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# Cardiff Economics Working Papers



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August 2015

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# **THE CDS-BOND BASIS PUZZLE IN THE FINANCIAL SECTOR**

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# 1. Introduction

A single-name credit default swap (CDS) is a contract committing one party (the seller) to reimburse the buyer if a credit event results in default by a third-party (the reference entity) on scheduled payments on a bond it has issued. Although trading only started in 1994, the market has grown so rapidly that by the time of the 2008 crisis, total CDS contracts were estimated to involve around \$30 trillion of notional principal, much of it relating to the kind of complex instruments which were central to the development of the shadow banking system. Since then, however, the market has contracted somewhat, but CDS remain one of the largest and most controversial of the financial markets, attracting considerable attention from policy-makers, commentators and academics.

Since a CDS in effect serves to insure a bond investor against default on the underlying, it might appear that a portfolio consisting of a long position in a bond and the associated CDS ought to pay the riskless rate, and the same ought to apply to a CDS sale with a matching short position in the underlying bond. In terms of spreads, arbitrage ought to make the cost of insuring in the CDS market (“the CDS spread”) just equal to the difference between the bond yield and the riskless rate (“the credit spread”). In reality, in the years since CDS trading began in the mid-1990’s, the two have rarely been equal, even after making the most meticulous adjustments to allow for transaction costs, cheapest-to-deliver options and other possible confounding factors. Broadly speaking, the excess of the CDS spread over the credit spread (“the basis”) was small and mostly positive before the 2008 financial crisis, but fell dramatically during the crisis, creating a negative basis that for the less creditworthy borrowers was measured in hundreds of basis points. Although the basis has narrowed somewhat in recent years, on average it remains negative.

This apparent arbitrage failure is puzzling. Pre-crisis researchers pointed to a number of possible causes of the small positive basis, but post-crisis experience with a persistently negative basis implies their explanations must have been incomplete, a fact which has generated a growing empirical literature in the last few years.<sup>1</sup> In this paper, we add to the recent literature which tries to account for movements in the basis before, during and after the crisis by examining real-time daily transactions for over 400 issuers in the USA from 2005 to 2011, derived from a raw dataset of over 500,000 observations. We focus particularly on the contrast between the behaviour of the basis in the cases of financial and nonfinancial firms, where it turns out that there was a clear divergence around the time of the Lehman bankruptcy as the market drastically reassessed the default risk of the major investment and deposit-taking banks. We show that while factors related to arbitrage failure may provide an explanation for much of the negative basis in the nonfinancial corporate sector, they do little to explain the basis in the case of bond issues by financial institutions. In fact, we find that its pre-crisis drivers appear to have become less important post-crisis. This is a puzzle which remains unresolved, though we point to a possible (very tentative) explanation in terms of the likely correlation risk.

After a brief literature review, we start by analysing in some detail the arbitrage mechanism, focusing especially on the complications involved in exploiting the profit opportunity offered by a negative basis. We break down the arbitrage trade into its component parts, so as to identify the different factors which affect its profitability, paying particular attention to the financing of arbitrage trades. It turns out that the payoff to basis arbitrage depends on five factors: the cost of funding the deal via the repo market, the quality of the collateral offered, the liquidity of both CDS and bond markets, the volatility of the basis itself

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<sup>1</sup> For an exhaustive survey of the literature, see Augustin et al (2014).

and counterparty risk i.e. the risk that, in the event of default by the underlying name, the CDS seller itself is unable to meet its commitment to compensate the buyer for losses on the bond. We then proceed to test how far these factors allow us to explain the behaviour of the basis over our data period centred on the 2008 financial crisis. At each stage, we compare the financial and nonfinancial sectors, with the latter as the benchmark since it is more or less free of the complications that arise when the reference entity is itself a financial institution. Our main approach to the large dataset involves panel data estimation, but we also present Fama-MacBeth estimates of the impact of the various factors.

The next section contains a brief overview of the literature. We then focus on the determinants of the cost of arbitrage in Section 2, which provides a framework for testing the time series of basis data over the period since 2005. Our dataset is discussed in Section 3 and our results are presented in the following sections, starting with the panel data estimates, then the Fama-macBeth results and ending with a number of robustness tests.

## 2. Literature Review

The literature on the basis divides clearly into pre- and post-crisis. Until 2007, the research question was how to explain a small but persistent, mostly positive basis (see Figure 1). The obvious places to look for an explanation were in the details of CDS contracts and in the costs of an arbitrage transaction, which in the case of a positive basis involves short-selling the underlying bond while writing the CDS.

As Blanco, Brennan and Marsh (2005) argued, the provisions of the cheapest-to-deliver option in CDS contracts and the scope they provided for additional yield in default scenarios would tend to expand CDS spreads to a level somewhat above the true cost of insuring the underlying credit risk, while the cost of repo funding would reduce the apparent credit spread, other things being equal. Both these considerations imply that, in normal conditions, the CDS-Bond basis should on average be slightly positive. The same authors also found the anomaly that, while bond credit spreads appear to react more to market-wide variables such as changes in interest rates and the slope of the yield curve, CDS prices reacted more to firm-specific factors such as the price and volatility of the individual firm's stock. Likewise, De Wit (2006) argued that the cheapest-to-deliver option along with technical factors such as the complications involved in shorting bonds suffice to explain the positive basis in 2004-5.

Another strand of the literature focused on liquidity as a potential explanation of the basis. The first research along these lines was by Longstaff et al (2005), who found a strong relationship between the basis and liquidity, albeit using a small sample of only 68 firms observed over barely 18 months. Their work was superseded by Nashikkar et al (2011), whose sample covered 1167 firms from July 2002 to June 2006. Using the weighted average turnover of funds holding each bond as their measure of what they called latent liquidity, they investigated the role of volatility in the bond and CDS markets. Among their findings, it is notable that volatility and liquidity in the CDS market appeared to play a larger part in determining the basis than the equivalent parameters of the bond market, which again seems to indicate that the CDS is the more sensitive of the two to firm-specific factors. Two aspects of their results are relevant to this paper. On the one hand, they conclude that the CDS spread fails to capture fully the credit risk of the underlying bond. On the other hand, they attribute this failure to a number of frictions that limit arbitrage between the two markets, in particular the cost of shorting corporate debt, which is one leg of the transaction involved in a positive basis arbitrage. This conclusion, while no doubt justified at the time, points to the need to revisit the research question in the light of that fact that, as already pointed out, the

basis has been almost invariably negative in the post-Lehman era, implying that arbitrageurs would need to buy the bond, a cheaper and less complicated proposition than shorting it.

Nevertheless, Gou and Bhanot (2012) focused on the role played by different types of liquidity over the crisis period itself. Funding liquidity variables were separated into three categories: arbitrageurs' capital availability/volatility (VIX index); arbitrageurs' funding – the shadow cost of capital (the LIBOR - T-bill spread, the repo – LIBOR spread); and arbitrageurs' rollover-funding risk (repo-rate volatility). The asset-specific liquidity factors considered included: short-term stock volatility, long-term stock volatility, bond credit rating, bond trading volume, bond bid-ask yield spread, in addition to the three standard Fama-French factors. The authors showed that asset-specific liquidity could account for a significant proportion of the negative basis during the crisis period, and Augustin (2012) arrive at similar conclusions using non-parametric estimation methods. Mitchell and Pulvino (2012) focused in detail on the situation faced by highly-leveraged hedge funds during the crisis and found evidence that their arbitrage activities were severely restricted by the inability of their prime-brokers to overcome the problem that the market for the assets they normally held as collateral had become illiquid.

In our paper, while allowing for liquidity as a potentially important factor, our main focus is on the behaviour of the basis in cases where the reference securities were issued by financial institutions. Of particular relevance in this regard, Fontana (2012), applying cointegration techniques to the time series for the basis for a sample of investment-grade US corporates, arrived at two important conclusions. First, the basis tended to be significantly more negative where the issuer of the reference security was a financial institution, and second, there was also a pronounced tendency for the basis to be more negative for lower-rated borrowers.

More recently, using Fama-MacBeth regressions on monthly data over a sample period from January 2006 to December 2011, Bai and Collin-Dufresne (2013) showed that variables proxying bond liquidity, funding cost, flight to quality, collateral quality and counterparty risk could account for around 35% of the cross-sectional variation in the credit basis for a large sample of firms during the 2007-2009 financial crisis. Notably, these authors find that, whereas the main determinants in the pre-Lehman period are funding risk, collateral quality and counterparty risk, the liquidity variables dominate post-Lehman. More surprisingly, their results suggest that most of the other variables, including counterparty risk, contribute little or nothing to explaining the data for the post-Lehman period. As a counterpoint to these results, Kim et al (2014) focus directly on the rewards to arbitrage net of the type of costs considered by Bai and Collin-Dufresne (2013), and conclude that a trading strategy based on exploiting this residual return would have yielded abnormal returns inexplicable by any identifiable risk factors.

At the theoretical level, Garleanu and Pedersen (2011) set out a dynamic general-equilibrium model in which leverage constraints would generate a pricing difference between two securities with nearly identical cash flows. The model starts from the assumption that investors can be separated into two groups of risk-averse and risk-tolerant agents respectively. Each risk-tolerant investor (typically a bank or financial institution) uses leverage, but is subject to margin requirements which it is able to fund with uncollateralized loans. In contrast, risk-averse investors are assumed to be constrained in their derivatives trading and cannot borrow without supplying collateral. In this framework, the authors show how negative shocks to fundamentals could lead to basis spreads (i.e. gaps between the prices of securities with identical cash-flows but different margin requirements). They proceed to test their model empirically, validating its predictions in the case of the CDS-Bond basis. In particular, their model predicts a nonzero covariance

between the time-series for the basis and the spread between LIBOR and the general collateral repo rate, which under their assumptions represents the true cost of arbitrage funding.<sup>2</sup>

A recurring theme in the literature is the relationship between the basis and equity markets. In other words, do changes in the return on equity, or in its volatility, have different effects on bond and CDS markets? These questions were investigated comprehensively in Norden and Weber (2009) using standard time-series methods including Granger causality and vector error-correction tests. They found that, although positive stock returns cause the spreads in both bond and CDS markets to narrow, as we would expect, the effect is generally stronger in the case of CDS. In both markets, the effect of stock returns is more marked in the case of firms with lower credit quality, which is consistent with the standard structural model of corporate debt pricing, but again the CDS leads the bond market. However, these results are based on a dataset which is relatively small (only 58 firms) and now out-of-date (from 2<sup>nd</sup> July 1998 to 2<sup>nd</sup> December 2002), which raises the question of how far they remain relevant today.

In this paper we present results based on US data starting in 2005 and going through the 2008 crisis and beyond as far as the end of 2011, which is a longer period than almost any of the published research. Moreover, using daily data for over 400 bond issuers, we are able to present panel estimates focussing on the difference between financial and nonfinancial firms over the period as a whole, as well as over three subperiods: before, during and after the Lehman Brothers collapse.

We start by analysing in detail the position of a potential arbitrageur between the CDS and bond markets.

### 3. Basis Arbitrage

A CDS contract is nothing more than an over-the-counter insurance policy against default by a particular borrower (the “name”). A portfolio made up of the underlying bond which is being guaranteed against a “credit event” (i.e. a default as defined under the terms of the contract) and the CDS contract is therefore riskless, and in the absence of frictions of one kind or another should yield a return no more or less than the current riskless rate. In other words, standard no-arbitrage considerations imply that the CDS price (or “spread”) ought to be equal to the excess of the bond yield over the riskless yield on Government debt, matched for maturity (or ideally for duration), otherwise known as the credit spread. Insofar as this is not the case, there is said to be a nonzero basis. In other words, we define the basis at time  $t$  as the excess of the CDS spread over the appropriately matched credit spread for the  $j^{\text{th}}$  bond as:

$$Basis_{j,t} = CDS_{j,t} - CS_{j,t}$$

In the analysis which follows, we drop the subscript  $j$  since we are dealing with the basis for a given reference bond issue throughout this section.

Now consider in more detail the mechanics of arbitraging a negative basis, which essentially involve setting up the zero-cost portfolio created by the following five transactions at the outset (time 0):

1. buy the reference bond at the current ask price,  $P_0^A$

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<sup>2</sup> See Kim (2013) for a very different model, also game-theoretic, but which focuses instead on the issues surrounding commitment by firms to creditors, as reflected in bond and CDS spreads.

2. neutralise the interest rate risk on the bond by entering a fixed-for-floating par-asset swap of the same size and tenor
3. eliminate the default risk by taking a long position in the appropriate CDS contract and depositing a margin payment on which interest is paid at the repo rate,  $R_0^{REPO}$
4. finance as much as possible of the net outlay for these three trades by entering a repo deal at the same rate,  $R_0^{REPO}$  using the bond as collateral
5. finance the remainder by raising an uncollateralized loan at the funding rate,  $R_0^{FUND}$

Notice that the last two trades imply that the greater the value of the bond, the less the need to borrow in the uncollateralized loan market and hence the less costly it is to arbitrage a negative basis. It follows that any change which increases the value of the bond would be expected to make the basis less negative, other things being equal.

The cashflows associated with the arbitrage portfolio are (in the same order as above):

$$\begin{aligned} \Pi_0 = & -P_0^A - [N - P_0] - M \\ & + N(1 - h) + [Nh + M + (P_0^A - P_0)] \end{aligned} \quad (1)$$

In the first line, the asset swap costs  $[N - P_0]$  to set up, where  $N$  is the face value of the bond,  $P_0$  is its mid-market price, and  $M$  is the margin required by the CDS seller. In the second line, the financing includes a repo loan of  $N(1 - h)$  where  $h$  is the haircut applied to the bond as collateral and the final square bracket summarises the remainder of the outlays, which have to be funded by the uncollateralized loan: the haircut on the repo deal,  $Nh$ , the margin on the CDS purchase,  $M$ , and the difference between the ask price paid to buy the bond and the mid-price at which it is swapped.<sup>3</sup>

Now consider the payoff to this portfolio one period later, at  $t = 1$  (for simplicity, one year later), when the arbitrageur unwinds the positions. There are two possibilities, depending on whether or not a default has occurred in the interim.

**In the absence of a default**, the investor sells the bond in the market, closes out the positions in the CDS and asset swap, and repays the loans. Then writing  $BASIS_0$  as the value of the basis at the outset and  $\Delta BASIS$  as the change in the basis from time 0 to 1, the net cashflow at the end of the period can be shown to be approximately (see Appendix 3):

$$\begin{aligned} \Pi_1^{ND} = & -N[(h + m - 1)(R_0^{LIBOR} - R_0^{REPO}) + (h + m)(R_0^{FUND} - R_0^{LIBOR}) + BASIS_0] \\ & -N \left[ S_{BOND}^{a-b} \left( 1 + \frac{1}{2} R_0^{FUND} \right) + S_{CDS}^{a-b} \left( RPV_{1,T} + \frac{1}{2} \right) + S_{ASW}^{a-b} \left( PV_{1,T} + \frac{1}{2} \right) \right] + N PV_{1,T} \cdot \Delta BASIS \end{aligned} \quad (2)$$

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<sup>3</sup> Note that the haircut on the underlying bond will depend on the uncertainty attaching to its value, which in theory reflects the standard variables in the structural model of bond pricing, in particular the variance of corporate cashflows (Merton (1974)). Here, however, the haircut is a given constant as of time 0, though of course its variability will be very relevant to the cost of rolling over arbitrage positions.



where  $S_{BOND}^{a-b}$  is the bid-ask spread on the bond, and similarly  $S_{CDS}^{a-b}, S_{ASW}^{a-b}$  for CDS and asset swaps, the margin ratio,  $m$ , is defined by  $M = mN$  and  $PV_{1,T}, RPV_{1,T}$  are respectively the current market value of a security paying \$1 on each due coupon date up to the final scheduled payment day and the value of a security making the same payments, but terminating if the underlying bond defaults.

The first line represents the carry of the negative basis trade. In the first line, the terms proportional to  $(R_0^{LIBOR} - R_0^{REPO})$  and  $(R_0^{FUND} - R_0^{LIBOR})$  represent the net funding cost over the elapsed time from 0 to 1 while the term proportional to  $BASIS_0$  is the carry earned on the negative basis. Note the presumption that  $R_0^{FUND} \geq R_0^{LIBOR}$ . The second line presents the total transaction costs on the different legs of the arbitrage: the losses incurred on bid-ask-spreads in the process of opening and closing out the bond, CDS and asset swap positions in each of the three terms. In the final term in the bottom line, we show the present value of the uncertain loss or gain resulting from the change in basis between time 0 and time 1  $\Delta BASIS$ . Note that this term, which can be either positive or negative, is the only unknown as of time 0.

