBOROIS_t = \alpha + \beta Amihud_{M,t} + \varepsilon_t$$

According to the Augustin (2012), the counterparty risk is measured by the covariance between a specific company stock return R^i with the value-weighted primary dealer index R^{Index} over CRSP value-weighted stock market return R^{MKT}:

$$\beta_{CP}^i = \frac{Cov(R^i,(R^{index} - R^{MKT}))}{Var(R^{index} - R^{MKT})}$$

As for Control Variables, Augustin (2012) used S&P's credit rating and collateral quality, the slope of the Treasury curve, the 10-year swap rate, the default risk premium and the sign of the basis. After a series of filtering process, the sample Augustin (2012) used is still quite large, with 177 reference entities and a total of 159,283 trading day data for calculating basis. There are 125 industrial companies in which more than half of them are from manufacturing. In addition, 21% of the firms are from financial industry and 9% are from utilities. There are 3 companies are rated AAA, 156 firms are rated A, BBB or BB, 6 of them are AA while 12 are B. After all of these prepared, the CDS-Bond basis model (Augustin (2012)) is constructed as follows:

$$B_{i,t} = \alpha + \beta_1 Amihud_{i,t} + \beta_2 ML_{i,t} + \beta_3 FL_(i,t) + \beta_4 CP_{i,t} +$$
$$\gamma Controls + \upsilon_i + \varepsilon_{i,t}$$

Where $B_{i,t}$ is the CDS-Bond basis, Amihud$_{i,t}$ is the asset-specific liquidity factor, market liquidity is ML$_{i,t}$, funding liquidity factor ($FL_{i,t}$), counterparty risk factor ($CP_{i,t}$) and control variables (Controls) representing collateral quality, the slope of Treasury curve, the 10-year swap rate, the default risk premium and the sign of basis. υ_i is the firm-specific fixed effects. Through building this regression model, regression coefficients β_is are expected to be negative based on the period of data selected.

After regression test, Augustin (2012) found that the basis is a reducing function with parameters of market and funding illiquidity. What beyond Austin's expectation is that liquidity factors shows no impact on financial companies with high counterparty risk after the fall down of Lehman Brothers. Among those high counterparty risk firms, the basis of financial companies decreased significantly less than those non-financial firms, which indicating the liquidity factors effects on CDS spreads.

2.2 Limits to Arbitrage

In a 2011 study, Bai and Collin-Dufresne methods for finding measures and performing cross-sectional regressions, to examine the negative CDS-bond Basis during the height of the financial crisis. They focus on the explanation of "limits to arbitrage": such as the inability of investors to raise vast sums of capital instantaneously to take advantage of an opportunity, and the invertors' unwillingness to take large positions (invest a lot now for small return over time) due to mark-to-market risk. However, this analysis is not a key feature of their, often referring to Gromb and Vayanos (2010) for many of the intricate details. Instead the authors proceed to modeling the Basis values using time series analysis and cross-sectional regressions. These two chapters require a substantial and varied array of historical data, for this purpose Bai and Collin-Dufresne used Markit Reference Data, the Mergent Fixed Income database, and Center for Research in Security Prices (CRSP). They examine the data in various categories such as corporate bonds, interest rate benchmarks, and summary statistics.

Using time series analysis, they begin by proposing nine possible biweekly indicator variables including: stock of primary dealer, LIBOR-OIS spread, repo-TBill spread, repo-collateral spread and others. Then they perform triple lagged regression with the following formula:

$$\Delta Basis_i = \alpha_0 \Delta Z_i + \alpha_1 \Delta Z_{i-1} + \alpha_2 \Delta Z_{i-2} + \alpha_3 \Delta Z_{i-3} + \varepsilon$$

Following each phase they would rank the indicators from worst to best fit, then drop the weakest and refine the time frame. This process was then repeated for both IG and HY firms. Interestingly the results differed when applied to deleveraging as measured by the change in bond position of the primary dealers; this had a strong affect on the HY basis, while for the IG basis, a more influential measure was collateral-quality-funding spread.

