The CDS-Bond Basis During the Financial Crisis of 2007-2009 *

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Abstract

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1 Introduction

Financial markets experienced tremendous disruptions during the 2007-2009 financial crisis. Credit spreads across all asset classes and rating categories widened to unprecedented levels.[1] Perhaps even more surprising, many relations that were considered to be text-book arbitrage before the crisis were severely violated. For example, in currency markets, violations of covered interest rate parity occurred for currency pairs involving the US dollar (Coffey, Hrung, Sarkar (2009)). In interest rate markets the swap spread, which measures the difference between Treasury bond yields and libor swap rates, turned negative. In Interbank markets, basis swaps that exchange different tenor LIBOR rates (e.g., 3-month for 6-month) deviated from zero. In inflation markets, break-even inflation rates turned negative implying an obvious arbitrage with inflation swaps (Fleckenstein, Longstaff, Lustig (2011)). In credit markets, the CDS-bond basis which measures the difference between CDS and cash-bond implied credit spreads turned negative.

These anomalies suggest that such relations are not, in fact, arbitrage opportunities in the traditional textbook sense. One possible explanation is that arbitrage relations broke down during the crisis because of institutional or contractual features. For example, many of these relations involve a fully funded (e.g., cash) instrument and one or more unfunded derivative positions. This raises the possibility that counterparty risk of the derivative issuer made the 'arbitrage' risky. An alternative hypothesis is that funding cost differentials between the cash instrument and derivative positions were responsible for the deviations. In the former case, the payoff to the 'arbitrage' trade is not risk-free for any investor, whereas in the latter case, the payoff to the arbitrage trade would still be risk-free for an investor with very deep pockets. In the latter case, therefore, violations can only arise in con-

[1]For example, investment-grade corporate credit spreads as measured by the CDX.IG index rose from 50bps in early 2007 to more than 250bps at the end of 2008. Even at the safest end of the spectrum the widening was dramatic. AAA-rated synthetic debt products, that would have been deemed virtually risk-free before the crisis, saw their spreads widen dramatically: CDX.IG super senior tranche widened from 5bps to 100bps, CMBX AAA "super duper" widened from 2bps to 700bps, ABS-HEL AAA tranche price rose from 0 to 20% upfront plus 500bps running. These numbers illustrate that it became much more expensive to insure AAA-rated debt across various markets (corporate, residential and commercial real estate).

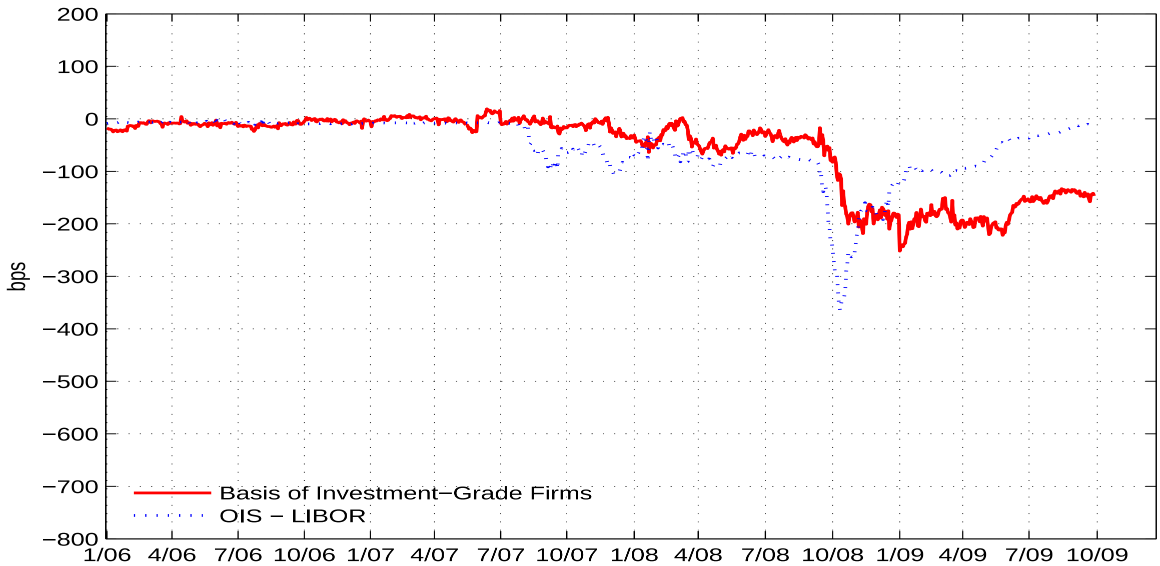
junction with ‘limits to arbitrage,’ such as the inability of arbitrageurs to raise capital quickly and/or their unwillingness to take large positions in these ‘arbitrage’ trades because of mark-to-market risk. Consequently, the dynamics of the arbitrage violations should be affected by the structure of funding markets, the ability of investors to process information, and the ability to move capital across markets (Duffie (2010)).