**In the event of default**, the payoff is almost identical, as indeed it has to be in a genuinely riskless arbitrage. However, it can be shown (see the Appendix) that the persistence of the asset swap in the event of default means there is room for a small degree of slippage, so that the payoffs in the two states of the world are only approximately equal:

$$\Pi_1^{ND} \approx \Pi_1^D$$

As already noted, all the variables on the RHS of (2) are observable at 0, with the sole exception of the basis change,  $\Delta BASIS$ , in the final term, which reflects the risk that the arbitrageur may find the negative basis actually widening – the trade running away from him – which would not only inflict a mark-to-market loss, but might also result in an unexpected margin call with the associated additional funding costs. Clearly, this is a risk which will be compensated in the market.

For the purposes of our empirical work, we proxy this risk premium by the basis volatility (defined over the previous three months' data) though we appreciate that a more sophisticated model would take account of other factors, including covariance with the market, which may be important in many cases.

The analysis so far ignores one other potentially important risk component. The assumption that in the event of default the CDS seller is able to deliver the shortfall between the bond's recovery value and its face value may not always be correct. For example, if there are connections between the reference entity which is in default and the protection seller or in scenarios involving widespread collapse (as in 2007-8), the CDS buyer may find the counterparty unable to meet its obligations. Clearly, the greater this perceived risk at time 0, the less valuable the CDS contract and hence the more negative (or less positive) the basis, other things being equal. Since counterparty risk was potentially important during our data period, especially during and immediately after the 2007-8 crisis, a way has to be found to incorporate it explicitly in our fitted equations. In the next section, we say how we propose to measure this risk factor, denoted by  $CP$  in the equation below.

Summarising the discussion in this section, we conclude that the basis depends on the following directly or indirectly observable variables:

$$BASIS = f(R^{REPO}, R^{LIBOR}, R^{FUND}, \sigma_{BASIS}^2, S_{BOND}^{a-b}, S_{CDS}^{a-b}, S_{ASW}^{a-b}, h, m, CP) \quad (3)$$

In qualitative terms, we postulate a relationship between the basis and its determinants as follows:

1. LIBOR and the repo rate will impact negatively on the basis, because when they are higher, the cost of funding a negative basis arbitrage is greater. Conversely, lower rates raise the return to arbitraging a positive basis.
2. The collateral quality of the underlying bond, as reflected in the size of the haircut,  $h$ , will be positively related to the basis. Better collateral implies a lower haircut, reducing the negative basis arbitrageur's need to borrow at the higher funding rate and increasing the overall return, other things being equal. By the same token, if the basis is positive, arbitrage is less profitable when collateral quality is high and therefore the net funding raised by a short position in the bond is reduced.
3. Illiquidity in the three markets involved, as measured by the respective bid-ask spreads on bonds, CDS and asset swaps, makes arbitrage more costly and hence will tend to allow a nonzero basis to persist for longer i.e. it will have a positive effect on a positive basis and a negative effect when the basis is negative.
4. The volatility of the basis itself,  $\sigma_{BASIS}^2$ , which again represents a risk for both negative and positive basis arbitrage and hence will tend to widen the basis in both cases.
5. Counterparty risk,  $CP$ , will reduce the value of CDS protections and hence have a negative effect on the basis.

In the next two sections, we discuss how to identify the empirical counterparts of the variables in equation (3), some of which can be observed directly while others require us to identify observable proxies.

## 4. Our Dataset

In this paper, we use daily data for the US market, taken from several different sources. CDS spreads and corporate bond yields were provided by MarkIt, a database widely used in the published literature. We extracted daily firm-level data on corporate bond and CDS spreads for the period from January 2003 to August 2013. The corresponding equity returns were obtained from the Center for Research in Security Prices (CRSP). Information relating to trading volume for each corporate bond was taken from the Trade Reporting and Compliance Engine (TRACE), which captures consolidated data on secondary market transactions in publicly traded securities, covering in particular all over-the counter and market dealing in corporate bonds. For accounting data, we turned to the COMPUSTAT database. All the raw datasets were cleaned to remove obvious outliers and erroneous data entries, and the datapoints were carefully matched across the different sources using CUSIP/ISIN identifiers to track issuers/specific-bond issues.

At the end of the process of imposing the unavoidable restrictions (excluding companies found in one database but not the other or unmatched across databases), then of cleaning and merging datasets, we ultimately rejected almost half of the initial observations, which still left us, however, with 506,279 daily transactions on the CDS-bond basis, spanning a period between January 2<sup>nd</sup> 2005 and December 31<sup>st</sup> 2011, and containing data on 403 unique US issuers. The dataset covers investment grade (IG) and high yield (HY) US companies, with both bonds and CDS spreads denominated (in the raw data) in US dollars. In what follows, we give a detailed description of the variables relevant to the analysis presented in subsequent sections.

### Corporate Bonds

The set of corporate bond data taken from Markit covers all investment grades and countries for the period from January 2003 to December 2011. We follow the practice in most of the literature by including only senior unsecured debt denominated in US dollars, with more than two years to maturity, fixed coupons, no attached options (i.e. no callable, puttable or convertible bonds) and no collateral, sinking fund or other enhancements. The accuracy of the prices is guaranteed by the fact that Markit exclude from the dataset any bonds for which it is unable to collect at least three quotes. We in any case follow the common practice of eliminating the top and bottom 1% of spreads on the grounds that they may very likely be the result of errors of one kind or another.

### Credit Spread Computation

Points on the US Treasury curve (our riskless rate) were taken from the Department of Treasury's own webpage, where they are given as a set of 10 discrete values of the yield, corresponding to standard maturities. A Matlab interpolation code was written in order to obtain the set of risk free yields corresponding to the date/maturity data points<sup>4</sup> in our corporate bond data set, then the corresponding credit yield spreads were calculated by taking the difference between the corporate yield to maturity and the corresponding risk free yield for every bond-date data point. For purposes of comparison in computing the basis, we ideally need the yields on a matched-maturity floating-rate note, which we proxy here by the par asset swap rate (de Wit (2006)) provided by Markit in the same dataset. In addition, for the sake of robustness testing, we also compute the credit spread from the z-spread (see Section 9).

### Equity Volatility

For reasons already given, we hypothesise that equity volatility plays a part in determining the basis. Following Campbell and Taksler (2003), we define this variable as follows:

$$\sigma_{jt} = \sqrt{\frac{1}{180} \sum_{i=1}^{180} (R_{j,t-i}^{excess} - \mu_{jt})^2}$$

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<sup>4</sup> Using a cubic spline interpolation of the yield curve.

$$\mu_{jt} = \frac{1}{180} \sum_{i=1}^{180} R_{j,t-i}^{excess}$$

where all stock prices are taken from the CRSP database<sup>5</sup>,  $\mu_{jt}$ ,  $\sigma_{jt}$  are the mean and volatility of the excess return on the equity of firm  $j$  on day  $t$ ,  $R_{j,t}^{excess} = R_{j,t} - \bar{R}_t$  is the excess return on the stock relative to the CRSP value-weighted index<sup>6</sup>.

### Basis Volatility

Our theoretical analysis of the profit function for a negative basis trade reveals that basis volatility itself may play an important role in determining the level of the basis. Higher volatility implies a greater risk that an arbitrageur may at some point find the negative basis widening rather than narrowing (the market might “run away”). Even if the adverse movement is only temporary, it may well inflict mark-to-market losses, with the likelihood of margin calls adding to costs and reducing the profitability of the overall position, and of course raising the possibility that the arbitrage may have to be closed out at a loss. We allow for the possibility that the basis incorporates a premium to compensate arbitrageurs for this risk by including basis volatility in our estimating equation, defined as follows:

$$\sigma_{j,t}^{BASIS} = \sqrt{\frac{1}{N_t} \sum_{k=1}^{N_t} (BASIS_{j,t-k} - \mu_{j,t-k}^{BASIS})^2} \text{ where } \mu_{j,t-k}^{BASIS} = \frac{1}{N_t} \sum_{k=1}^{N_t} BASIS_{j,t-k}$$

and  $N_t$  is equal to the number of days in the 3-month period ending on day  $t$ .

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<sup>5</sup> The data from MarkIt and CRSP were matched along the lines set out in a data appendix available from the authors on request.

<sup>6</sup> Note that, in the case of financial stocks, the observed volatility may have been distorted during the fortnight following the collapse of Lehman Brothers, when the SEC imposed a short-sales ban to protect many of the largest and most heavily-traded firms in the sector (see, for example, Boehmer et al (2013) and Beber and Pagano (2012)). However, tests not reported here suggested the ban had little effect on our results.

## 5. Proxy Variables

Since the remaining variables determining the basis in our model – liquidity in the three markets involved (CDS, bonds and repo), counterparty risk and collateral quality - are not directly observable, we now need to address the problem of which data to use as proxy series.

### Funding and Market Liquidity

Market liquidity risk can be measured in a number of different ways. In the present case, we use the spread between the 3-month general-collateral repo rate (i.e. for loans collateralized by Treasuries) and the 3-month T-Bill rate, a measure constructed using daily rates of 3-month T-Bill and Repo General Collateral (Treasury) taken from the Board of Governors of the Federal Reserve System (Federal Reserve Economic Data). The justification for using this proxy is that, since repo collateralized by Treasuries is free of default risk, any deviation from the rate on T-bills must be purely liquidity-related (Bai and Collin-Dufresne (2013)).

While funding cost is conceptually quite distinct from liquidity issues, in practice we are forced to rely on indirect measures which inevitably overlap to some extent with liquidity. Here, we use the spread between 3-month LIBOR and overnight index swaps (OIS), taken from the Federal Reserve Bank of St. Louis and Bloomberg respectively as our index of arbitrage funding cost, though it could equally be interpreted as a measure of the degree of stress in the market for interbank loans<sup>7</sup> and hence indirectly of liquidity.

### Collateral Quality

For the reasons given above, the value of the reference bond as collateral in repo trades affects both the cost of borrowing and, insofar as the haircut has to be financed by borrowing in the overnight market, potentially the availability of credit too. In any case, lower collateral value means a larger haircut, which makes arbitrage less profitable when the basis is negative and hence potentially makes the apparent mispricing greater and more persistent.

However, since bond haircuts are not directly observable, we are forced to use proxy variables as indicators of collateral quality. We select two firm-specific characteristics for the purpose: the average of Moody's and S&P credit rating<sup>8</sup> and equity return volatility over the previous 180 days. The former is directly related to the default probability, as assessed by the two largest credit rating agencies, while the latter is a more general reflection of the riskiness of the firm's expected cashflows.

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<sup>7</sup> This spread, which rose from near-zero to over 3.5% as the crisis progressed, was widely cited as an indicator of the intensity of the credit squeeze which started in mid-2007.

<sup>8</sup> The widespread criticism of the credit rating agencies' performance during the crisis is not very important for our purposes here, because our concern is only with the market's willingness to accept the underlying security as collateral. We only need to assume that, either the institutions in the market took the credit ratings at face value or, at least, that they accepted the credit-rating based constraints imposed by the regulatory authorities.

## Liquidity in CDS and Bond Markets

Our analysis of the arbitrage trading strategy shows that asset specific liquidity may have an important part to play in explaining a negative basis. Intuitively, the less liquid the bond and/or CDS markets, the more costly it is to arbitrage a negative basis. Unfortunately, however, the MarkIt database does not give bid or ask prices nor is the bid-ask spread on asset swaps easily obtainable, so that we were forced to look for proxies for the variables  $S_{BOND}^{a-b}$ ,  $S_{CDS}^{a-b}$ ,  $S_{ASW}^{a-b}$  in equation (3).

The most obvious index way to capture asset-specific liquidity (i.e. for individual bonds) is to use a modified version of the well-known Amihud (2002) measure:

$$Amihud_{j,t} = \frac{|r_{j,t}|}{Vol_{j,t}}$$

where  $r_{j,t}$  is the weighted average return for the  $j^{\text{th}}$  issuer on day  $t$ , and  $Vol_{j,t}$  is total trading volume on day  $t$  in millions of US dollars.<sup>9</sup> The Amihud measure gives an indication of the impact of trade volume on price change, so that an increase indicates greater illiquidity. The data on which it is based are taken from the TRACE database for bond transactions, including both prices and trading volumes. We exclude from our dataset any cases where we have only a single trade for a bond in any particular day, a restriction which is crucial for calculation of the weighted average price (depending on the volume of trade) for each issuer over the day  $t$ .

This sort of measure has been widely used in research on corporate bonds (and of course equities), but has only recently been applied in the context of research on the CDS basis (Augustin (2012), Wang, 2014))<sup>10</sup>.

We restrict ourselves to liquidity measures in the bond market, relying on the fact that since investors trade off the cash and the synthetic market, turning to the CDS market when bonds become too expensive (i.e. when liquidity premia are high), a single measure should be sufficient to cover both markets (Augustin (2012)). In any case, Fontana (2010) showed that liquidity in the bond and CDS market are positively correlated.

A more general indicator of the effect of liquidity on funding costs is the gap between the repo rate for general (i.e. non-special) collateral and the 3-month T-bill rate, which allows for the flight-to-quality that was seen in the crisis period and has reappeared at occasional intervals ever since, creating a temporary market-wide rise in liquidity premia (Bai and Collin-Dufresne (2013)).

## Counterparty Risk

In the CDS context, counterparty risk is the risk that, in the event of default on the underlying bond, the protection seller might be unable to honour its side of the contract i.e. that it might fail to pay the protection buyer an amount equal to the unrecoverable portion of the bond value. Clearly, the greater the

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<sup>9</sup> Since the Amihud measure is typically extremely small, we multiply it by a factor of 100 million in the results reported in the tables in this paper.

<sup>10</sup> See also the results in Goyenko et al (2009) which are broadly supportive of the Amihud measure. Note that, while quoting the figure of over one hundred papers in top finance journals using the Amihud liquidity measure, Lou and Shu (2015) claim that in fact its explanatory power (at least in equity markets) is almost entirely due to the turnover in the denominator rather than the absolute return in the numerator. For a bond market-specific liquidity measure, see Nashikkar et al (2005).

likelihood that the CDS seller will fail to honour its commitment in a future default scenario, the lower the current market value of the CDS contract it sells. Hence, if higher counterparty risk is associated with a lower CDS spread other things being equal, it will also imply a more negative basis.

Although this factor has been extensively discussed in the literature (Bai and Collin-Dufresne (2013), Augustin (2012), Fontana (2010), Wang (2014)), the results are unclear and complicated by measurement problems. CDS contracts are traded in an over-the-counter market, which makes it difficult to identify counterparties, and the fact that the transactions are often carried out under netting and collateral agreements further complicates matters.

In this paper, we take an approach which is both more general and less direct. Specifically, we construct a measure of the creditworthiness of the major CDS dealers in the form of an index of capitalization-weighted CDS quotes on the debt issued by the major CDS sellers themselves:<sup>11</sup>

$$CDSIndex_t = \frac{\sum_{i=1}^N CDS_{i,t} \times Capitalization_{i,t}}{\sum_{i=1}^N Capitalization_{i,t}}$$

where  $CDS_{i,t}$  is the spread for the  $i^{th}$  CDS-dealer and  $N$  is the number of major CDS dealers in the Fed list of primary dealers (see Appendix 2).<sup>12</sup> This index has the virtue of being a direct measure of average counterparty risk across all the protection sellers in the market.

The daily composite CDS spreads for the individual dealers were taken from our MarkIt CDS dataset. We used fixed annual weights for each dealer, computed from annual stock price data and the number of shares outstanding collected from the CRSP database and Datastream, respectively.

In the absence of any correlation between the riskiness of the protection seller and the risk of default by the issuer of the underlying bond, we would expect a negative coefficient on the counterparty risk variable in our regression, reflecting the fact that when CDS dealers become more risky, the contracts they offer become less valuable i.e. the CDS spread falls.

However, since zero correlation cannot be taken for granted, especially in the case of contracts on bonds issued by financial institutions, the situation is unclear. To see why, consider the possible consequences of a sudden increase in the perceived risk attaching to a primary dealer (call it A) i.e. a financial institution engaged in writing CDS contracts. On the one hand, the spread on CDS contracts on A's own debt as reference security will increase, thereby raising our index of counterparty risk to an extent that will depend both on the market's reassessment of the riskiness of A and the relative weight of A in the primary dealer sector as a whole. Against this, the spreads on the protection A itself sells (on an underlying bond issued by B) will have to be reduced to reflect A's lower creditworthiness. Other things being equal, and most importantly if we can rely on a low correlation between changes in the riskiness of A and B, we would expect increases in the CDS index to be associated with lower spreads and hence a smaller (more negative)

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<sup>11</sup> We also experimented with an index of the same form based on the credit spreads of CDS dealers. The results were broadly similar to those using CDS quotes, as reported here.

<sup>12</sup> The Markit dataset is collected from the primary brokers listed in Appendix 2, but for obvious reasons it does not make it possible to link individual brokers to specific transactions.

basis. In this scenario, we unambiguously expect a negative coefficient on the counterparty risk variable in our regression.