Bai and Collin-Dufresne proceed to perform Fama-McBeth cross-sectional regression using beta measures for the four most influential indicators from the previous section: funding, liquidity, collateral, and counterparty risk defined below. They study the cross-sectional determination of the CDS-bond basis with the following regression:

$$Basis^i = \alpha^i \gamma_f \beta^i_{funding} + \gamma_1 \beta^i_{liquidity} + \gamma_{coll} Collateral^i + \gamma_{cp} \beta^i_{cp} + \gamma_k \beta^i_{Controls} + \varepsilon_t$$

However the key aspect highlighted throughout this section is the transition between Crisis Phase 1 (prior to Lehman bankruptcy) and Crisis Phase 2 (post-bankruptcy). Many measures especially Counterparty risk Increased in the negative direction upon entering Crisis Phase 2.

Finally, Bai and Collin-Dufresne take into account post crisis numbers, details and repercussions to enforce conclusions made throughout the publication. Also in the first part of Section 6 the authors describe two additional experiments they ran on the effect of deleveraging on firms: Price Pressure in Bond Market, and Price Discovery across Markets, where they draw on ideas from Blanco, Brennan and Marsh (2005).

However the authors' choice of restricting themselves to a linear model may not be sufficient in such a crisis period. As is repeatedly highlighted in the publication, counterparty risk has nonlinear behavior, as many financial companies default in a chain reaction style in very short period of time. Thus to improve the model for future publications it would be advisable to use nonlinear or exponential parametrization. An approach such as this would raise its own problems for mathematical analysis but lead to more representative results.

Additionally, this study only examines one year of pre-crisis time, and during this time many undercover problems were already starting to arise. It might be beneficial to extend this theory to a period of 30 or even 50 years to cover more than one crisis period, to observe if the conclusions still hold true. The goal is to make a model that accurately predicts non-crisis times, and then begins raising flags (i.e. adding dummy variables) and accurately indicating future basis drops such as observed in this publication.

3. Numerical Analysis

3.1 Methods

The CDS bond basis and CDS spread, and bond yields of thirty firms were collected for three different maturities: three, five, and ten years. All data was collected from Thomson Reuters Eikon. The firms are represented in Table 1. Analysis of means and variances were conducted across groups like sector and Standard and Poor's ratings. The firms were seperated into two cetegories by their Standard and Poor's rating. The category "Above A" represents companies that were rated either AA-, A, AA, AA+ or AAA+ while the category "Below A" represents entities that were rates either A-, BBB+, BB+ or BBB.

3.1.1 Vasicek Modeling

Using data from 2009 to 2015, we modeled the CDS bond basis using a Vasicek model:

$$r_t = \mu(1-\phi) + \phi r_{t-1} + \varepsilon_t$$

The optimal values for μ, ϕ, and σ^2 were estimated using a maximum likelihood estimator with likelihood function:

$$l(\theta) = cst + \frac{1}{2}\log(1-\phi^2) - \frac{1-\phi^2}{2\sigma^2}(y_{1,1}-\mu)^2 - \frac{1}{2}\log\sigma^2 - \frac{(T-1)}{2}\log\sigma^2 - \frac{1}{2\sigma^2}\sum_{t=2}^{T}(y_{1,t} - \mu(1-\phi) - \phi y_{1,t-1})^2$$

The initial values of the model were taken from a simple regression of the historical CDS basis on the one period lag of CDS basis:

$$r_t = \beta_0 + \beta_1 r_{t-1} + u_t$$

Therefore, the initial values of the optimization are as follows:

Firm Name	Ticker	Sector	Rating (S&P)
Altria	MO	Tobacco	BBB+
American Express	AXP	Financial	BBB+
Bank of America	BAC	Financial	A-
Caterpilar	CAT	Machinery	A
General Electric	GE	Industrials	AA+
Goldman Sachs	GS	Financial	A-
Johnson & Johnson	JNJ	Pharmaceutical	AAA
Morgan Stanley	MS	Financial	A-
News Corp	NWSA	Media	BBB+
Pfizer	PFE	Pharmaceutical	AA
Walmart	WMT	Retail	AA
BNP Paribas	BNPP	Financial	A+
HSBC	HSBA	Financial	A
JP Morgan	JPM	Financial	A
Merryl Lynch	MER	Financial	NR
Apple	AAPL	Technology	AA+
Intel	INTC	Technology	A+
Oracle	ORCL	Technology	A+
IBM	IBM	Technology	AA-
Cisco	CSCO	Technology	AA-
AMD	AMD	Technology	B
Microsoft	MSFT	Technology	AAA
Applied Materials	AMAT	Technology	A-
ExxonMobil	XOM	Energy	AAA
Chevron	CVX	Energy	AA
Haliburton	HAL	Energy	A
Williams Companies	WMB	Energy	BB+
Total	TOTF	Energy	AA-
ENEL	ENEI	Energy	BBB
Shell	RDS	Energy	AA

Table 1. List of firms included in study with Standard and Poor's ratings.

$$\theta_0 = \begin{pmatrix} \mu_0 \\ \phi_0 \\ \sigma^2 \end{pmatrix} = \begin{pmatrix} \dfrac{\widehat{\beta}_0}{1-\phi_0} \\ \widehat{\beta}_1 \\ Var(u_t) \end{pmatrix}$$

After the optimal values for the Vasicek model $(\widehat{\theta})$ were found, the asymptotic covariance matrix, $\mathscr{A}$, of the parameters was found using these values:

$$\mathscr{A}(\theta) = \begin{pmatrix} 2\sigma^4 & 0 & 0 \\ 0 & 1-\phi^2 & 0 \\ 0 & 0 & \dfrac{\sigma^2}{(1-\phi)^2} \end{pmatrix}$$

Additional Vasicek modeling was conducted using a stochastic differential equation model, rather than a time series model with one lag. The model is as follows:

$$dX_t = k(\theta - X_t)dt + \sigma dW_t$$

where W_t is a Brownian Motion under the risk neutral probability measure Q. Therefore:

$$X_t \sim \mathscr{N}\left(X_0 e^{-kt} + \theta\left(1-e^{-kt}\right), \frac{\sigma^2}{2k}\left(1-e^{-2kt}\right)\right)$$

We can then calculate the probability if the basis being negative:

$$Q(X_t < 0) = \Phi\left(\frac{E[X_t]}{\sqrt{Var(X_t)}}\right)$$

3.1.2 Ordinary Multivariate Regression

We then conducted multivariate ordinary least squares regressions of the CDS basis on a set of market variables:

1. **United States Overnight Indexed Swap Rate Spread (USDOIS)** is the spread of the interest rate swap involving the overnight rate being exchanged for the Fed Funds Rate. USDOIS is a good risk barometer because the Fed Funds Rate is risky in the sense that the lending bank loans cash to the borrowing bank, and the OIS is stable in the sense that both counterparties only swap the floating rate of interest for the fixed rate of interest. The spread between the two is, therefore, a measure of how likely borrowing banks will default. This reflects counterparty credit risk premiums in contrast to liquidity risk premiums. However, given the mismatch in the tenor of the funding, it also reflects worries about liquidity risk as well (Sengupta and Tam 2008).

2. **LIBOR Overnight Indexed Swap Rate Spread (LIBOROIS)** is spread of the interest rate swap involving the overnight rate being exchanged for London Interbank Offered Rate (LIBOR). This is the same as USDOIS except LIBOR is being using a swap rate instead of the Federal Funds Rate. The same reasoning for why LIBOROIS is a good risk barometer is the same as those for USDOIS.

3. **T-Bill Three Month LIBOR Overnight Indexed Swap Rate Spread (USD3MOIS)** is the spread of the interest rate swap between a three month treasury bill issued by the United States Treasury and the LIBOR Overnight Indexed Swap rate. This indicator captures effect like the rush of investors to safer or higher quality assets, such as treasury bills. As more investors move to treasury bills and other safe government bonds, the demand for risker corporate bonds decreases and therefore there should be an effect on corporate bond yields and subsequently coporate CDS-bond bases.