These apparent arbitrage violations thus provide an interesting opportunity to test several of the ‘limits to arbitrage’ theories (as surveyed, for example, by Gromb and Vayanos (2010)).

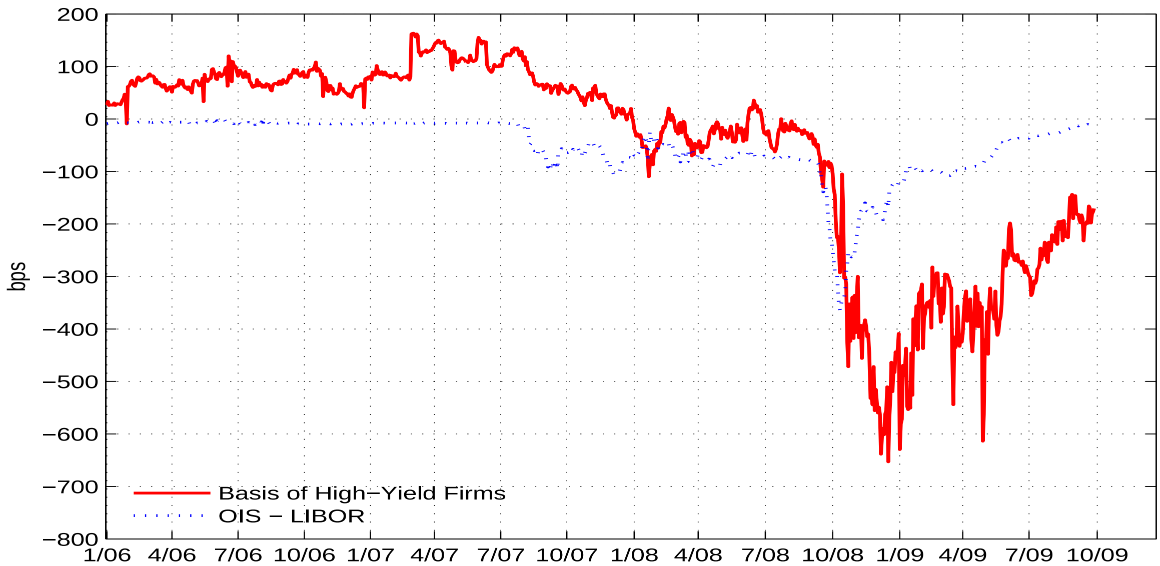
In this paper, we focus on the CDS-bond basis, which measures the difference between the credit default swap (CDS) spread of a specific company and the credit spread paid on a bond of the same company. Figure 1 plots the time series of the average CDS-bond basis for investment-grade (IG) and high yield (HY) bonds, where the funding cost is measured by the libor swap curve. The figures show that the basis, which hovers usually around +5 bps for IG firms, fell to -250 bps and slashed to -650 bps for HY firms. At first sight, a large negative basis smacks of arbitrage since it suggests that an investor can purchase the bond, fund it at libor swap, and insure the default risk on the bond by buying protection via the CDS contract. The resulting trade is ‘virtually’ risk-free and yet, as the figures show it generates between 250 and 650 bps in guaranteed return per annum.

Studying the CDS-bond basis during the crisis is interesting for several reasons. First, early studies of this basis found that the arbitrage relation between CDS and cash-bond spreads holds fairly well (Blanco, Brennan, Marsh (2005), Hull, Predescu and White (2004), Nashikkar, Subrahmanyam and Mahanti (2010)) during the pre-crisis period. In fact, if anything, these studies typically conclude that the basis should be slightly positive. Indeed, the arbitrage is, in general, not perfect (Duffie (1999)), and there are a few technical reasons (such as (i) the difficulty in short-selling bonds, (ii) the cheapest-to-deliver option) that tend to push the basis into the positive domain (Blanco, Brennan, Marsh (2005)). However, during the crisis the basis was tremendously negative, which suggests the need for alternative explanations. Second, there is a large cross-sectional variation in the observed