Now consider the situation where the market's perception of the riskiness of A and B is correlated, perhaps because of direct links between the two or simply because both are subject to similar risks, which will be especially likely where B is also a financial institution, or even a primary dealer itself. First, it means that accompanying an increase in A's perceived risk, there will also be a rise in the riskiness of B, so that the positive impact on the CDS index will be more marked than where there is zero correlation. In fact, if the rise in risk is viewed as affecting the whole of the financial sector, the CDS index will be pushed up to a substantial degree. But the effect on the cost of CDS protection sold by A is unclear. On the one hand, the spread ought to decrease because the counterparty risk has risen and is further inflated by the prospect that A will fail in precisely the same situations where B fails. On the other hand, the underlying debt being insured is also riskier, implying a wider spread on the CDS, though the effect of this on the basis may well be small if it is matched by a widening of the credit spread in the market for B's debt.<sup>13</sup>

This is more or less the scenario which prevailed during the crisis months surrounding the Lehman Brothers collapse in September 2008. Whenever there was a rise in the market's assessment of the risk of default by a large bond issuer, especially a financial institution, worries would almost certainly have arisen over the impact on the primary dealers who had sold protection on the debt in question, reducing the value of the CDS contract to buyers, other things being equal. The result would most likely be that, in response to the increased risk of the reference bond, the associated CDS spread would rise, but by less than sufficient to compensate for the additional risk, the difference reflecting an extra premium to allow for the possibility of default by the protection seller.

This discussion implies that counterparty risk is likely to reduce the basis, and the effect is likely to be most noticeable where the correlation is strongest, in particular for contracts on financial sector issuers, and most especially at a time when systemic risk threatens the banking system as a whole, as happened in 2007-8.

The situation is further complicated by the official designation of Systemically Important, more popularly known as Too-Big-To-Fail (TBTF) institutions, which cuts across the issues discussed here in ways which will be considered empirically later in this paper.<sup>14</sup>

## 6. Summary statistics

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<sup>13</sup> A number of authors find that the initial impact of news is seen first in the CDS spread and only later in the price of the underlying bond (e.g. Blanco et al (2005), Fontana (2012)).

<sup>14</sup> Note, however, to reduce moral hazard, TBTF status was defined in a way vague enough to leave doubt about exactly how far bondholders would be protected. At the very least, the prospect of legal battles in the event of a default by a primary dealer, with all the delay and expense involved, would have had to be priced even in TBTF cases. Moreover, there was almost certainly a penumbra of "possible-TBTF" – large institutions, financial and nonfinancial which, though not on the official list, might well have benefited from a bailout by the authorities if they were ever in danger of failing – as indeed happened in the case of General Motors in mid-2009.



Table 1 presents the summary statistics for the CDS-bond basis dataset averaged over time, issuers by industry, and rating for each of the years 2005 to 2011. The largest number of transactions came from mid-rated A and BBB companies. Overall, the smallest number of observations (54,877) was for 2005, compared to 108,826 for 2011. For completeness, we also show the data for the AAA rating class, though they are excluded from our estimation results due to the limited number of data points (mostly for firms in the Energy and Healthcare industries).

The different sectors are well represented in our dataset. As can be seen from the bottom half of Table 1, each of the Consumer Goods, Consumer Services and Financial sectors provides over 80,000 observations, spread across all ratings below AAA.

Panel C summarises the broad patterns over our data period. For all but the lowest rating categories, the basis was on average positive, but small and getting smaller in the pre-crisis years, averaging under 5 basis points for all rating classes above B in 2007. In subsequent years, it turned negative and far greater in absolute terms.

This history is illustrated in more detail in Figure 1, which graphs daily movements in the basis averaged across the issuers in each rating class. Having fluctuated around zero in the years running up to the crisis, with little difference between the rating classes, the basis moved into negative territory during 2007, then more dramatically below zero in 2008. In fact, in the immediate aftermath of the Lehman bankruptcy, the basis on BB and BBB-rated bonds fell to -350bp and to nearly -150bp for AA-ratings. In the years since 2008, the apparent anomaly has become less extreme, but it is still clearly present nonetheless, especially for lower-rated bonds.

The graph also shows why most researchers have analysed investment grade (IG) and high-yield (HY) debt separately. Clearly, the basis is more volatile for lower-rated bonds than for investment grades, a fact attributed to the effect of differences in clienteles and/or degrees of liquidity (Da and Gao (2010), Acharya et al (2013)).

The difference between financial and non-financial sectors is illustrated in Figure 2, where the divergence begins in the months between October 2007 and March 2008<sup>15</sup>, when the basis for financials fluctuates quite widely around the zero level, with a few jumps into positive territory, while for non-financials it was already significantly negative. In the aftermath of the Lehman collapse, in October 2008, the basis for financial institutions was at first high and positive (around 50bp), while for non-financials it fell to -50bp. Over succeeding months, the basis for non-financials fell to a minimum of -260bp, compared to -200bp for financials.

Anticipating what follows in the rest of the paper, we entertain two possible explanations for this surprising divergence between the financial sector and the rest. First, we have already argued that the collateral quality of the underlying bond is positively related to the level of the basis, so if the market believed that, post-Lehman, many of the financial institutions in our sample counted as systemically too important to be allowed to fail, it may well be the case that their debt was subject to a smaller haircut in the repo market than the debt issued by nonfinancial companies, making them cheaper to arbitrage. Second, for similar reasons, financial sector debt may have become more liquid than (or, possibly, its liquidity may have fallen by less than) the debt issued by nonfinancials.

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<sup>15</sup> the month of the Bear Stearns bailout and subsequent sale.

## 7. Empirical Results

In linear form, the cross-section testing equation implied by equation (3) and the succeeding discussion is, for firm  $j$ :

$$Basis_{j,t} = \alpha_j + \beta_{1,j}STDV_{j,t} + \beta_{2,j}Rating_{j,t} + \beta_{3,j}FC_t + \beta_{4,j}AggLiq_t + \beta_{5,j}BondLiq_{j,t} + \beta_{6,j}CR_t + \beta_{7,j}BasisVol_{j,t} + \varepsilon_t^j \quad (4)$$

where we anticipate the following sign-pattern:

Variable	Description	Measured by:	Expected Sign
<b><i>STDV</i></b>	Collateral quality of bond	Standard deviation of daily excess return relative to CRSP value-weighted index	-
<b><i>Rating</i></b>	Collateral quality of bond	credit rating dummy	-
<b><i>FC</i></b>	Funding cost risk,	3-month LIBOR- OIS	-
<b><i>AggLiq</i></b>	Aggregate liquidity risk	3-month RepoGC-Treasury	-
<b><i>BondLiq</i></b>	Bond liquidity	Amihud illiquidity index	-
<b><i>CR</i></b>	Counterparty Risk	CDS seller Index	-
<b><i>BasisVol</i></b>	Basis Volatility	3- or 6-month standard deviation of basis	-

We fit this equation to both financial and nonfinancial sectors, allowing us to compare the two and highlight divergences in the way the basis responds to the right-hand side variables. Likewise, in the light of the published evidence suggesting qualitative differences between the behaviour of investment grade (IG) and (HY) markets, separate estimates for these two rating classes are presented.

The model was estimated in levels of the variables (i.e. with the basis as the dependent variable), fitting a pooled ordinary least square (OLS) regression with each observation treated as independent. We also present regressions with fixed and random panels, relying on a Hausman specification test to choose between the two models.

### The Nonfinancial Sector

We start by examining the behaviour of the basis for non-financial firms. Table 2 shows results for the period as a whole which are then broken down into pre- and post-crisis in Table 3. In both cases, we show fixed effects, random effects and pooled OLS estimates for IG and HY separately.

The regressions in Table 2 show that the chosen variables explain well over 30% of movements in the basis for the non-financial sector investment grades (columns 1-3) compared with 15-20% of the high-yield basis, which is perhaps surprising since one would expect lower-rated issues to be more sensitive to default-related variables.<sup>16</sup>

The sign pattern of the coefficients is broadly as anticipated. The standard deviation of the excess return on equity, our indicator of the firm-specific volatility, has a negative coefficient for both IG and HY borrowers (statistically significant in the IG case), which means that an increase in firm-specific volatility leads to the basis becoming more negative. This is consistent with our analysis, since firm-specific volatility reflects the riskiness of the bond issuer, and as a result the quality of the bond which is to be used as collateral in an arbitrage deal. The lower the quality of the bond, the larger the haircut on the collateral, forcing the investor to look for additional funding in the LIBOR market. The resulting increase in the funding cost makes negative basis arbitrage more expensive. However, we note that the estimated coefficient for HY bonds is significantly smaller than for IG bonds, perhaps reflecting the relative insensitivity of the already high level of haircuts required for HY bond repos.

The coefficients on the credit rating dummies are significantly negative for the IG group which means that, when IG debt is downgraded, the basis widens. The logic here is the same as for firm-specific volatility i.e. downgraded debt is worth less as collateral and hence implies a higher cost of arbitrage. In addition, the negative coefficient can probably be attributed to the fact that downgrades are a direct judgement on the value of the debt, which is then marked down almost automatically, irrespective of sentiment in the CDS market, which may well remain unchanged.

There is, however, an alternative interpretation of the negative coefficient here. If, as implied by Da and Gao (2010) and Acharya et al (2013), CDS traders are more likely to be institutions and hence presumably better informed than bond market investors, they may well greet the news of a downgrade with insouciance, either because they have anticipated the announcement and already raised the CDS spread some days earlier, or because they in any case pay less attention to credit ratings than traders in the cash market.

In this context, the positive coefficient for a downgrade on BB bonds, implying a narrowing of the basis, looks surprising, but it is probably a reflection of the illiquidity of the CDS market for bonds rated B or lower.

For both HG and IY issuers, the estimated coefficients for the LIBOR-OIS spread are significantly negative, in line with results in the published literature (Fontana (2010), Bai and Collin-Dufresne (2013), Garleanu and Pedersen (2011)). Since a rise in this variable is an indication of a funding squeeze in the interbank money market and more generally in the market for uncollateralized loans, the results show the expected widening of the negative basis when liquidity diminishes, raising funding costs and making arbitrage unprofitable until the basis becomes more negative. Again, we find that in general IG bonds are more sensitive than HY bonds, presumably because funding liquidity plays less of a role in arbitrage decisions for the most risky borrowers.

Table 3 shows how the behaviour of the basis changed after September 2008. Unsurprisingly, in the feverish post-Lehman market conditions, the sensitivity of the basis to arbitrage cost factors rose

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<sup>16</sup> bearing in mind that, in terms of the structural model, the put option component of investment-grade debt will often be so far out-of-the-money as to be more or less unaffected by fluctuations in the value of the firm.

dramatically. Hence, the coefficients on equity volatility, downgrades, the LIBOR-OIS spread and the Amihud illiquidity index are all several times as great in absolute terms as before the crisis. In general, our results seem to indicate that funding cost and funding liquidity risk became more prominent as explanatory factors for the basis in the post-Lehman period, in contrast to the findings of Bai and Collin-Dufresne (2013), who argue that funding costs become less important as explanations of the negative basis in the postcrisis period. However, it needs to be borne in mind at this point and throughout the discussion of our results that we now know that, from at least 2007 onwards, the LIBOR fixings were being distorted by traders at a number of banks on the rate-setting panel.<sup>17</sup> The precise impact of this manipulation on the pricing of the associated financial instruments and the consequent effect on the CDS-bond basis remains an open avenue for research, but one that lies beyond the scope of this paper.

Finally, an unexpected result in Table 3 is that our counterparty risk measure appears to have become less important, which may be due either to the fact that post-Lehman CDS contracts were more often collateralized than they had been before (Arora et al (2012)) or to the perception that CDS writers – mostly associated with major investment banks - were perceived by the market as Too Big To Fail (TBTF), or both.<sup>18</sup> We shall return to this point later.

## The Financial Sector

We might well anticipate different results for the financial sector, because when both the borrower and the insurer come from the same industry, we can expect the picture to be complicated by correlations between explanatory variables which were not present in the case of nonfinancial firms. In particular, for financial firms the correlation between basis volatility and the volatility of the return on equity is high, 0.73 before Sept 2008, but it fell after the Lehman collapse to only 0.44, a level comparable to the figure for the nonfinancial sector. We surmise that, while equity volatility served as a proxy for the collateral quality of nonfinancial firms, exactly as we assumed in Section 3, in the finance sector it was highly correlated with counterparty risk in the pre-crisis period (see Table 5). It is interesting to note that after the crisis, the correlation dropped from 0.62 to 0.27, which again may be a sign that the market viewed the sector as being to some extent protected from the threat of default.

Since our dataset covers only two financial institutions in the high-yield category (with a total of only 404 data points), we focus our attention on the 45 investment grade financials, for which we have 82,344 daily values of the basis. The results of fitting the model to this dataset are presented in Table 4, for the period as a whole and for pre- and post-Lehman periods. As can be seen from the table, our explanatory variables can account for a far smaller percentage of the variation in the basis for financial firms than for nonfinancial - only 11% and 6% under pooled OLS and panel data estimation methods respectively, compared to over 30% in each case for nonfinancial issuers.

In fact, after September 2008, the model fails almost completely to explain the basis for financial institutions. The multicollinearity between the volatility of financial sector equity and the volatility of the

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<sup>17</sup> see e.g. Financial Times 27<sup>th</sup> July 2015 and earlier.

<sup>18</sup> It is also surprising that the effect of basis volatility is smaller after Lehman than before, albeit insignificantly different from zero.

basis itself may have generated the perverse sign pattern for the coefficients in the middle of Table 4, where we see the basis volatility appears with a highly significant positive coefficient. Equity volatility appears with the expected negative coefficient, but it is insignificant after the crisis. Not surprisingly, the LIBOR-OIS spread widens the basis throughout the period, but most especially post-crisis, when it was widely perceived as an indicator of bank solvency and more generally as an index of stress in the credit markets.<sup>19</sup>

## Counterparty Risk

Since arbitrage is by definition riskless, an arbitrageur has no reason to be active across all markets unless he or she has unlimited funds available for trading. But in the light of the obvious problems in the credit markets in the year or so before the Lehman Brothers collapse, it would almost certainly have been the case that many potential arbitrageurs were operating under very tight funding constraints.<sup>20</sup> Under these circumstances, a rational arbitrageur would have had every reason to concentrate on (or at least give priority to) the market where the basis was greatest in absolute terms, driving the CDS quote up and/or the credit spread down until the payoff fell to the level of the next most profitable opportunity. Moreover, other things being equal, the risk of loss from reversals will be lowest where the basis is greatest at the time the arbitrage trades are initiated.<sup>21</sup>

If this hypothesis is correct, in cases where the basis was relatively small, arbitrage might have been almost totally absent, so that our model might be expected to work poorly as an explanation of the facts. Instead, we might expect the issues surrounding limits to arbitrage to be most clearly visible in the most extreme cases.<sup>22</sup> We therefore examine in this section the results for regressions involving the subset of the 10% most negative bond-CDS pairs on each day in the sample period, broken down as before into three categories: the financial sector taken as a whole, and IG and HY for nonfinancial firms.<sup>23</sup>

The first thing to note in Table 6 is that the same factors used in earlier regressions on the full dataset explain a far higher proportion of the variation in the 10%-quantile of the basis on nonfinancial issues (60% and above, compared to barely 30%). While a substantial improvement was only to be expected, the transformation in the goodness of fit for the financial sector is more surprising. An equation which

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<sup>19</sup> Regressions with the LIBOR-OIS spread replaced by the REPO-Treasury spread were almost identical, so are not reported here.

<sup>20</sup> The credit markets appeared at the time to have ceased to function properly so that some dealers would have been facing binding capital constraints. Apparently, many prime brokers found their usual source of loans, by rehypothecation of the bonds they took as collateral on CDS sales, had dried up, making it impossible to continue normal trading (Nashikkar et al (2011)). This means that the type of cost-of-arbitrage considerations discussed in Section 3 may well have been completely inoperative in their situation.

<sup>21</sup> Of course, there may have been arguments for diversification, but given that we are dealing with what are still basically arbitrage transactions, the arguments would not have been very compelling, especially as some of the risk (especially counterparty risk) would have been largely undiversifiable, given the links between the small number of prime brokers.

<sup>22</sup> The argument here is in the spirit of the smooth transition models (e.g. ESTAR, LSTAR etc), which have been widely applied to financial markets, especially exchange rates (Michael et al (1997)) and which are often justified in terms of transaction costs generating a convergence process whose strength is in proportion to the distance from fair value (Dumas (1992)). Viewed from that perspective, we are conjecturing that there are probably additional costs or barriers to arbitrage which have not been fully captured in the equations fitted here.

<sup>23</sup> Note that Bai et al (2013) fit their model to the subset of negative basis observations, on the grounds that the sources of arbitrage friction are likely to differ in positive and negative basis scenarios.

explained almost none of the variation in the basis across the sector as a whole appears to account for nearly 70% of variation in the subset of cases most likely to attract arbitrageurs.