4. **Chicago Board Options Exchange Market Volatility Index (VIX)** is the a popular measure of the implied volatility of S&P 500 index options. The VIX is quoted in percentage or basis points and measures the annualized expected movement with 68% confidence (or one standard deviation when assuming normality) in the S&P 500 index over the next 30-day period. VIX is a measure of market perceived volatility in either direction, including to the upside.

5. **Individual Firm's Credit Default Swap Spread (CDSSPREAD)** is the spread of a CDS of a specific firm. As explained in the introduction, the spread is the insurance premium that the CDS issuer charges for the insurance plan that protects the CDS buyer if a credit event occurs.

The following model was created:

$$\text{Basis}= X\beta + u$$

where X is a matrix of the values of the variables listed above.

3.1.3 Logistic and Probit Regression

In order to determine the probability of the basis being negative, we conducted logistic and probit regressions of an indicator variable of whether the basis was positive or negative:

$$y_t = \mathbb{1}_{\{Basis_t<0\}}$$
$$p_t = P(y_{t+1} < 0|\mathscr{F}_t)$$
$$y = X\beta + u$$
$$\text{Probit: } y_t = \Phi^{-1}(p_t)$$
$$\text{Logit: } y_t = \ln\left(\frac{p_t}{1-p_t}\right)$$

3.2 Results

During the crisis the CDS-bond basis is consistently negative for a number of entities. Figure 4 shows the time series of the cross-sectional averages of the basis separately for the financial, energy, and technology sectors. The mean and volatility of bases across three different sectors is shown in Table 2.

Sector	**Mean (bp)**	**Volatility (bp)**
Financial	-71.8138	75.0741
Technology	3.6911	15.6820
Energy	5.6251	11.7171

Table 2. Mean and volatility of firm bases across sectors.

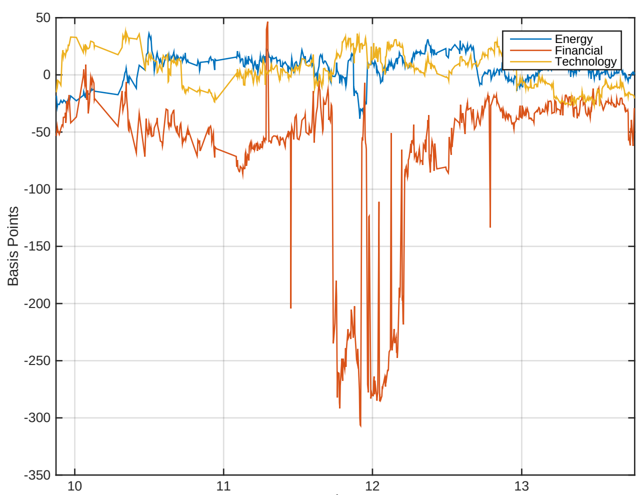

Figure 4. Cross sectional mean of bases by sector.

Figure 5 shows the cross-sectional average of the basis classified into two categories.

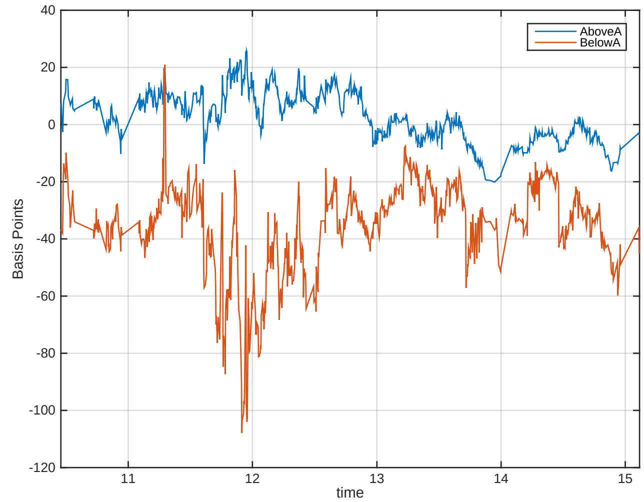

Figure 5. Cross sectional mean of bases by rating category.

Rating	**Mean (bp)**	**Volatility (bp)**
Above A	2.3689	8.5424
Below A	-35.9659	15.6820

Table 3. Mean and volatility of the basis across rating categories.