On the whole, the results in Table 6 are consistent with those in Tables 3 and 4, with the signs of the coefficients largely unchanged, but considerably more significant. It is interesting to note that the results confirm the conclusion that the Amihud liquidity measure plays no significant role in any of the regressions either for the financial or nonfinancial sectors. The other noteworthy feature is the importance for these extreme cases of the CDS index, our proxy for counterparty risk. In fact, for nonfinancials, increases in counterparty risk reduced the basis by far more than downgrades of the reference entity. The most likely explanation here is that exceptionally low CDS quotes were overwhelmingly seen in situations where the protection seller was viewed as a possible defaulter, especially in the crisis conditions of 2008-9, so any increase in the general level of counterparty risk across the CDS market as a whole had an especially powerful effect on the most negative basis cases.

If this is a correct conclusion, the effect will have been most noticeable when the market was most stressed in and around the Lehman crisis. In Table 7, we concentrate on the financial sector and break the period into three: pre-crisis (up to the end of July 2007), crisis (August 2007 to the end of September 2008) and postcrisis (October 2008 onward). In Panel A, we show results for the financials as a whole. The first point to note is that the equity return volatility plays relatively little part and actually attracts a significantly positive sign postcrisis, while the CDS index has a perversely positive effect in all three periods.

In contrast, when we concentrate on the ten most negative basis cases (Panel B), we see that the CDS index attracts the coefficient sign we would expect if it predominantly reflected counterparty risk in times of stress, becoming significantly negative in the early stages of the crisis and heavily negative in the postcrisis period.

The other clue to the explanation of the puzzle is in the behaviour of the LIBOR-OIS spread, which accounted for nearly one and a half percentage points of the basis postcrisis for the financial sector as a whole and just under one percentage point for the ten most negative basis cases.

The most plausible way to reconcile these results is as follows. Start from a hypothetical classification of the financial firms in our sample into three categories: giant institutions, low-risk medium or relatively small financial firms, and high-risk medium and small firms. We surmise that, in the early years of our data period, even the smallest institutions benefitted from a degree of confidence (nonzero, but certainly not one hundred percent) that in the event they ever faced a liquidity or solvency crisis, the authorities would feel bound to bail them out for fear of a systemic collapse. In this regard, the memory of the LTCM bailout in 1998 may well have played a part. As a result, counterparty risk had little or no effect on large or small protection sellers precrisis, and rises in the CDS index simply reflected microstructural changes which made arbitrage more costly and hence allowed the positive basis we observed in the early years to persist. The situation changed, however, after the crisis, as the value of protection sold by the riskier institutions declined whenever the CDS index for the sector rose. In this scenario, those institutions perceived as being most at risk would have been forced to sell CDS at a lower spread other things being equal, especially when the risks were viewed as being correlated. Moreover, if the risk of a default by the CDS seller was viewed as being highly correlated with the riskiness of the bond issuer, increased volatility in the return on the issuer's equity would raise the risk of both, reducing the market value of the contract, other things being equal, a fact which would explain the large negative coefficients in the first line of Panel B.

To investigate this possibility, we show in Table 8 the results of fitting our equation to the data for the subset of financial sector bond issuers classed as TBTF, a status which became far more valuable in the banking crisis following the Lehman bankruptcy.<sup>24</sup> In interpreting these results, we rely on the Blanco et al (2005) finding that, while the CDS market is more or less dominated by institutions, retail investors are more important in the cash market. This may help to explain why, after 2008, the TBTF dummy appears with a highly significant negative sign while the impact of a downgrade from AA to BBB was actually positive. On the one hand, news that cast doubt on the solvency of the major institutions shocked the cash market and drove up the yield on their debt, but left the derivatives market relatively unmoved. On the other hand, downgrades may have forced some investors to seek insurance in situations where they would not previously have felt the need to cover. For example, before 2008, institutions like pension funds may have held the bonds of the largest issuers without feeling the need to insure, even in the face of the occasional downgrade, whereas in the post-Lehman world, they felt forced to cover in the CDS market, thereby driving up the spread and making the basis more positive.

## 8. Fama-Macbeth Tests

As an alternative approach, we treat the variables as risk factors and implement the Fama-Macbeth procedure (Bai and Collin-Dufresne (2013))<sup>25</sup>. In the present case, this amounts to estimating the following individual regressions for each issuer  $j$ :

$$Basis_{j,t} = \alpha_j + \sum_{i=1}^K \beta_{ij} f_{i,t} + \epsilon_{j,t} \quad j = 1, \dots, N \quad t = 1, \dots, T \quad (5)$$

Where  $Basis_{j,t}$  is the value of the CDS-bond basis observations for the issuer  $j$  at time  $t$ ,  $f_{i,t}$  is the level of the  $i^{th}$  factor at  $t$ ,  $\alpha_j$  is the intercept and  $\beta_{ij}$  is the estimated loading on factor  $i$  for issuer  $j$ . Following this, the fitted values  $\hat{\beta}_{ij}$  are used in the second-pass regression:

$$Basis_{j,t} = \hat{\alpha}_{j,t} + \sum_{i=1}^K \gamma_{i,t} \hat{\beta}_{ij} + e_{j,t} \quad (6)$$

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<sup>24</sup> We use the 2014 list of institutions designated as systemically important. In any case, whatever announcement might have been made, there could never have been a hard-and-fast separation between TBTF and non-TBTF institutions, even if the authorities had intended to make a clear distinction (which they probably did not). After all, even after the announcement, there was (and still is) no reason to suppose that a non-TBTF institution might not actually be rescued, if circumstances dictated. On the other hand, a rescue may not involve a bailout for the bondholders or may be conditioned on them accepting a significant haircut on their holdings.

<sup>25</sup> Petersen (2006) and Skoulakis (2008) present Fama-Macbeth regressions as robustness tests of their explanations of the basis.

where the coefficients  $\gamma_{i,t}$  are the time-dependent contributions (risk premiums) of the given factor to the observed level of the basis at time  $t$ , where the factors are the RHS variables in equation (4). The mean levels of the  $\gamma_{i,t}$  over the sample period provide estimates of the average effect of each factor on the basis.

The results are presented in Tables 9 and 10 for the nonfinancial and financial sectors respectively. In each case, the top panel (Table A) reports the average values of the factor loadings  $\hat{\beta}_{ij}$  calculated from first-pass regression of the basis on collateral quality, funding cost, counterparty risk, liquidity risk and basis volatility, and Table B reports the time-averages for the risk-premia  $\gamma_{ti}$  from the second-pass regression. In both cases, Column 1 shows the results for whole period, while Columns 2, 3 and 4 consider the pre-crisis, crisis and post-crisis periods, respectively.

In both cases, the results of the first-pass regression are broadly consistent with those obtained using OLS and panel regressions. The sign pattern and magnitude of the  $\hat{\beta}_{ij}$  coefficients are as reported in the preceding tables, with the estimated average coefficients of collateral quality, funding cost (LIBOR-OIS) and basis volatility all having the expected statistically significant negative signs, while funding cost (Repo-Treasury), liquidity and counterparty risk are not statistically significant. The only anomalous result is that, until the crisis, counterparty risk seems to have had a significant positive rather than negative effect, as would have been expected.

In the cross-section regressions, it is noteworthy that the adjusted R-squared rises markedly during the crisis period from 27% before the crisis to 48% during the crisis and 33% afterwards for the nonfinancials and from 28% to 56% and 47% for the financial sector. In fact, as can be seen from Figures 4 and 6 which show the movements in the adjusted R-squared over time, the model explained up to 80% of the variation in the basis during the most acute phase of the crisis. For the financials, the results are disappointing, with a number of estimates wrongly signed and/or insignificant.

In order to visualize the implications of these estimates, we compute the contribution of each factor to movements in the basis by plotting the time-dependent factor prices by the corresponding loadings in Figures 3 and 5 for the two sectors. It is clear from Figure 3 that collateral quality, funding cost (LIBOR-OIS) and basis volatility are the most important determinants of the basis in the case of the nonfinancial sector, accounting on average for -9bp, -3bp and -4bp respectively over the period as a whole, and -42bp, -25bp and -10bp during the crisis. As far as the role of counterparty risk is concerned, the results of the first pass regression for the whole period from 2005 to 2011 indicate no significant contribution. However, in the crisis period, the estimated loading is significant and negative, suggesting that counterparty risk did affect the basis when the markets were at their most turbulent. This result is in line with findings of Bai and Colin-Dufresne (2013) who find that counterparty risk became significant only at the end of 2007, contributing to the basis only in the period after Lehman's collapse. Note, however, that even during the crisis, the contribution of counterparty risk to the overall explanation, while significant, was small, amounting to only -8bp at a time when the basis was approaching -200bp.

By contrast, the results for the financial sector in Figure 5 are problematic. None of the factors makes any serious contribution outside of the crisis period, and the results for counterparty risk are a puzzle. A clue to the interpretation may possibly lie in the fact that the results are almost the complete reverse of those for the nonfinancial sector. When the CDS spread on prime brokers rises, other than narrowing the spreads on the contracts they write on bonds of unrelated companies in other sectors of the economy, they see no reason to change their business model. In particular, they would normally hedge their CDS sales by taking offsetting short positions in the underlying bond, driving up the yield and further reducing the basis



relative to CDS spreads. However, when the underlying is the debt of a comparable financial institution, this hedging strategy might appear more risky than remaining unhedged. If there is a high correlation between the yield on the debt of the reference entity and the yield on the debt of the prime broker, hedging may actually be damaging if it feeds back on to the broker's own cost of funds.

In general, the Fama-MacBeth analysis reinforces our conclusion that the factors introduced in this paper account for little of the variation in the (tiny positive) basis in 2005 and 2006, but become extremely important for nonfinancial spreads when the credit squeeze begins in 2007 and continued to play an important role through to the end of our data period in 2011, as can be seen in Figure 4, which plots the time series of R-squared for the cross-section regressions. The behaviour of the financial sector, however, remains a puzzle, not because the factors tested here are unable to contribute to a statistical explanation of movements in the basis – as we can see from Figure 6, they explain between 20% and 80% - but rather because it is unclear how to interpret the explanation.

## 9. Robustness Tests

In this section we test the robustness of our findings. Firstly, we report on regressions using an alternative proxy of CDS-bond basis. The Z-spread is an alternative measure of credit spread,<sup>26</sup> corresponding to the flat spread that has to be added to the LIBOR curve in order to make the bond's discounted cash flow equal in value to the observed price of the bond.<sup>27</sup> Tables 11 and 12 report the results of the regressions using Z-spreads (see also (Kim et al (2015))). It is reassuring to find that the results of the regressions, including signs and magnitudes of coefficients as well as the explanatory power of the regressions are largely consistent with the estimates obtained in earlier sections of this paper, where we used par-asset swap spreads.

Finally, in order to avoid estimation errors associated with possible serial correlation in our panel data, we fitted our equation to time-averaged data. For monthly averaging<sup>28</sup> of IG issuers from the two sectors, the results are presented in Table 13. Regressions using weekly averaging and/or HY issuers yielded analogous results (not reported here). As can be seen, time averaging left the signs and magnitude for the regression coefficients broadly consistent with the results presented in Tables 2 and 4, which suggests that our conclusions are not sensitive to observation frequency, which might have been expected to be the case if, as suggested in the literature, information is incorporated more rapidly into CDS spreads than into bond yields.

## Conclusions

In this paper, we have investigated possible explanations for the anomaly of the large negative CDS-bond yield basis since the financial crisis of 2008, starting from a detailed analysis of the costs of arbitrage. Although the model derived in this way seems to account adequately for the behaviour of the basis where the bond issuer is from the nonfinancial corporate sector, it gives puzzling results where the reference

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<sup>26</sup> Its correlation with the par-asset swap spread is 0.98

<sup>27</sup> Z-spread values were actually provided in the MarkIt dataset.

<sup>28</sup> We also tested weekly averaging. Results are available from the authors.

entity is itself a financial institution, an outcome which seems to be related to the correlation between the risk of issuer and insurer in these situations. It may be that the anomaly will only be resolved when researchers are given access to data from individual CDS sellers.<sup>29</sup>

One other research issue which needs to be addressed relates to liquidity. On the basis of our results with the widely-used Amihud measure, liquidity seems unimportant, but experimentation with other measures (for example Liu (2006) may change this counter-intuitive conclusion.

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<sup>29</sup> Note that, for obvious reasons of confidentiality, the MarkIt dataset does not reveal the names of the brokers in any particular deal.

## BIBLIOGRAPHY

Acharya, V, Amihud, Y and Bharath, S (2013) Liquidity risk of corporate bond returns: A conditional approach, *Journal of Financial Economics* 110, 358-386

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets* 5, 31-56

Arora, N., Gandhi, P. and Longstaff, F. (2012) Counterparty credit risk and the credit default swap market, *Journal of Financial Economics*, 103, 280-293

Augustin P. (2012). Squeezed everywhere: Can we learn something new from the CDS-Bond Basis, *Working paper, Stockholm School of Economics*

Augustin P, Subrahmanyam, M G, Tang D Y and Wang S Q (2014) Credit Default Swaps – a Survey, *Foundations and Trends in Finance: Vol 9: No. 1-2*, pp 1-196

Bai J and Collin-Dufresne P (2013) The CDS-Bond Basis during the Financial Crisis of 2007-2009, presented at AFA San Diego 2013

Beber A and Pagano M (2013) Short-Selling Bans Around the World: Evidence from the 2007–09 Crisis, *Journal of Finance* Volume LXVIII (1), pages 343–381, February

Blanco, R., Brennan, S. and Marsh, I. (2005) An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps, *Journal of Finance*, LX, 5, 2255-2281

Boehmer E, Jones CM and Zhang X (2013) Shackling Short Sellers: The 2008 Shorting Ban, *Review of Financial Studies* 26 (6), 1363-1400

Campbell, J. Y., & Taksler, G. B. (2003) Equity Volatility and Corporate Bond Yields, *Journal of Finance*, LVIII, 6, 2321-2349

Collin-Dufresne, P, Goldstein R S and Martin, S J (2001) The Determinants of Credit Spreads, *Journal of Finance*, LVI, 6

Da, Z and Gao, P (2010) Clientele change, liquidity shock, and the return on financially distressed stock, *Journal of Financial and Quantitative Analysis* 45, 27-48

De Wit, J (2006) Exploring the CDS-Bond Basis, National Bank of Belgium Working Paper No. 104, November

Driscoll J and Kraay A C (1998) Consistent Covariance Matrix Estimation with Spatially Dependent Data, *Review of Economics and Statistics*, 80, 549-60

Dumas, B (1992) Dynamic Equilibrium and the Real Exchange Rate in a Spatially Separated World, *Review of Financial Studies*, 5, 153-80

- Fontana, A. (2010) The persistent negative CDS-Bond basis during the 2007-2008 financial crisis, *Working paper, University of Ca'Foscari Venice*
- Fontana A (2012) The Negative CDS-Bond Basis and Convergence Trading during the 2007-2008 Financial Crisis, Working Paper, University of Ca' Foscari, Venice
- Garleanu N and Pedersen L H (2011) Margin-based asset pricing and deviations from the law of one price, *Review of Financial Studies*, 24(6):1980–2022
- Gou, L. and Bhanot, K. (2012) Types of liquidity and limits to arbitrage – the case of credit default swaps, *Journal of Futures markets*, 32, 4 301-29
- Goyenko R Y, Holden C W and Trzcinka C A (2009) Do Liquidity Measures Measure Liquidity? *Journal of Financial Economics*, 92, 153-181
- Kim G H (2013) Credit default swaps, strategic default and the cost of corporate debt, Warwick Business School Working Paper
- Kim G H, Li H and Zhang W (2014) CDS-Bond Basis Arbitrage: A Stabilizing Force in the Corporate Bond Market, Warwick Business School Working Paper
- Labonte M (2015) Systemically Important or “Too Big to Fail” Financial Institutions, Congressional Research Service Report , June 30<sup>th</sup>
- Liu, W (2006) A Liquidity-Augmented Capital Asset Pricing Model, *Journal of Financial Economics*, 82, 631-71
- Longstaff, F. A., Mithal, S., & Neis, E. (2005) Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market, *Journal of Finance*, LXIII (5), 2213-2253
- Lou X and Shu T (2015) Price Impact or Trading Volume: Why is the Amihud (2002) Illiquidity Measure Priced? presented at AFA <http://dx.doi.org/10.2139/ssrn.2291942>
- Merton, R. (1974) On the pricing of corporate debt: the risk structure of interest rates, *Journal of Finance*, 29, 449–470
- Michael P., Nobay A R. and Peel D.A. (1997) "Adjustment in Real Exchange Rates: An Empirical Investigation", *Journal of Political Economy*, 105 (4), August, 862-79
- Mitchell M and Pulvino T (2012) Arbitrage crashes and the speed of capital, *Journal of Financial Economics*, 104(3):469–490
- Nashikkar, A., Subrahmanyam, M., & Mahanti, S. (2011) Liquidity and arbitrage in the market for credit risk, *Journal of Finance and Quantitative Analysis*, 46., 627-654
- Newey W K and West K D (1987) A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*, 55: 703–708.

Norden L and Weber M (2009) The co-movement of credit default swap, bond and stock markets: An empirical analysis. *European Financial Management*, 15, (3):529–562

O'Kane, D. (2008) *Modelling single-name and multi-name credit derivatives*, John Wiley & Sons

Petersen, M. A. (2006). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches . *Working paper, National Bureau of Economic Research (NBER)*

Skoulakis, G. (2008). Panel Data Inference in Finance: Least-Squares vs Fama-MacBeth. *Working paper, University of Maryland*.

Wang, L. (2014) Margin-based asset pricing and the determinants of the CDS basis, *Journal of Fixed Income*, 24:2, 61-78

## Table 1 CDS – BOND BASIS SUMMARY STATISTICS

The tables provide descriptive statistics of the CDS–Bond basis (in basis points) over the period between 02/01/2005 and 31/12/2011. Panels A and Panel B report the number of transactions in each credit rating class, by year and industrial sector respectively. Panel C presents average CDS-Bond basis according to issuers' credit rating and year.

### Panel A: Number of transactions

	AAA	AA	A	BBB	BB	B	Total
<b>2005</b>	577	4415	20450	19868	6362	3205	54877
<b>2006</b>	614	4788	25893	21987	7346	3422	64050
<b>2007</b>	756	4926	24844	18708	5125	3529	57888
<b>2008</b>	1702	4308	27188	19049	4610	2756	59613
<b>2009</b>	1933	4402	35265	30489	7161	2098	81348
<b>2010</b>	1381	4864	36275	33776	10008	1607	87911
<b>2011</b>	1173	7086	46029	42897	9916	1725	108826

### Panel B: Number of transactions

	AAA	AA	A	BBB	BB	B	Total
<b>Sector</b>							
<b>Industrials</b>	N/A	4809	18733	15529	2988	90	42149
<b>Utilities</b>	N/A	46	5142	14383	4291	531	24393
<b>Financials</b>	N/A	4560	68047	10927	415	N/A	83949
<b>Technology</b>	N/A	2212	19961	10154	1528	2056	35911
<b>Consumer Goods</b>	N/A	4327	22453	38505	12698	8854	86837
<b>Healthcare</b>	4697	980	25807	7186	110	2741	41521
<b>Consumer Services</b>	N/A	17076	12490	46426	7031	3462	86485
<b>Telecomms</b>	N/A	N/A	25660	2030	5872	206	33768
<b>Basic Materials</b>	N/A	N/A	8666	21006	6722	3	36397
<b>Energy</b>	3439	779	8985	20628	8873	399	43103

**Panel C: Basis Points**

	<b>AAA</b>	<b>AA</b>	<b>A</b>	<b>BBB</b>	<b>BB</b>	<b>B</b>
<b>2005</b>	14.05	10.68	6.17	13.51	4.53	29.15
<b>2006</b>	10.53	4.64	-0.67	12.93	-7.72	52.5
<b>2007</b>	3.81	4.21	0.34	4.92	4.73	90.93
<b>2008</b>	-35.48	-18.52	-53.87	-49.2	-60.24	149.36
<b>2009</b>	-74.24	-17.66	-84.71	-120.43	-131.32	157.97
<b>2010</b>	-33.6	-12.35	-34.64	-49	-91.68	-29.34
<b>2011</b>	-0.52	-6.25	-21.29	-40.14	-66.84	52.04

**Table 2 DETERMINANTS OF CDS-BOND BASIS FOR NONFINANCIAL SECTORS 2005-11**

Using panel data between 2005 and 2011 for nonfinancial sectors, we regress the CDS-Bond basis (computed from the asset swap spread and measured in basis points) against the list of variables below. The table reports the results of panel estimation (with Fixed and Random effects) and Pooled OLS approaches for IG and HY companies. Standard errors are adjusted according to Newey and West (1987) and Driscoll and Kraay (1998) for panel data, with associated *t*-statistics in parentheses underneath.

	INVESTMENT GRADE				HIGH YIELD			
	Fixed effect(within)	Random effect	Pooled OLS	Pooled OLS	Fixed effect (within)	Random effect	Pooled OLS	Pooled OLS
<b>STDV(excessRET) (%)</b>	<b>-30.46</b>	<b>-30.48</b>	<b>-25</b>	<b>-28.03</b>	<b>-13.08</b>	<b>-13.47</b>	-3.43	-1.8
	(-14)	(-13.3)	(-11)	(-12)	(-2)	(-2)	(-0.6)	(-0.3)
<b>Downgrade From AA to A</b>		-13.25	<b>-18.46</b>	<b>-17.21</b>				
		(-0.5)	(-4)	(-4)				
<b>Downgrade From AA to BBB</b>		-38.58	<b>-38.61</b>	<b>-35.42</b>				
		(-1.5)	(-7.9)	(-7.3)				
<b>Downgrade From BB to B</b>						<b>60.32</b>	<b>74.19</b>	<b>67.23</b>
						(3.2)	(7.5)	(7)
<b>LIBOR-OIS (%)</b>	<b>-31.49</b>	<b>-31.14</b>	<b>-40.03</b>		<b>-24.79</b>	<b>-24.01</b>	-8.92	
	(-6)	(-6.3)	(-13)		(-2)	(-2)	(-0.5)	
<b>Repo GC-Treasury (%)</b>				-3.34				<b>11.08</b>
				(-1.1)				(8)
<b>CDS Index (%)</b>	<b>-22.86</b>	<b>-22.04</b>	<b>-19.5</b>	<b>-28.35</b>	<b>-80.84</b>	<b>-80.59</b>	<b>-65.89</b>	<b>-53.42</b>
	(-7.6)	(-7.2)	(-14)	(-17)	(-7.1)	(-7.2)	(-9.3)	(-7)
<b>Daily Amihud</b>	-0.03	-0.05	<b>-1.07</b>	<b>-1.63</b>	-0.53	-0.68	-0.36	-0.13
	(-0.18)	(-0.11)	(-5.1)	(-7.5)	(-0.63)	(-0.63)	(-0.4)	(-0.1)
<b>Basis Volatility (%)</b>	<b>-30.24</b>	<b>-33.6</b>	<b>-48.02</b>	<b>-79.14</b>	<b>323.08</b>	<b>323.22</b>	<b>297.37</b>	<b>288.56</b>
	(-2.1)	(-2.1)	(-2)	(-2.8)	(3.2)	(3.2)	(3.7)	(3.4)
<b>Intercept</b>		<b>69.9</b>	<b>59.72</b>	<b>62.15</b>		<b>- 18.27</b>	<b>-19.87</b>	<b>-47.6</b>
		(2.8)	(14)	(15)		(-3)	(-2.3)	(-5.3)
<b>Total Sum of Squares:</b>	106180	106930			167230	168170		
<b>Residual Sum of Squares</b>	67794	68276			136400	137080		
<b>R-squared</b>	<b>0.36</b>	<b>0.36</b>	<b>0.35</b>	<b>0.32</b>	<b>0.15</b>	<b>0.16</b>	<b>0.19</b>	<b>0.21</b>
<b>Number of panels</b>	1524	1524			311	311		
<b>Number of observations</b>	326340	326340	326340	326340	67342	67342	67342	67342



**Table 3 CDS-BOND BASIS BEFORE AND AFTER LEHMAN: NON-FINANCIAL INVESTMENT GRADE**

Notes as for Table 2. Results for Before Lehman are based on data from January 2005 to August 2008, After Lehman from October 2008 to December 2011.

	Before Lehman		After Lehman	
	Pooled OLS	Fixed effect	Pooled OLS	Fixed effect
<b>STDV (excess RET) (%)</b>	<b>-2.05</b>	<b>-6.8</b>	<b>-25.74</b>	<b>-29.82</b>
	(-1)	(-1.9)	(-10)	(-10)
<b>Downgrade From AA to A</b>	<b>-5.41</b>	<b>-0.8</b>	<b>-31.06</b>	<b>-31.39</b>
	(-3)	(-0.11)	(-5)	(-4)
<b>Downgrade From AA to BBB</b>	<b>-20.23</b>	<b>-28.7</b>	<b>-56.18</b>	<b>-56.0</b>
	(-10)	(-4.9)	(-8)	(-7.2)
<b>LIBOR-OIS (%)</b>	<b>-36.66</b>	<b>-37.82</b>	<b>-62.18</b>	<b>-49.11</b>
	(-16)	(-19)	(-15)	(-15)
<b>CDS Index (%)</b>	<b>-11.01</b>	<b>-7.6</b>	<b>-4.11</b>	<b>-1.09</b>
	(-5)	(-3.5)	(-2)	(-7.2)
<b>Daily Amihud</b>	<b>-0.35</b>	<b>-0.05</b>	<b>-2.22</b>	<b>-0.11</b>
	(-3)	(-0.56)	(-5)	(-0.4)
<b>Basis Volatility (%)</b>	<b>-46.8</b>	<b>-19.24</b>	<b>-21.37</b>	<b>-5.76</b>
	(-2)	(-2)	(-1)	(-1)
<b>Intercept</b>	<b>19.51</b>	<b>22.4</b>	<b>51.03</b>	<b>61.03</b>
	(8)	(5.2)	(8)	(9)
<b>Total Sum of Squares:</b>		7942		68685
<b>Residual Sum of Squares</b>		6090.2		45646
<b>R-squared</b>	<b>0.29</b>	<b>0.23</b>	<b>0.31</b>	<b>0.34</b>
<b>F- statistic</b>	7844	4968	10680	12144
<b>Number of panels</b>		789		746
<b>Number of observations</b>	130600	130739	192389	192494

**Table 4 DETERMINANTS OF CDS-BOND BASIS: FINANCIAL SECTOR**

Notes as for Table 3.

	Whole period: 2005-2011			Before Lehman				After Lehman			
	Fixed effect (within)	Random effect	Pooled OLS	Pooled OLS	Fixed effect	Pooled OLS	Pooled OLS	Pooled OLS	Fixed effect	Pooled OLS	Pooled OLS
STDV(excessRET) (%)	<b>-3.61</b>	<b>-3.59</b>	<b>-2.95</b>	<b>-10.27</b>	<b>-12.96</b>	<b>-10.25</b>		-0.05	-1.65	<b>-2.55</b>	
	(-2.6)	(-2.5)	(-2)	(-2.1)	(-5.2)	(-2)		(-0.03)	(-1.1)	(-2)	
Downgrade From AA to A		<b>-15.81</b>	<b>-20.23</b>	<b>-14.02</b>	<b>-22.33</b>	<b>-15.56</b>	<b>-17.29</b>				
		(-2.6)	(-6)	(-4.4)	(-2.2)	(-5.2)	(-6)				
Downgrade From AA to BBB		<b>-63.13</b>	<b>-40.73</b>	<b>-31.59</b>	<b>-45.01</b>	<b>-32.19</b>	<b>-33.94</b>				
		(-7.4)	(-6)	(-8)	(-3.2)	(-9)	(-9)				
Downgrade A to BBB								<b>-21.05</b>	<b>-93.16</b>	<b>-18.05</b>	-18.59
								(-2)	(-4.5)	(-2)	(-1.6)
LIBOR-OIS (%)	<b>-18.55</b>	<b>-18.68</b>	<b>-26.64</b>	<b>-43.03</b>	<b>-36.19</b>			<b>-72.16</b>	<b>-46.41</b>		
	(-3.5)	(-3.5)	(-4)	(-8)	(-4)			(-8)	(-6.3)		
CDS Index (%)	<b>-13.42</b>	<b>-13.47</b>	<b>-24.35</b>	9.59	<b>25.52</b>	<b>-13.63</b>		8.72	6.92	<b>-17.5</b>	
	(-3.4)	(-3.5)	(-8)	(1.7)	(3.5)	(-2.6)		(1.6)	(1.9)	(-2.9)	
Daily Amihud	0.79	0.76	-1.01	<b>-0.91</b>	-0.07	<b>-1</b>	<b>-0.97</b>	1.4	0.7	1.33	1.16
	(1.7)	(1.5)	(-0.9)	(-3.4)	(-0.4)	(-3.7)	(-3.4)	(0.8)	(1.2)	(0.8)	(0.8)
Basis Volatility (%)	20.67	20.9	<b>52.56</b>	<b>99.46</b>	<b>66.89</b>	<b>81.71</b>	-2.57	<b>64.18</b>	36.81	27.21	5.22
	(1)	(1.01)	(3)	(3.5)	(3.1)	(3)	(-0.1)	(3.2)	(1.5)	(1.4)	(0.3)
Intercept			<b>23.76</b>	23.37	22.01	24	12.65	-51.52	-37.81	-23	-52.63

			(6)	(4)	(1.9)	(4.3)	(5)	(-6)	(-3.4)	(-2.8)	(-12)
<b>Total Sum of Squares:</b>	30205	30463			3140				18667		
<b>Residual Sum of Squares</b>	28455	28664			2892				17491		
<b>R-squared</b>	<b>0.06</b>	<b>0.06</b>	<b>0.11</b>	<b>0.15</b>	<b>0.08</b>	<b>0.12</b>	<b>0.06</b>	<b>0.08</b>	<b>0.06</b>	<b>0.02</b>	<b>0.005</b>
<b>Number of panels</b>	257	257			184				184		
<b>Number of observations</b>	82344	82344	82336	39783	39791	39783	39783	41775	41782	41782	41782

**Table 5 CORRELATION OF EXPLANATORY VARIABLES FOR FINANCIAL SECTOR PRE- AND POST-LEHMAN**

Data and variables as in Table 4.

*Top numbers January 2005 – August 2008*

*Bottom numbers: October 2008 –December 2011*

	<b>Basis</b>	<b>Equity Volatility</b>	<b>Amihud Liquidity</b>	<b>CDS Index</b>	<b>LIBOR-OIS</b>	<b>Basis Volatility</b>
CDS-Bond basis	1					
Firm-specific volatility	-0.13	1				
	-0.05	1				
Amihud liquidity index	-0.04	-0.005	1			
	0.02	0.02	1			
CDS Index	-0.18	0.62	0.004	1		
	-0.09	0.27	0.02	1		
LIBOR- OIS	-0.24	0.57	0.001	0.84	1	
	-0.22	0.42	0.02	0.56	1	
Basis Volatility	0.01	0.73	-0.005	0.53	0.54	1
	0.02	0.44	0.01	0.31	0.5	1

**Table 6: Most Negative Daily Basis Financial and Nonfinancial**

Using panel data between January 1<sup>st</sup> 2005 and December 31<sup>st</sup> 2011 for financial and non-financial sectors, we regress the 10% most negative CDS-Bond basis dataset against the factors discussed in the paper. Other notes as for Table 4.