The results of the Vasicek modeling using the regression are shown in Table 4. The results of the multivariate ordinary least squares regression are shown in Table 5. Tables 6 shows the probabilities of the basis being negative using the stochastic differential equal

Results from the multivariate regressions show that the relevant determinants we chose in our analysis are all significant for most cases (i.e. low p-values for the LIBOR-OIS Spread, the volatility index VIX, the OIS-TBill spread and the bid-ask spread on the CDS across different entities). Furthermore, the adjusted R-squared were reasonably high ranging from 0.19 for Goldman Sachs to 0.74 for Williams Companies and averaging at 0.40 across our companies.

The LIBOR-OIS spread and the Volatility Index drives the bond spread larger and hence drives the basis negative as expected (coefficients respectively standing at -1.160 and - 0.53 for American Express). The VIX captures the deterioration of the value of the bond as a collateral. The cost of funding a negative basis trade depends upon the haircut applied on the repo-transaction through which the bond is financed (Fontana, 2010). Markets' excessive volatility has an adverse impact on the value of the bond as a collateral and thus contributes to an increase in haircuts. Among this lines the sectors on which the VIX have a the highest impact on the basis are the financial and energy sectors with VIX coefficients ranging from -1.2 to -3.9 as compared to the technology sector (raging from -0.8 to 2) and the health care sector standing at values near 0. However the OIS-TBill makes an exception: for 7 out of 25 companies it has an unexpected negative sign. This variable is expected to capture the "flight to quality" phenomenon

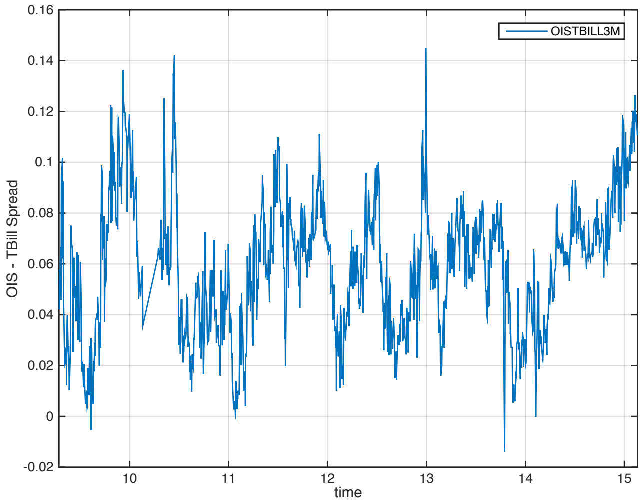

Figure 6. Time series of OSTBILL3M, the spread between USD3MOIS and 3MTBILL.

driving bond spreads larger and hence driving the basis down to negative territories. It turns out not to be the case for JP Morgan, Exxon, Goldman Sachs, Chevron and Bank of America which are Above-A rated financial and energy companies. This suggests that non-transient unobservable factors have influenced the relation between CDS spread and bond spread have come into play.

3.3 Analysis

The cross sector analysis shows us that the technology and energy sectors display lower volatility than financial entities which were more exposed to funding, liquidity and counterparty risks immediately after Lehman Brothers defaulted in 2008. Furthermore, the financial sector is characterized by a significantly negative basis.

The cross rating analysis shows us that for firms rated above A, the average basis is positive standing at 2.37 bps (± 8.54) because CDS are floored at near zero, while bond spreads for highly rated entities are very low. For the below-B category, instead, the average basis is -35.96 bps (± 15.68) pointing to the fact that economics and risk factors have different impacts across ratings groups, notably because of counterparty and liquidity risk premia.

Vasicek modeling yields interesting results, both on an overall scale and across categories. First, we see that longer term maturities have lower (more negative) means. We believe this is due to the higher long term default risks of a firm, meaning that the risk of default is higher in a longer time horizon and therefore will increase the difference between the difference between the CDS spread and bond spread since the bond spread will decrease due to the higher default risk. However, there is no overall trend for the volatility values that we obtained from the Vasicek model.