	Non-financial Sector						Financial Sector	
	IG	IG	IG	HY	HY	HY	IG	IG
	Panel	Pooled OLS	Pooled OLS	Panel	Pooled OLS	Pooled OLS	Panel	Pooled OLS
STDV(excessRET) (%)	<b>-49.06</b> (-12)	<b>-40.42</b> (-20)	<b>-40.1</b> (-18)	<b>-40.16</b> (-5.9)	<b>-20.35</b> (-5)	<b>-15.13</b> (-4)	<b>-26.22</b> (-5.4)	<b>-20.7</b> (-8)
Downgrade From AA to A	-0.55 (-0.08)	<b>-10.88</b> (-4)	<b>-7.66</b> (-3)				<b>-149</b> (-3.9)	<b>-141.5</b> (-6)
Downgrade From AA to BBB	0.37 (0.07)	<b>-11.58</b> (-6)	<b>-9.82</b> (-5)				<b>-193.4</b> (-5)	<b>-183.3</b> (-7)
Downgrade From BB to B				21.32 (1.7)	<b>43.75</b> (6)	<b>33.16</b> (6)		
LIBOR-OIS (%)	<b>-48.93</b> (-6.7)	<b>-59.81</b> (-4)		-38.05 (-1.2)	5.64 (0.2)		-12.93 (-1.5)	-16.6 (-1.2)
Repo GC-Treasury (%)			12.13 (0.9)			<b>146</b> (5.4)		
CDS Index (%)	<b>-58.38</b> (-17)	<b>-56.86</b> (-17)	<b>-70.67</b> (-15)	<b>-81.73</b> (-4.2)	<b>-139.15</b> (-14)	<b>-126.73</b> (-14)	<b>-77.8</b> (-10)	<b>-79.1</b> (-17)
Daily Amihud	0.33 (1.1)	-0.04 (-0.13)	<b>-0.8</b> (-3)	0.31 (0.02)	1.15 (0.8)	0.73 (0.5)	-0.003 (-0.02)	-0.2 (-0.7)
Basis Volatility (%)	<b>-94.41</b> (-2)	<b>-92.59</b> (-5)	<b>-126.9</b> (-6)	<b>-250.8</b> (-3)	<b>-173.7</b> (-4)	<b>-195.87</b> (-4)	<b>-77.07</b> (-2.5)	<b>-53.2</b> (-3)
Intercept	<b>51.49</b> (7.5)	<b>40.53</b> (10)	<b>36.41</b> (6)	<b>49.36</b> (2.6)	-0.21 (-0.03)	<b>-38.45</b> (-3)	<b>209.08</b> (5)	<b>180.3</b> (7)
Sum of Squares	22562			7160			5964	
RSS	7604			2980			1957	
R-sq fixed (within)	<b>0.66</b>	<b>0.68</b>	<b>0.64</b>	<b>0.58</b>	<b>0.68</b>	<b>0.71</b>	<b>0.67</b>	<b>0.7</b>
Number of panels	646			200			180	
Number of obs	33155	33147	33147	7250	7250	7250	8770	8770

**Table 7 Financial Sector Before, During and After the Crisis**

Pooled OLS Estimates. Data and definition of variables as for Table 4 (Panel A) and Table 6 (Panel B)

	<b>Pre Crisis</b> January 1 <sup>st</sup> 2005 to July 31 <sup>st</sup> 2007	<b>Early crisis</b> Aug 1 <sup>st</sup> 2007-Aug 30 2008	<b>Post-Lehman</b> Oct 1 <sup>st</sup> 2008 to Dec 31 <sup>st</sup> 2011
<b>A. All Financial</b>			
STDV(excessRET)	-5.43 (-3)	-11.01 (-1)	3.01 (2)
Downgrade AA to A	-8.5 (-10)	-43.5 (-2)	
Downgrade AA to BBB	-19.82 (-9)	-84.63 (-3)	-22.93 (-2)
LIBOR-OIS	27.42 (2)	-22.58 (-3)	-143.96 (-12)
CDS Index	53.31 (10)	19.7 (2)	26.35 (5)
Daily Amihud	-0.94 (-3)	-0.71 (-1)	1.31 (1)
Basis Volatility	-172.21 (-5)	100.6 (2)	85.32 (4)
Intercept	6.77 (2.43)	32.01 (1)	-69.48 (-9)
R-squared	0.32	0.1	0.14
Number of observations	16012	13203	41303

## B. Financial Sector 10% most negative basis

STDV(excessRET)	-1.53 (-2)	-15.6 (-11)	-17.9 (-29)
Downgrade AA to A	-10.17 (-1)	-73.99 (-8)	
Downgrade AA to BBB	-17.85 (-3)	-100.43 (-11)	-72.78 (-40)
LIBOR-OIS	75.27 (3)	-9.07 (-2)	-98.04 (-27)
CDS Index	20.7 (4)	-26.26 (-10)	-56.44 (-25)
Daily Amihud	-0.72 (-5)	-0.49 (-1)	-0.03 (0)
Basis Volatility	-150.94 (-9)	-17.82 (-2)	-26.41 (-4)
Intercept	-11.3 (-2)	64.55 (6)	22.55 (7)
R-squared	0.15	0.32	0.67
Number of observations	1697	1411	4378

## Table 8 Too-Big-To-Fail Before and After the Crisis

The dependent variable is the basis where the reference bond is issued by a systemically-important institution. Other variables are as defined in previous tables.

	Before Sept 2008	After Sept 2008
<b>STDV(excess RET)</b>	<b>-10.27</b> (-3)	1.52 (1)
<b>Downgrade From AA to A</b>	<b>-14.02</b> (-8)	N/A
<b>Downgrade From AA to BBB</b>	<b>-31.59</b> (-11)	<b>45.54</b> (-4)
<b>LIBOR-OIS</b>	<b>-43.03</b> (-16)	<b>-73.09</b> (-12)
<b>CDS Index</b>	<b>9.59</b> (3)	<b>6.7</b> (2)
<b>Daily Amihud</b>	<b>-0.91</b> (-4)	0.97 (1)
<b>Basis Volatility</b>	<b>99.46</b> (7)	<b>70.99</b> (7)
<b>TBTF Dummy</b>		<b>-40.32</b> (-4)
<b>Intercept</b>	<b>23.37</b> (5)	<b>-26.42</b> (-3)
<b>R-squared</b>	0.15	0.11
<b>Number of observations</b>	39783	41774



## Table 9 Fama-MacBeth Regressions: Investment Grade Non-financials

Tables A and B present results of Fama-MacBeth regression of the CDS-Bond basis on collateral quality, funding cost, counterparty risk, liquidity of bonds and basis volatility. The first-pass regression (Table A) is equation (5):

$$Basis_{j,t} = \alpha_j + \sum_{i=1}^K \beta_{ij} f_{i,t} + \epsilon_{j,t} \quad j = 1, \dots, N \quad t = 1, \dots, T \quad (5)$$

Where  $f_{i,t}$  is the vector of  $m$  market factors, and for each individual issuer  $j$ ,  $\alpha_j$  is the intercept and  $\beta_{i,j}$  is the loading on the  $i^{th}$  factor, which are then used in the second-pass regression equation (6), which in this case amounts to the following:

$$Basis_{j,t} = \hat{\alpha}_{j,t} + \sum_{i=1}^6 \gamma_{i,t} \hat{\beta}_{i,j} + e_{j,t}$$

Where the cross section regression runs at daily frequency and the 6 factors are given in the first column of Table A below, which shows the results of the first-stage regression, involving a set of regressions equal in number to the number of corporate bonds issued. The results are given as weighted averages of the estimates of the  $\beta_{i,j}$  and z-statistics (in parentheses) for different periods. Coefficient estimates are given in basis points for comparison with previous results. Table B reports results of the second stage Fama-MacBeth regressions, equal in number to the number of time periods. The table reports average estimates of the  $\gamma_i$  and standard errors (in parentheses). Estimated coefficients are given in percentages, with bold font to indicate statistical significance of 5% or below.

**Table A**

	Whole period Jan 2005- Dec 2011	Pre-crisis Jan 2005- July 2007	Crisis Period Aug 2007- Sept 2009	Post Crisis Oct 2009 -Dec 2011
Collateral quality	<b>-30.55</b> (-6.5)	-3.82 (-0.6)	<b>-84.62</b> (-9.3)	<b>-22.11</b> (-4.1)
Funding Cost (LIBOR-OIS)	<b>-13.2</b> (-2.3)	<b>27.03</b> (2.4)	<b>-43.38</b> (-9.5)	<b>-31.83</b> (-3.5)
Funding Cost (Repo-T-bill)	-3.95 (-0.9)	-0.84 (-0.5)	9.76 (1.7)	<b>-57.89</b> (-8.4)
Counterparty Risk	0.59 (0.2)	31.22 (3.9)	<b>-8.43</b> (-3.7)	<b>-3.73</b> (-2.2)
Liquidity (Daily Amihud)	-3.83 (-0.3)	-3.36 (-0.8)	-3.95 (-0.3)	-3.11 (-0.2)
Basis Volatility	<b>-63.98</b> (-4.9)	<b>-47.22</b> (-1.9)	<b>-93.6</b> (-3.5)	<b>-56.12</b> (-3.1)
Number of observation	325369	52152	90522	143159
Number of panels	1372	502	677	967

**Table B**

Collateral quality	<b>0.28</b>	0.05	<b>0.58</b>	<b>0.22</b>
	(0.33)	(0.27)	(0.08)	(0.06)
Funding Cost (Libor-OIS)	<b>0.2</b>	<b>0.02</b>	<b>0.55</b>	<b>0.06</b>
	(0.04)	(0.02)	(0.08)	(0.03)
Funding Cost (Repo-T-bill)	0.02	-0.002	0.1	<b>0.02</b>
	(0.05)	(0.04)	(0.08)	(0.02)
Counterparty Risk (CDS Index)	0.56	<b>0.09</b>	<b>0.92</b>	<b>0.72</b>
	(0.07)	(0.02)	(0.13)	(0.08)
Liquidity (Daily Amihud)	0.01	0.02	0.004	-0.003
	(0.06)	(0.06)	(0.1)	(0.03)
Basis Volatility	<b>0.03</b>	<b>0.002</b>	<b>0.06</b>	<b>0.02</b>
	(0.01)	(0.005)	(0.01)	(0.01)
R-Square	0.33	0.27	0.48	0.33

## Table 10 Fama-MacBeth Regressions: Investment Grade Financials

Notes as for Table 9

### Table A

	Whole period Jan 2005- Dec 2011	Pre-crisis Jan 2005- July 2007	Crisis Period Aug 2007- Sept 2009	Post Crisis Oct 2009 -Dec 2011
Collateral quality	<b>-20.98</b> (-3)	-17.9 (-0.9)	<b>-49.16</b> (-5)	-5.42 (-0.5)
Funding Cost (LIBOR-OIS)	<b>-37.69</b> (-2.1)	-35.01 (-1)	-28.53 (-1.8)	-65.08 (-1.2)
Funding Cost (Repo-T-bill)	-9.55 (-0.6)	3.3 (1.5)	-12.52 (0.5)	<b>-67.63</b> (-2.3)
Counterparty Risk	<b>26.06</b> (3.5)	<b>40.69</b> (3.1)	<b>58.19</b> (6.2)	<b>22.8</b> (3.7)
Liquidity (Daily Amihud)	-76.56 (-0.9)	<b>-10.03</b> (-2.2)	-35.58 (-0.8)	-125.19 (-0.9)
Basis Volatility	<b>-106.07</b> (-3.1)	<b>-232.52</b> (-4)	-13.92 (-0.2)	<b>-89.59</b> (-2.4)
Number of observation	82262	15922	23052	31835
Number of panels	236	123	130	150

### Table B

Collateral quality	<b>0.57</b> (0.19)	0.06 (0.04)	<b>1.11</b> (0.35)	0.55 (0.2)
Funding Cost (Libor-OIS)	<b>0.15</b> (0.1)	-0.01 (0.03)	0.45 (0.22)	0.02 (0.07)
Funding Cost (Repo-T-bill)	0.004 (0.13)	-0.02 (0.05)	0.02 (0.27)	<b>0.02</b> (0.07)
Counterparty Risk (CDS Index)	<b>0.57</b> (0.18)	<b>0.05</b> (0.03)	<b>0.98</b> (0.32)	<b>0.72</b> (0.21)
Liquidity (Daily Amihud)	-0.002 (0.06)	<b>0.01</b> (0.02)	0.01 (0.1)	-0.03 (0.06)
Basis Volatility	<b>0.07</b> (0.03)	<b>0.0003</b> (0.01)	0.13 (0.05)	<b>0.07</b> (0.03)
R-Square	0.44	0.28	0.56	0.47

**Table 11 CDS-Bond Basis (from Z- spread): Non-financial sector**

Using panel data between 2005 and 2011 for non - financial sectors, we regress CDS-Bond basis (calculated from the Z-spread) against the list of variables below. Associated t-statistics appear in parentheses. The standard errors of estimated parameters are adjusted using Newey –West method and Driscoll and Kraay method for panel data. Table reports results of Panel estimation approaches (Fixed and Random effect) and Pooled OLS approach for IG and HY companies.

	IG	IG	IG	HY	HY	HY
	<b>Fixed effect(within)</b>	<b>Random effect</b>	<b>Pooled OLS</b>	<b>Fixed effect (within)</b>	<b>Random effect</b>	<b>Pooled OLS</b>
STDV(excess RET) (%)	<b>-40.96</b> (-14)	<b>-40.87</b> (-15.3)	<b>-32.98</b> (-14)	<b>-25.59</b> (-3.3)	<b>-25.14</b> (-3.3)	<b>-12.93</b> (-2.7)
Downgrade From AA to A		<b>-12.35</b> (-2.1)	<b>-16.56</b> (-3.4)			
Downgrade From AA to BBB		<b>-32.84</b> (-6.5)	<b>-37.05</b> (-7.2)			
Downgrade From BB to B					<b>49.02</b> (3.1)	<b>67.18</b> (8)
LIBOR-OIS (%)	<b>-44.12</b> (-7.7)	<b>-44.55</b> (-18.5)	<b>-51.39</b> (-16)	-15.09 (-1)	<b>-15.5</b> (-1)	<b>-29.66</b> (-2)
CDS Index (%)	<b>-18.39</b> (-5.4)	<b>-18.07</b> (-9.5)	<b>-16.09</b> (-12)	<b>-78.45</b> (-7.2)	<b>-74.40</b> (-7.2)	<b>-63.45</b> (-10)
Daily Amihud	<b>-0.43</b> (-2.4)	<b>-0.45</b> (-2.4)	<b>-1.65</b> (-6.8)	-1.49 (-1.4)	-1.5 (-1.5)	<b>-2.42</b> (-2.1)
Basis Volatility (%)	<b>-38.31</b> (-2.5)	<b>-36.13</b> (-1.5)	<b>-57.98</b> (-2.2)	<b>193.92</b> (2.5)	<b>196.2</b> (2)	<b>167.18</b> (2.4)
Intercept		<b>75.01</b> (16)	<b>69.97</b> (16)		<b>41.07</b> (4)	<b>10.99</b> (1.6)
Total Sum of Squares:	133170	134100		92820	93342	
Residual Sum of Squares	78007	78575		72327	72739	
R-squared fixed (within)	<b>0.41</b>		<b>0.4</b>	<b>0.2</b>		<b>0.18</b>
R-squared random		<b>0.4</b>			<b>0.2</b>	
Number of panels	1574	1574		311	311	
Number of observations	326349	326349	326340	65117	65117	67342

**Table 12 CDS-Bond Basis (from Z- spread): Financial sector**

Using panel data between 2005 and 2011 for financial sectors, we regress CDS-Bond basis (calculated with Z-spread) against the list of variables below. Associated t-statistics appear in parentheses. The standard errors of estimated parameters are adjusted using Newey –West method and Driscoll and Kraay method for panel data. Table reports results of Panel estimation approaches (Fixed and Random effect) and Pooled OLS approach for IG financial US companies.

	IG	IG	IG	IG
	Fixed effect(within)	Random effect	Pooled OLS	Pooled OLS
<b>STDV(excess RET) (%)</b>	<b>-9.1</b> (-6.4)	<b>-9.11</b> (-6.4)	<b>-8.43</b> (-6)	<b>-8.88</b> (-6)
<b>Downgrade From AA to A</b>		<b>-17.39</b> (-3.4)	<b>-18.62</b> (-5)	<b>-16.74</b> (-5)
<b>Downgrade From AA to BBB</b>		<b>-69.28</b> (-7.3)	<b>-48.58</b> (-6)	<b>-44.11</b> (-5.4)
<b>LIBOR-OIS (%)</b>	<b>-32.1</b> (-6.8)	<b>-32.23</b> (-6.8)	<b>-37.62</b> (-7)	
<b>Repo GC-Treasury (%)</b>				<b>26.32</b> (5)
<b>CDS Index (%)</b>	<b>-12.57</b> (-3)	<b>-12.61</b> (-3.1)	<b>-22.17</b> (-7)	<b>-26.45</b> (-7)
<b>Daily Amihud</b>	0.33 (1)	0.24 (0.7)	-0.54 (-0.06)	-0.71 (-0.06)
<b>Basis Volatility (%)</b>	30.5 (1.4)	30.72 (1.4)	<b>56.18</b> (3)	30.98 (1.5)
<b>Intercept</b>		<b>28.03</b> (8.3)	<b>31.47</b> (8)	<b>21.86</b> (5)
<b>Total Sum of Squares:</b>	34501	34831		
<b>Residual Sum of Squares</b>	29537	29762		
<b>R-squared fixed (within)</b>	<b>0.14</b>		<b>0.19</b>	<b>0.17</b>
<b>R-squared random</b>		<b>0.15</b>		
<b>Number of panels</b>	257	257		
<b>Number of observations</b>	82336	82336	82336	82336

**Table 13 CDS-Bond basis over determinants: aggregated monthly data**

Using aggregated monthly panel data between 2005 and 2011, we regress the CDS-Bond basis (calculated from the asset-swap spread) against the list of variables below. Associated t-statistics appear in parentheses. Standard errors of estimated parameters are adjusted using the Newey –West and Driscoll and Kraay methods for panel data. Coefficients estimates are given in basis points.