With further study, we see that there are some trends across sectors. For example, in the energy sector, volatility is extremely high for three year maturities and drops tremendously for the five and then year maturities. This could be due to the fact that oil and energy prices are more volatile in the short term rather than long term since they are very prone to price shocks that could happen at any moment. Although, it should be pointed out that our data for the energy sector may be biased since it is all from a time period when oil and energy prices were very high. Additionally, there is very high volatility for financial firms. This is expected since most of our data is from the post-crisis period. These values are especially high for firms that were affected drastically during the crisis like Bank of America and Merrill Lynch.

Since the onset of the financial crisis, the perceived counterparty risk on interbank loans in the economy has increased dramatically. CDS dealers are paying higher funding rates, the latter being captured by the changes in the LIBOR-OIS spread. As previously discussed, the cost of financing affects investors that seek to enter into a negative basis trade. During the crisis and shortly after (where our analysis begins) the cost of financing has substantially increased, limiting the returns to arbitrageurs. Besides, the high market volatility as measured by the VIX, has contributed to a jump in haircuts (margin requirements) reducing the profitability for investors when they implement negative basis trade. This might explain the cross-sectional difference in the basis across ratings, our below-A category exhibiting the most negative basis. In addition, liquidity has migrated from the corporate bond market to treasuries, driving risky bond yields larger, this 'flight to quality" phenomenon being captured jointly by the evolution of the VIX and the OIS-TBill. Eventually, in the post-crisis environment, counter-party risk has made bond spreads outstrip CDS spreads. In fact, during and shorty after the crisis, CDS protection sellers have higher default correlation to the assets being protected. Default risk between banks is jointly captured by the LIBOR-OIS spread and the evolution of the CDS on banks. This risk is priced into CDS contracts of financial institutions driving their spreads lower irrespective of the actual default intensity.

4. Conclusion

We have analyzed the cross-sectional variation in the CDS-bond basis during the crisis. Focusing on the cross section of the CDS-bond basis is interesting as it provides a good testing ground for the literature that models "limits to arbitrage," and specifically the behavior of arbitrageurs with limited capital facing multiple 'arbitrage' opportunities (Gromb and Vayanos (2010)). The results of our Fama-French style regressions show that after the crisis, some risk-factors can explain the basis. Factors, which we interpret as proxying for counterparty risk, collateral quality, and funding risk have signicant impact on the cross-sectional differences in the levels of the basis for high-yield firms. Instead, for investment-grade firms, the overall explanatory power of the regressions is lower. We find that the bases are mostly driven by counterparty and flight to quality risk. We find that the previously documented result that the CDS market tends to lead the bond market (Blanco-Brennan and Marsh) changed dramatically during the crisis, especially for high yield bonds. These results seem at least qualitatively consistent with some of the implications of the 'limits to arbitrage' literature. Much work remains to be done to test these more formally.