	Non-financial Sectors		Financial Sector	
	Panel Estimation	Pooled OLS	Panel Estimation	Pooled OLS
Collateral quality (%)	<b>-33.09</b> (-15)	<b>-26.96</b> (-16)	0.12 (0.19)	-3.25 (-1)
Downgrade From AA to A	<b>-15.78</b> (-3)	<b>-18.07</b> (-8)	-7.24 (-0.45)	<b>-9.37</b> (-2)
Downgrade From AA to BBB	<b>-35.4</b> (-7)	<b>-39.07</b> (-15)	<b>-54.85</b> (-3.3)	<b>-45.1</b> (-9)
Funding Cost (%)	<b>-25.34</b> (-11)	<b>-32.8</b> (-6)	<b>-22.54</b> (-7.9)	<b>-39.94</b> (-3)
Counterparty Risk Proxy (%)	<b>-28.2</b> (-17)	<b>-24.04</b> (-11)	<b>-28.42</b> (-15)	<b>-35.96</b> (-8)
Liquidity (Daily Amihud)	-0.09 (-0.2)	<b>-2.14</b> (-3)	<b>-1.39</b> (-1.6)	<b>-4.89</b> (-2)
Basis Volatility (%)	<b>-23.51</b> (-2)	<b>-47.59</b> (-2)	48.02 (0.96)	81.08 (1.9)
Intercept	<b>76.95</b> (16)	<b>64.19</b> (19)	19.04 (1)	<b>17.2</b> th(3)
R-squared	<b>0.37</b>	<b>0.35</b>	<b>0.08</b>	<b>0.13</b>
Number of panels	1574		257	
Number of observations	32563	32558	6728	6720

Figure 1 CDS-Bond Basis for different rating groups (AA, A, BBB, BB)

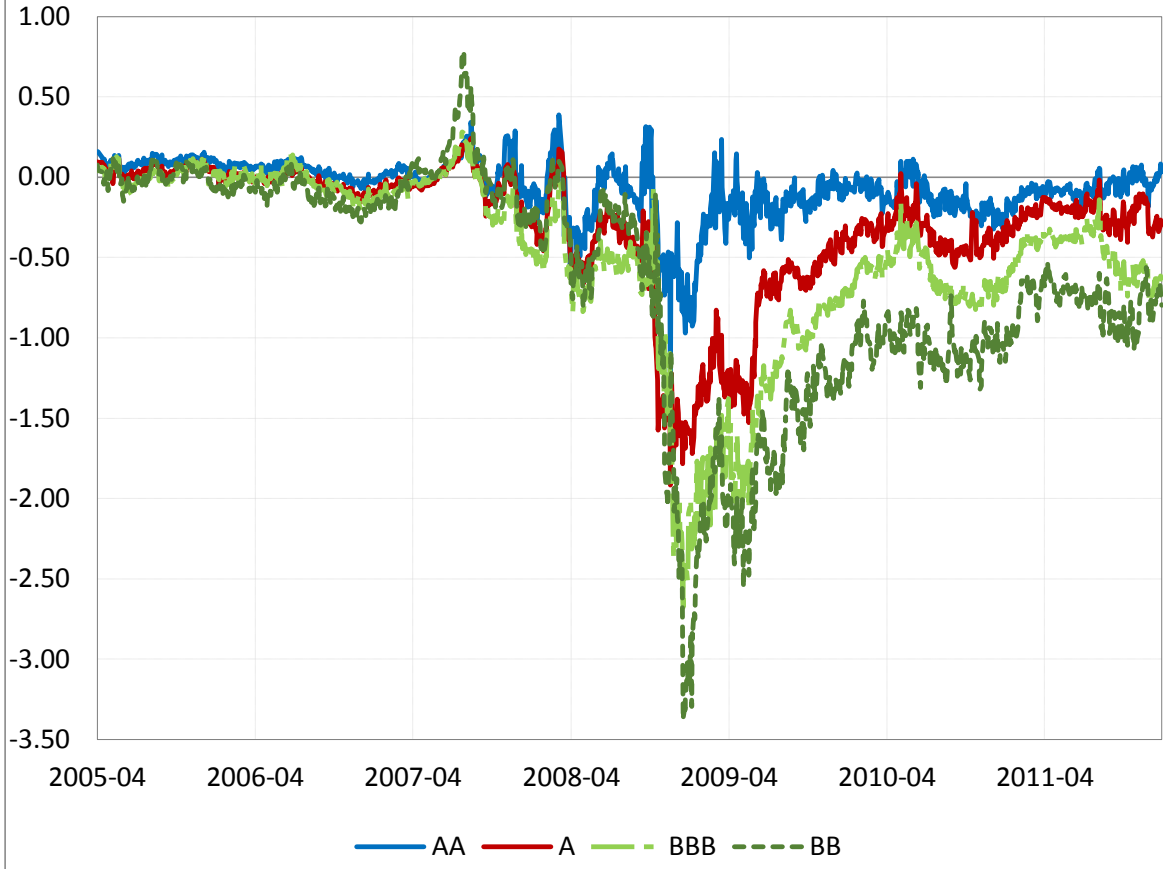


Figure 2 Aggregate CDS-Bond Basis for Financial and Non-Financial Sectors

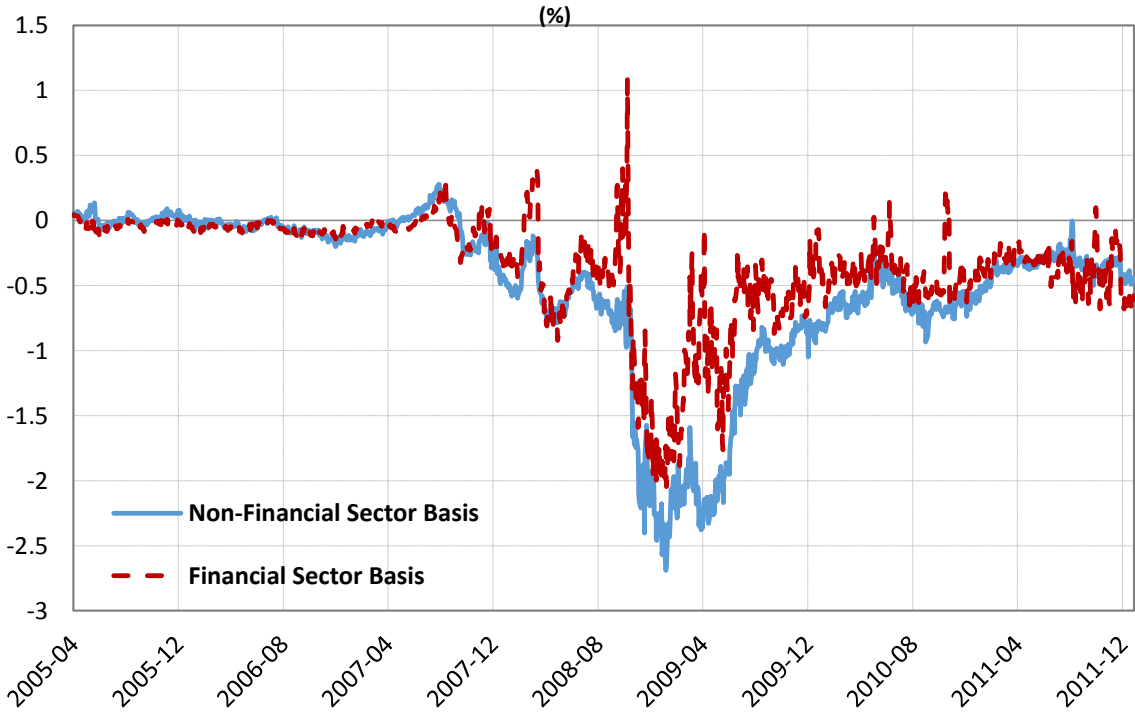




Figure 3 Cross Section Fama-Macbeth Equation: Nonfinancial Sector

Gamma estimates of each variable ( $\gamma_{t, factor}$ ) are multiplied by beta estimates of variable aggregated across companies ( $\beta_{factor}$ ) and plotted in monthly frequency. These graphs represent contribution effect of each explanatory variable on CDS-Bond basis obtained by cross sectional Fama-MacBeth regression. Coefficients are given in percentages and cover the period between 2005 and 2011. The counterparty risk\* dynamic coefficient was calculated with average  $\beta_{factor}$  of crisis period to show its contribution.

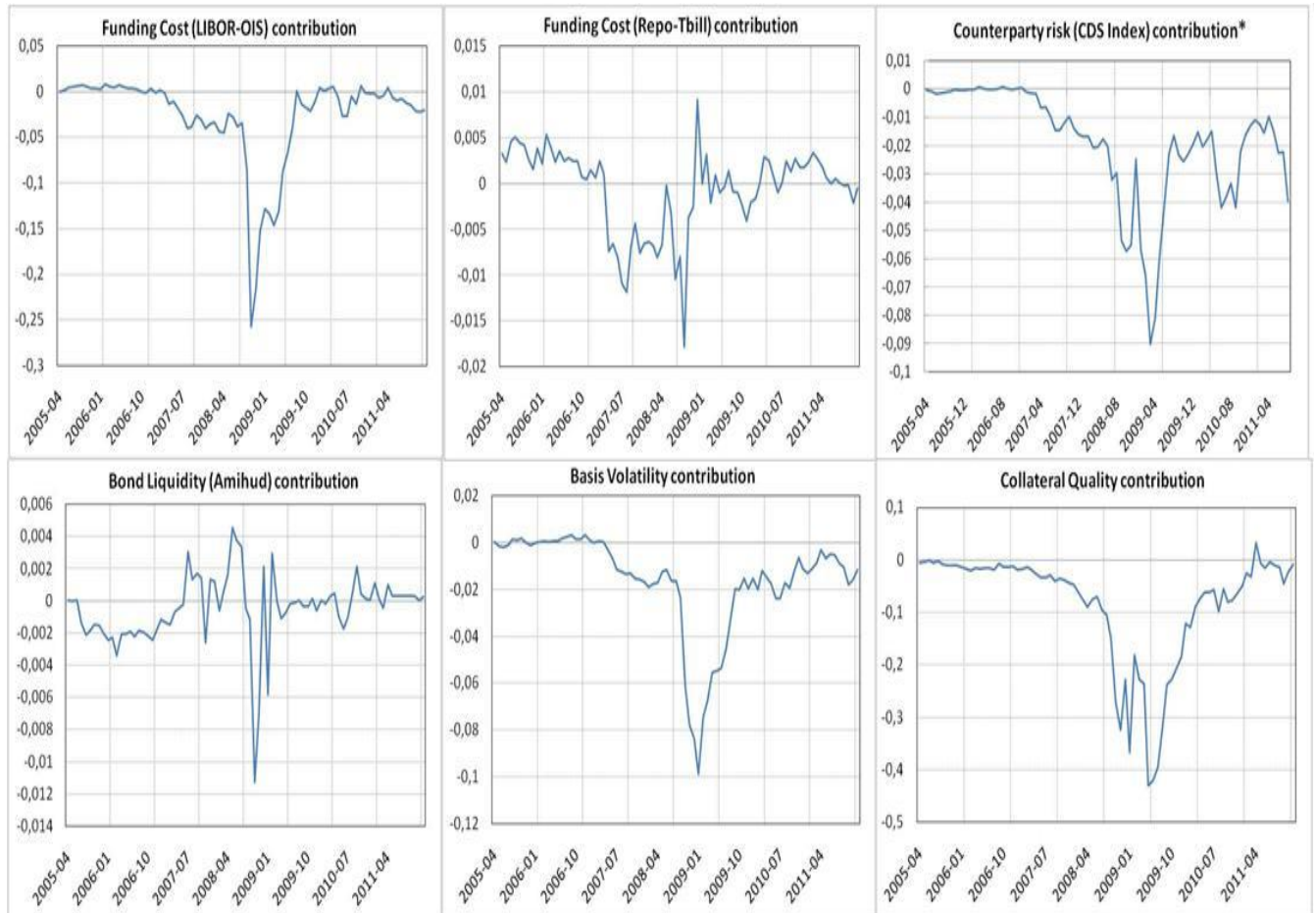
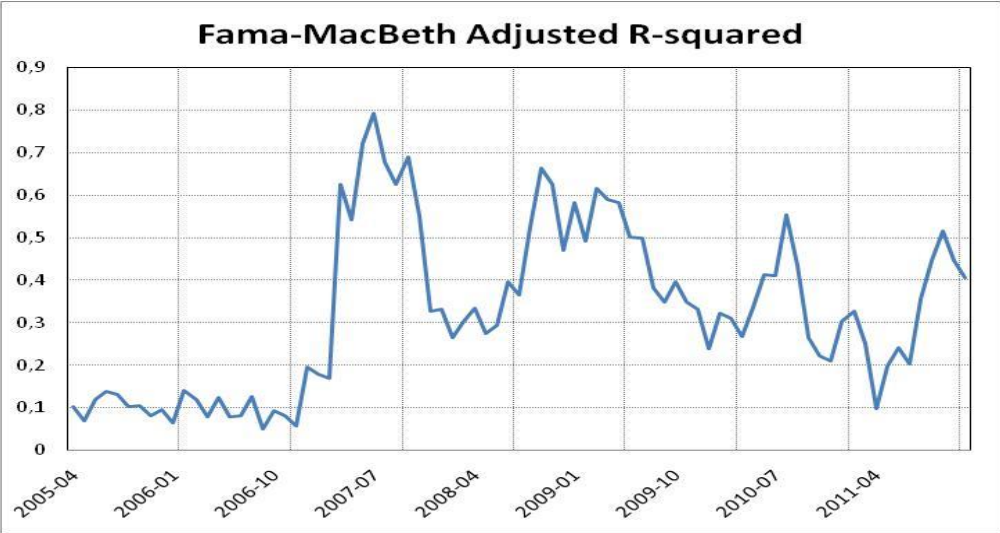


Figure 4 Fama-Macbeth Adjusted R-Square: Nonfinancial Sector



**Figure 5 Cross Section Fama-Macbeth Equation: Financial Sector**

Notes: as for Figure 4.

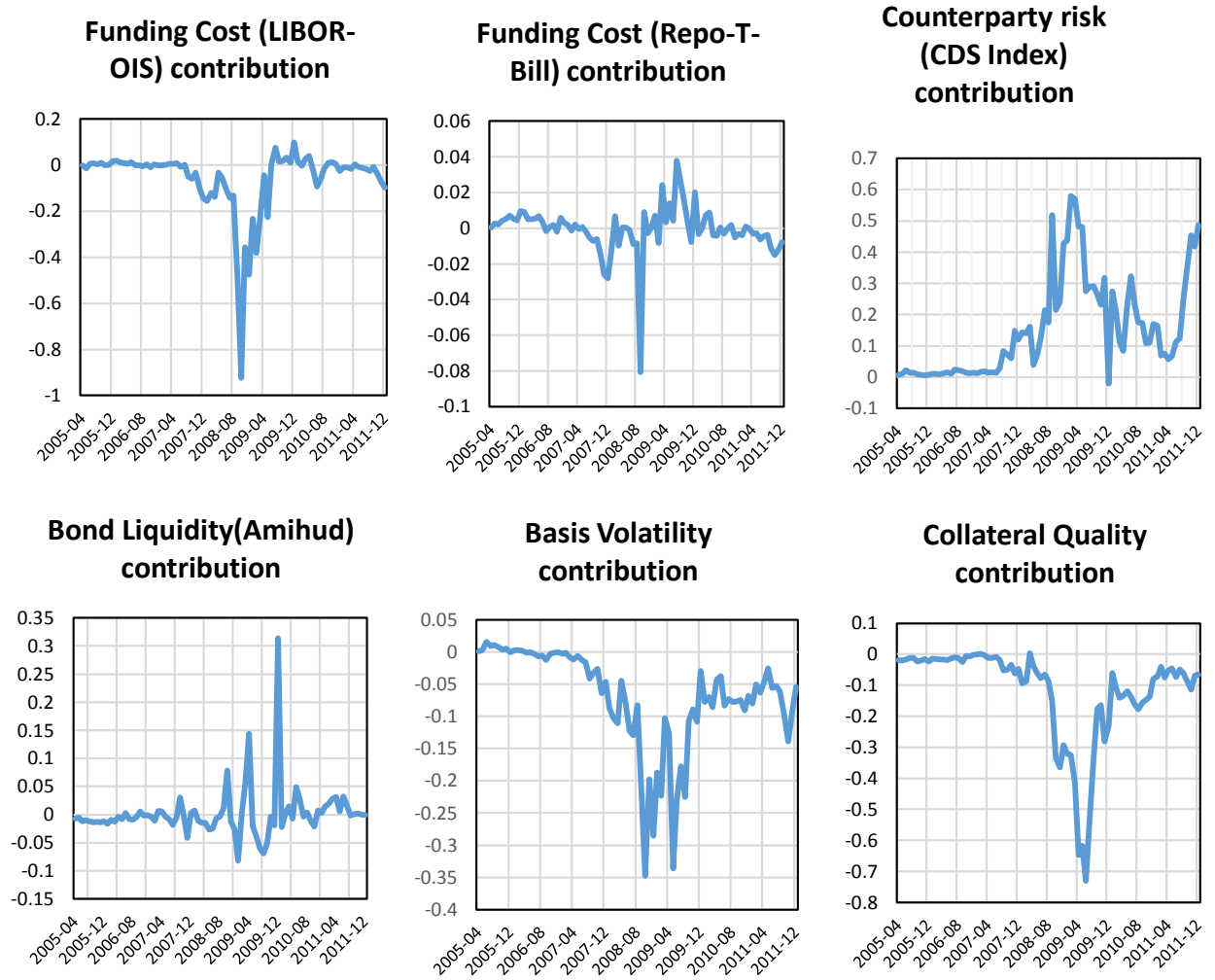
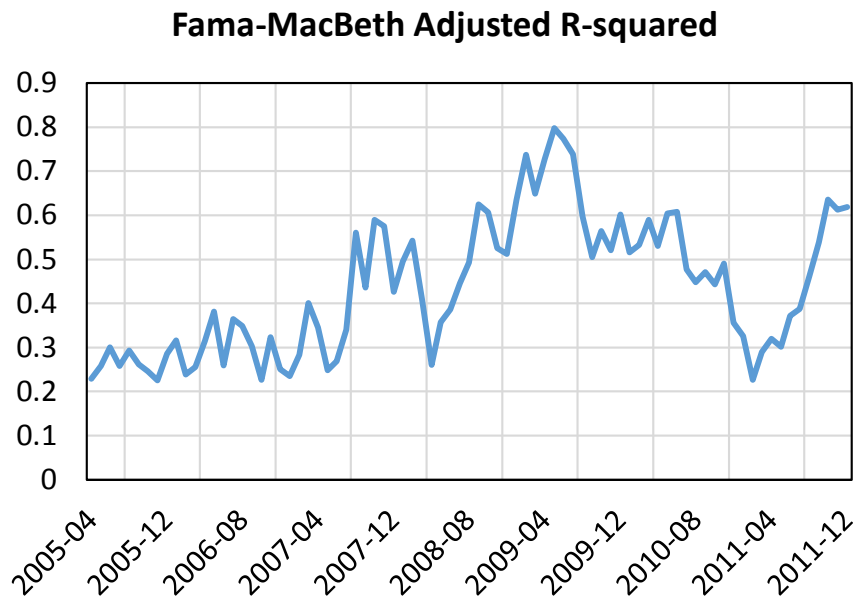


Figure 6 Fama-Macbeth Adjusted R-Squared: Financial Sector



## Appendix 1

### Financial Dataset Description and Rating Migration

Our Financial sector dataset contains:

#### IG (AA, A, BBB)

Number of observations 82344.

Number of companies: 43 (plus Lehman Brothers and Bear Stearns until their bankruptcies) of which 5 are on the TBTF list (JPMorgan, Citigroup, Goldman Sachs, Jefferies, Morgan Stanley).

#### HY (BB, B)

Number of observations 404

Number of companies: 2

#### Annual Rating Migrations of Financial Companies

CUSIPS	2006	2007	2008	2009	2010	2011	Issuer Name	Down grade	Up grade
001055	A	A	#N/A	#N/A	A	A	AFLAC Inc		
020002	BBB	BBB	BBB	BBB	BBB	BBB	Allstate Corp		
025816	A	A	A	A	A	A	Amern Express Co		
04621X	BBB	BBB	BBB	BBB	BBB	BBB	Assurant Inc		
073902	A	AA	AA	#N/A	#N/A	#N/A	Bear Stearns & Co Inc / J P Morgan		1
084423	BBB	#N/A	BBB	BBB	BBB	BBB	WR Berkley Corp		
125581	A	BBB	#N/A	#N/A	#N/A	#N/A	CIT Gp Inc	1	
126117	BBB	BBB	BBB	BBB	BBB	BBB	CNA Finl Corp		
14040H	A	A	A	A	A	A	Cap One Finl Corp		
171232	A	A	A	A	A	A	Chubb CORP		
172062	BBB	BBB	#N/A	#N/A	#N/A	#N/A	Cincinnati Finl Corp		
172967	AA	A	A	A	A	A	Citigroup Inc*	1	
354613	A	#N/A	#N/A	#N/A	#N/A	A	Franklin Res Inc		
38141G	AA	A	A	A	A	A	Goldman Sachs Gp Inc*	1	
203233	BBB	BBB	BBB	BBB	BBB	BBB	Comwlth REIT		
416515	A	BBB	BBB	BBB	BBB	BBB	Hartford Finl Services Group Inc	1	
47102X	BBB	BBB	BBB	BBB	BBB	BBB	Janus Cap Gp Inc		

475070	A	#N/A	#N/A	#N/A	#N/A	#N/A	Jefferson Pilot Corp	
524908	AA	A	#N/A	#N/A	#N/A	#N/A	Lehman Bros Hldgs CAP TR VII	1
534187	BBB	BBB	BBB	#N/A	#N/A	#N/A	Lincoln Natl Corp	
540424	A	A	A	A	A	A	Loews Corp	
55262C	A	A	A	A	A	A	MBIA Inc.	
570535	BBB	BBB	#N/A	BBB	#N/A	BBB	Markel Corp	
571748	BBB	BBB	BBB	BBB	BBB	BBB	Marsh & Mclennan Cos Inc	
59156R	A	A	A	A	A	A	MetLife Inc	
617446	AA	A	A	A	A	A	Morgan Stanley & Co Inc*	1
638612	BBB	BBB	BBB	#N/A	#N/A	#N/A	Nationwide Finl Svcs	
743315	A	A	A	A	A	A	Progressive Corp	
743674	BBB	BBB	#N/A	#N/A	#N/A	#N/A	Prot Life Corp	
750236	A	A	A	#N/A	#N/A	#N/A	Radian Gp Inc	
786429	BBB	BBB	BBB	#N/A	#N/A	#N/A	Safeco Corp	
89417E	A	A	A	A	A	A	Travelers Cos Inc	
91529Y	BB	BB	BBB	BBB	BBB	BBB	Unum Group	1
67612W	#N/A	BBB	BBB	BBB	#N/A	#N/A	Odyssey Re Hldgs Corp	
959802	#N/A	A	A	A	A	A	Western Union Co	
254709	#N/A	#N/A	BBB	BBB	BBB	BBB	Discover Finl Services	
44106M	#N/A	#N/A	BBB	BBB	BBB	BBB	Hospitality Pptys Tr	
472319	#N/A	#N/A	BBB	#N/A	#N/A	BBB	Jefferies Gp Inc*	
31620R	#N/A	#N/A	#N/A	BB	BB	#N/A	Fid Natl Finl Inc	
026874	#N/A	#N/A	#N/A	#N/A	BBB	BBB	AIG Life Hldgs US Inc	
084670	#N/A	#N/A	#N/A	#N/A	A	A	Berkshire Hathaway Fin Corp	
09247X	#N/A	#N/A	#N/A	#N/A	A	#N/A	BlackRock Inc	
361448	#N/A	#N/A	#N/A	#N/A	#N/A	BBB	G A T X Corp	
Total								6 2

## Appendix 2

### COMPANIES (PRIMARY DEALERS) INCLUDED IN CDS INDEX

Source: Federal Reserve Bank of New York on July 2009

BNP Paribas Securities Corp.\*  
Bank of America Securities LLC\*<sup>§</sup>  
Barclays Capital\*  
Cantor Fitzgerald & Co<sup>§</sup>  
Citigroup \*<sup>§</sup>  
Credit Suisse\*  
Daiwa Securities America Inc.  
Deutsche Bank\*  
Goldman Sachs\*<sup>§</sup>  
HSBC\*  
Jefferies & Company, Inc. <sup>§</sup>  
JP Morgan\*<sup>§</sup>  
Mizuho Securities\*  
Morgan Stanley\*<sup>§</sup>  
Nomura  
RBC Capital Markets Corporation\*  
RBS Securities\*  
UBS Securities LLC\*

\* Denotes systemically important bank, as designated globally (by BIS) or domestically (by national regulator) in 2014

<sup>§</sup> Denotes issuer of bonds included in the Markit dataset of reference bonds.

## Appendix 3

### NEGATIVE BASIS ARBITRAGE STRATEGY: DERIVATION OF EQUATION (2)

In this appendix, we derive the formula used in Section 3. For the purposes of the derivation, we make the following assumptions:

- bid-ask spreads for bond prices, CDS spreads and asset swap spreads do not change from 0 to  $T$ .
- the margin account pays interest at the repo rate  $R^{REPO}$ .
- In the analysis above, we ignore the effects of counterparty risk on CDS and asset swap spreads.
- default, if it occurs, happens at time 1. At default, the bond pays recovery and the accrued bond coupon.

The negative basis trading strategy involves a long position in a bond, CDS protection, a Par Asset Swap and loans to fund the transaction. We shall assume that at time  $t = 0$  the investor buys the corporate bond, at the same time buying protection from the credit risk by taking a long position in a matching CDS contract and hedging the interest rate risk by entering into a par asset swap contract with a derivatives dealer. The position is funded as far as possible by borrowing in the repo market, pledging the bond as collateral. To the extent that there is a shortfall due to the haircut applied to the bond's value as collateral, the remaining funds have to be borrowed as an uncollateralized loan.

The cashflows associated with this zero-cost portfolio at inception are set out in Equation (1), repeated here for convenience:

$$\begin{aligned} \Pi_0 = & -P_0^A - [N - P_0] - M \\ & + N(1 - h) + [Nh + M + (P_0^A - P_0)] \end{aligned} \tag{A1}$$

where:

$P_0, P_0^A$  are the time 0 mid-market and ask price of the bond respectively

$M$  is the margin payment

$h$  is the haircut applied by the market to bonds of the type in question

$N$  is the notional size of the trade (the bond principal)

We shall assume that at time  $T$  the investor closes out the position in the bond and the derivative, and at the same time repays the principal and interest on the repo and the uncollateralized loan. Our concern here is with the resulting net cashflow. There are two cases to consider, depending on whether or not the bond has defaulted by time  $T$ .



### **No-default case**

In this case, the investor closes out his positions by selling the bond in the market, closing out his positions in the CDS and the asset swap, and repaying the associated loans. The net cashflow at time 1 is given by:

$$\begin{aligned}\Pi_1^{ND} = & + P_1^B \\ & - N(1-h)(1+R_0^{REPO}) - [Nh + M + (P_0^A - P_0)](1+R_0^{FUND}) \\ & + M(1+R_0^{REPO}) \\ & + \Pi_1^{ND(ASW)} + \Pi_1^{ND(CDS)} \\ & + NC + N[R_0^{LIBOR} + ASW_0^b - C] - N \cdot CDS_0^a\end{aligned}$$

(A2)

where:

$P_1^B$  is the bid price of the bond at 1

$R_0^{REPO}$ ,  $R_0^{FUND}$ ,  $R_0^{LIBOR}$  are the repo, funding and LIBOR quotes at time 0 respectively

$\Pi_1^{ND(ASW)}$ ,  $\Pi_1^{ND(CDS)}$  are the closeout prices at 1 for the asset swap and the CDS in the no-default scenario

$C$  is the bond coupon rate

$CDS_0^a$  is the cost of buying default protection at time 0 i.e the CDS spread quoted at the ask

$ASW_0^b$  is the cost of entering the asset swap at time 0 i.e. the asset swap spread quoted at the bid

Each line of this equation covers a leg of the overall arbitrage deal, starting with the payoff from selling the bond in the market. The second line represents the principal and accumulated interest paid out on the loans. In particular,  $-N(1-h)(1+R_0^{REPO})$  is the repayment due on the repo loan and  $-[Nh + M + (P_0^A - P_0)](1+R_0^{FUND})$  is the principal and interest on the uncollateralized loan. The margin is assumed to earn interest at the repo rate, hence the inflow of  $M(1+R_0^{REPO})$ . The fourth line covers the payoffs from closing out the asset swap and the CDS itself, which will be considered in detail below. Finally, in the last line we include the accruals from coupon payments on the bond,  $NC$ , from the asset swap  $N[R_0^{LIBOR} + ASW_0^b - C]$  and from the CDS premium payments  $-N \cdot CDS_0^a$ .

The calculation of closeout prices for the CDS and asset swap contracts involves straight forward but lengthy calculations. We refer the reader to O'Kane (2008) for details. The resulting expressions are as follows:

$$\Pi_1^{ND(ASW)} = (N - P_1) + N(ASW_0^b - ASW_T^a) \cdot PV_{1,T} \quad (A3)$$

and:

$$\Pi_1^{ND(CDS)} = -N(CDS_0^a - CDS_1^b) \cdot RPV_{1,T} \quad (A4)$$

where  $PV_{1,T}$  is the market price of a risk-free annuity paying \$1 on the bond coupon days throughout the life of the CDS contract, and  $RPV_{1,T}$  is the same notional security, but with the difference that it assumes payouts cease in the event of default.

Now if we assume the bid-ask spread is constant between time 0 and time T and symmetric around the mid-price, we can write in each case:

$$X_t^a = X_t + \frac{1}{2}S_X^{b-a} \quad \text{and} \quad X_t^b = X_t - \frac{1}{2}S_X^{b-a} \quad (A5)$$

where  $X_t$  is the time  $t=0$  or  $1$  mid-market level of the various financial instruments in the arbitrage trade (the bond price, the asset swap, the CDS),  $X_t^a, X_t^b$  are the ask and bid prices respectively of  $X$  and  $S_X^{b-a}$  is the bid-ask spread on deals involving  $X$ .

Using (A3), (A4) and (A5) in (A2) and ignoring a term in  $(RPV_{1,T} - PV_{1,T})\Delta CDS$  which has to be extremely small, gives equation (2) in the paper.

### **Default case**

In the case where the bond issuer defaults, we make two simplifying assumptions. First, the default occurs at time 1. Secondly, we assume that immediately upon default, the issuer pays both the accrued coupon and the recovery value of the bond. Under these circumstances, the cashflow at 1 takes the form:

$$\begin{aligned}
\Pi_1^D = & + N \cdot R + N \cdot (1 - R) + N \cdot C + \Pi_1^{D(ASW)} \\
& - N(1 - h)(1 + R_0^{REPO}) - [Nh + M + (P_0^A - P_0)](1 + R_0^{FUND}) + M(1 + R_0^{REPO}) \\
& + N \cdot [R_0^{LIBOR} + ASW_0^b - C] - N \cdot CDS_0^a
\end{aligned} \tag{3}$$

The terms in the first line of this equation represent respectively the recovery value,  $R$ , and the accrued coupon payments on the bond, as received following default, plus the closeout value of the outstanding asset swap in the default state,  $\Pi_1^{D(ASW)}$ . We shall look at this term in detail below. The remaining terms have the same interpretation as in equation (A2).

We rely again on O'Kane (2008) to rewrite the value of the asset swap as follows:

$$\Pi_1^{D(ASW)} = N[R_{0,T} - (C - ASW_0^b)]PV_{1,T} - \frac{1}{2}N S_{ASW}^{b-a} PV_{1,T} \tag{A7}$$

where  $R_{0,T}$  is the rate quoted at time 0 on swaps involving fixed rates against LIBOR, with a tenor equal to the maturity of the reference bond (i.e. maturing at  $T$ ), and the final term is added so as to take into account the bid-ask spread faced by the investor when the position is closed out. Noting that the closeout value of the assets swap depends on movements in the fixed-for-variable swap rate from 0 to 1, we can write the payoff on the asset swap as (O'Kane (2008)):

$$\Pi_1^{D(ASW)} = N \cdot \Delta R^{ASW} \cdot PV_{1,T} + (N - P_0) \frac{PV_{1,T}}{PV_{0,T}} - N \cdot S_{ASW}^{b-a} \tag{A8}$$

where  $\Delta R^{ASW}$  is the change in the swap rate from 0 to 1. After some manipulation, this gives:

$$\Pi_1^{ND} = -N[(h + m - 1)(R_0^{LIBOR} - R_0^{REPO}) + (h + m)(R_0^{FUND} - R_0^{LIBOR}) + BASIS_0]$$

(4)

$$-N \left[ S_{BOND}^{a-b} \left( 1 + \frac{1}{2} R_0^{FUND} \right) + S_{CDS}^{a-b} \left( RP_{V_{1,T}} + \frac{1}{2} \right) + S_{ASW}^{a-b} \left( PV_{1,T} + \frac{1}{2} \right) \right] + N PV_{1,T} \cdot \Delta BASIS + N \cdot \Delta R^{ASW} \cdot PV_{1,T} + (N - P_0) \frac{PV_{1,T}}{PV_{0,T}}$$

This reduces to:

$$\Pi_1^D = \Pi_1^{ND} + N \cdot \Delta R^{ASW} \cdot PV_{1,T} + (N - P_0) \frac{PV_{1,T}}{PV_{0,T}} + O(S)$$

Where  $O(S)$  denotes terms proportional to changes in the various bid-ask spreads. Given that these are likely to be negligibly small, it follows that the payoff to the arbitrage portfolio will be the same whether or not a default occurs, provided the swap and annuity rates remain unchanged.