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Appendix

		μ	ϕ	σ^2	σ
MO	3	-51.294	0.945	382.937	19.569
	5	-52.505	0.931	416.480	20.408
	10	-87.309	0.988	215.651	14.685
AXP	3	-8.204	0.984	581.130	24.107
	5	-38.844	0.893	228.374	15.112
	10	-49.217	0.973	138.467	11.767
BAC	3	-89.096	0.963	1274.994	35.707
	5	-83.505	0.865	1905.900	43.657
	10	-69.280	0.851	2747.500	52.417
CAT	3	5.751	0.966	119.000	10.909
	5	9.760	0.961	139.210	11.799
	10	-5.115	0.975	228.860	15.128
GE	3	65.346	0.965	414.600	20.362
	5	41.893	0.937	353.880	18.812
	10	24.305	0.923	457.730	21.395
GS	3	-28.342	0.844	773.970	27.820
	5	-36.145	0.687	613.560	24.770
	10	-40.391	0.726	1682.300	41.016
JNJ	3	12.027	0.918	55.570	7.455
	5	10.907	0.886	58.654	7.659
	10	3.463	0.933	70.111	8.373
MS	3	-27.463	0.938	732.130	27.058
	5	-53.241	0.746	1350.700	36.752
	10	-53.264	0.858	1581.400	39.767
NWSA	3	-87.497	0.985	189.030	13.749
	5	-64.268	0.970	79.940	8.941
	10	0.322	0.996	231.510	15.215
PFE	3	-0.710	0.729	118.130	10.869
	5	-2.485	0.921	48.611	6.972
	10	-20.323	0.873	54.537	7.385
WMT	3	1.174	0.910	74.942	8.657
	5	5.043	0.943	51.917	7.205
	10	-23.463	0.821	645.670	25.410
BNPP	3	26.304	0.174	212.270	14.569
	5	33.593	0.118	136.320	11.676
	10	-9.877	0.272	559.750	23.659
HSBA	3	-0.156	0.846	34.165	5.845
	5	-0.202	0.998	21.962	4.686
	10	55.526	0.237	247.840	15.743
JPM	3	-28.743	0.941	248.090	15.751
	5	-44.497	0.957	181.670	13.479
	10	-50.296	0.935	342.520	18.507
MER	3	-102.110	0.951	817.980	28.600
	5	-155.270	0.921	11957.000	109.348
	10	-75.964	0.637	4282.900	65.444
AAPL	3	4.033	0.868	19.418	4.407
	5	-3.054	0.867	15.881	3.985
	10	-21.371	0.929	16.651	4.081
INTC	3	0.396	0.879	54.011	7.349
	5	9.952	0.935	50.043	7.074
	10	-11.518	0.819	39.137	6.256

		μ	ϕ	σ^2	σ
ORCL	3	0.119	0.850	119.790	10.945
	5	-11.298	0.899	47.378	6.883
	10	-19.862	0.969	38.490	6.204
IBM	3	-5.114	0.875	67.312	8.204
	5	-9.260	0.952	51.909	7.205
	10	-27.480	0.980	67.542	8.218
CSCO	3	14.294	0.956	46.582	6.825
	5	4.344	0.978	69.405	8.331
	10	0.946	0.981	44.131	6.643
AMD	3	-156.560	0.952	414.020	20.347
	5	3.631	0.937	300.620	17.338
	10	82.068	0.828	459.920	21.446
MSFT	3	13.108	0.873	88.539	9.410
	5	16.311	0.885	75.195	8.672
	10	-1.225	0.878	53.761	7.332
AMA	3	-1.182	0.960	66.785	8.172
	5	-15.328	0.966	55.291	7.436
	10	-12.549	0.966	34.595	5.882
XOM	3	-14.921	0.938	188.240	13.720
	5	-17.944	0.953	113.360	10.647
	10	-44.757	0.926	123.300	11.104
CVX	3	-5.449	0.974	99.091	9.954
	5	-24.203	0.988	57.110	7.557
	10	-5.207	0.250	2919.800	54.035
HAL	3	-14.454	0.978	77.523	8.805
	5	-36.292	0.986	57.352	7.573
	10	-1.543	0.992	106.920	10.340
WMB	3	-107.720	0.988	530.360	23.030
	5	-100.480	0.989	426.540	20.653
	10	-101.660	0.982	271.300	16.471
TOTF	3	10.134	0.909	145.720	12.071
	5	24.672	0.760	120.860	10.994
	10	25.465	0.968	34.656	5.887
ENEI	3	45.461	0.984	422.090	20.545
	5	46.410	0.986	221.700	14.890
	10	39.252	0.981	201.030	14.179
RDS	3	18.587	0.802	1212.700	34.824
	5	25.218	0.959	44.307	6.656
	10	37.246	0.966	58.741	7.664

Table 4. Results of Time Series Vasicek Modeling

COMPANY	3Y	5Y	10Y
AXP	0.5271	0.5672	0.6364
BAC	0.5251	0.5171	0.5097
CAT	0.4733	0.4694	0.498
CSCO	0.3838	0.4579	0.5007
CVX	0.4596	0.4168	0.4205
ENEI	0.5148	0.5234	0.5094
GS	0.5658	0.6877	0.7308
HAL	0.5274	0.5584	0.6284
IBM	0.4141	0.4272	0.4773
JNJ	0.5497	0.5907	0.5575
JPM	0.5523	0.5051	0.5070
MER	0.5497	0.5480	0.6230
MO	0.5171	0.5156	0.5133
MS	0.6460	0.7799	0.6968
NWSA	0.4989	0.5923	0.6791
ORCL	0.5026	0.5234	0.6443
PFE	0.4938	0.2826	0.2604
RDS	0.4727	0.4190	0.230
TOTF	0.5596	0.5688	0.6367
WMB	0.4939	0.4657	0.5149
WMT	0.5259	0.5508	0.6369

Table 5. Probabilities of basis being negative using Vasicek model.

	Constant	CDS	USD3MOIS	OISTBILL	VIX
MO5YUSAX	-44.12	1.06	-1.26	-22.09	-3.33
0.33	4.63	0.05	0.12	47.15	0.27
	0	0	0	0.64	0
AXP5YUSAX	-20.25	-0.02	-0.53	299.76	-1.16
0.28	2.98	0.02	0.09	30.74	0.16
	0	0.35	0	0	0
BAC5YUSAX	18.94	0.26	-3.85	-15.23	-3.07
0.5	6.28	0.03	0.15	64.89	0.32
	0	0	0	0.81	0
CAT5YUSAX	27.46	0.03	-0.52	-88	-0.17
0.03	4.21	0.05	0.14	43.92	0.22
	0	0.57	0	0.05	0.42
GS5YUSAX	2.78	0.08	-1.14	-138.54	-1.05
0.19	3.23	0.02	0.1	33.38	0.15
	0.39	0	0	0	0
JNJ5YUSAX	-18.03	0.69	0.16	76.35	-0.04
0.28	1.54	0.05	0.04	14.82	0.08
	0	0	0	0	0.6
MS5YUSAX	-16.25	0	-1.68	353.04	-1.24
0.27	4.86	0.02	0.15	50.13	0.24
	0	0.98	0	0	0
NWSA5YUSAX	-37.14	-0.28	-1.69	231.06	0.64
0.49	2.63	0.04	0.07	27.02	0.16
	0	0	0	0	0
PFE5YUSAX	-26.48	0.73	-0.84	23.27	0.22
0.37	1.69	0.03	0.06	16.83	0.09
	0	0	0	0.17	0.01
IBM5YUSAX	-15.98	0.14	-0.7	36.16	0.74
0.12	3.11	0.09	0.06	23.03	0.1
	0	0.1	0	0.12	0
CSCO5YUSAX	-36.72	1.76	-1.26	15.01	-1.61
0.6	2.58	0.04	0.06	25.04	0.12
	0	0	0	0.55	0
2CVX5YUSAX	-15.54	0.82	-0.1	-45.06	-0.83
0.04	3.48	0.13	0.11	35.68	0.21
	0	0	0.38	0.21	0
ENEI5YEUAM	-66.57	0.29	0.47	-216.43	2.57
0.52	5.1	0.02	0.08	23.5	0.25
	0	0	0	0	0
HAL5YUSAX	6.04	0.64	-0.5	157.97	-3.82
0.42	3.18	0.03	0.08	32.01	0.16
	0.06	0	0	0	0
JPM5YUSAX	13.8	0.4	-1.41	-163.69	-2.78
0.28	4.48	0.06	0.13	39.88	0.19
	0	0	0	0	0
MER5YUSAX	83.03	-1.36	-7.31	223.59	8.71
0.4	29.39	0.14	1.09	303.49	1.55
	0	0	0	0.46	0
ORCL5YUSAX	-26.01	0.41	-0.27	61.45	-0.04
0.03	3.08	0.09	0.06	16.62	0.08
	0	0	0	0	0.63
RDS5YEUAM	-1.17	1.13	-0.05	73.35	-1.97
0.6	1.44	0.03	0.02	5.49	0.07
	0.42	0	0.01	0	0

Table 6: Ordinary multivariate regression results. First row depicts coefficients of regression, second row depicts standard error of regression, and third row depicts p-value of regressor. The R^2 of the regression is shown under the firm name. All values rounded to two decimal places.