Figure 1: A. The CDS-bond Basis of IG Firms vs OIS-LIBOR spreads



B. The CDS-Bond Basis of HY Firms vs OIS-LIBOR spreads



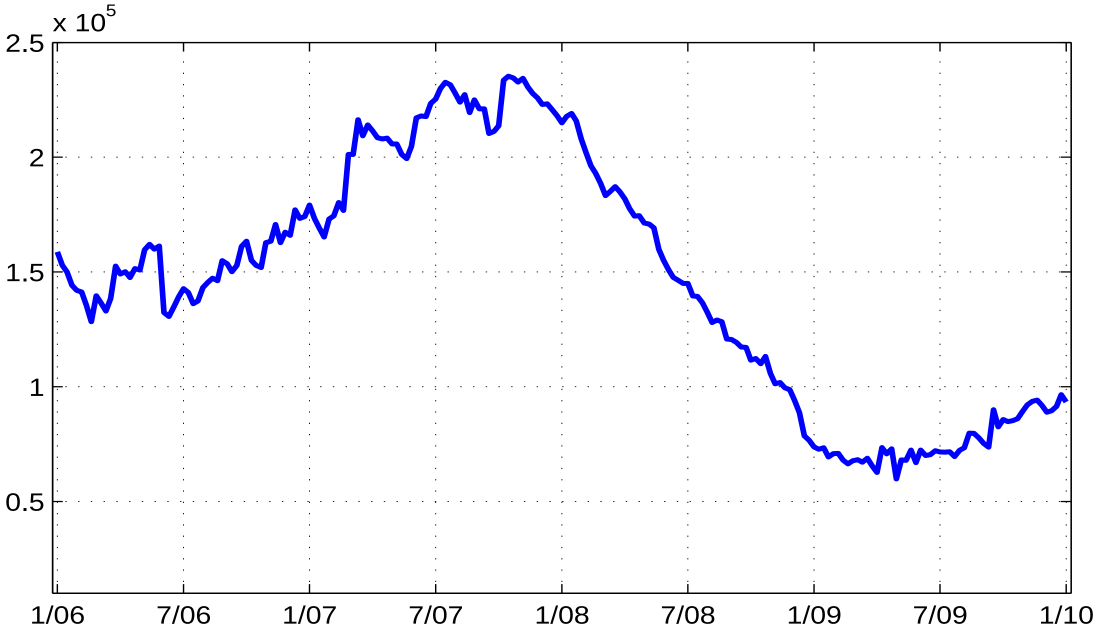
basis across individual firms. One obvious dimension of variation is rating, as shown in the picture above. There are several other sources of variation that offer the potential to test a wide range of hypotheses about the determinants of the basis.[2] We discuss these next.

There are several reasons why one might expect the basis to become negative during the financial crisis of 2007-2009. Anecdotes for the negative basis claim that several major financial institutions, pressed to free up their balance sheet and improve their cash balance, reduced their leverage by selling-off bonds. Some evidence for this deleveraging is presented in Figure 2 below, which shows primary dealers' position in long-term (maturity larger than one year) corporate securities. This exerted downward pressure on bond prices, and upward pressure on credit spreads relative to CDS spreads that represent the 'fair' value of the default risk insurance. This however cannot be the whole story, since in a perfect frictionless market, investors would simply borrow cash to buy the bonds, buy protection and finance the position until maturity (or default). For deleveraging to have a persistent impact on the basis, there must be some 'limits to arbitrage' (Shleifer and Vishny (1997)). In particular, if risk-capital is limited then the (mark-to-market) basis trade becomes risky and investors will tend to buy the bonds-basis packages that are (ex-ante) most attractive from a risk-return trade-off.

In this paper we analyze the risk-return trade-off in a basis trade for an investor with limited capital. We find that the investor is exposed to (a) the basis becoming more negative, (b) increased uncollateralized funding costs, (c) increased collateralized funding costs (repo rates), and (d) increased hair-cuts. Further, the profitability of the trade per unit of capital is decreasing in the collateral that must be posted to enter the basis trade (essentially the hair-cut). All else equal, this suggests that the basis should be less negative for bonds with smaller hair-cuts (i.e., better collateral quality), and for bonds with a basis that have a lower covariance with funding costs (i.e., lower funding cost risk). In this explanation for the negative basis, the corporate yield spread is temporarily too high relative to

[2]As we discuss in the next section, the cross-sectional variation in the basis is also useful to circumvent the potential bias that arises when estimating the corporate bond credit spread from the fact that the risk-free rate is possibly estimated with error.

Figure 2: Primary Dealer Position in Long-term Corporate Securities (in Mil.$)



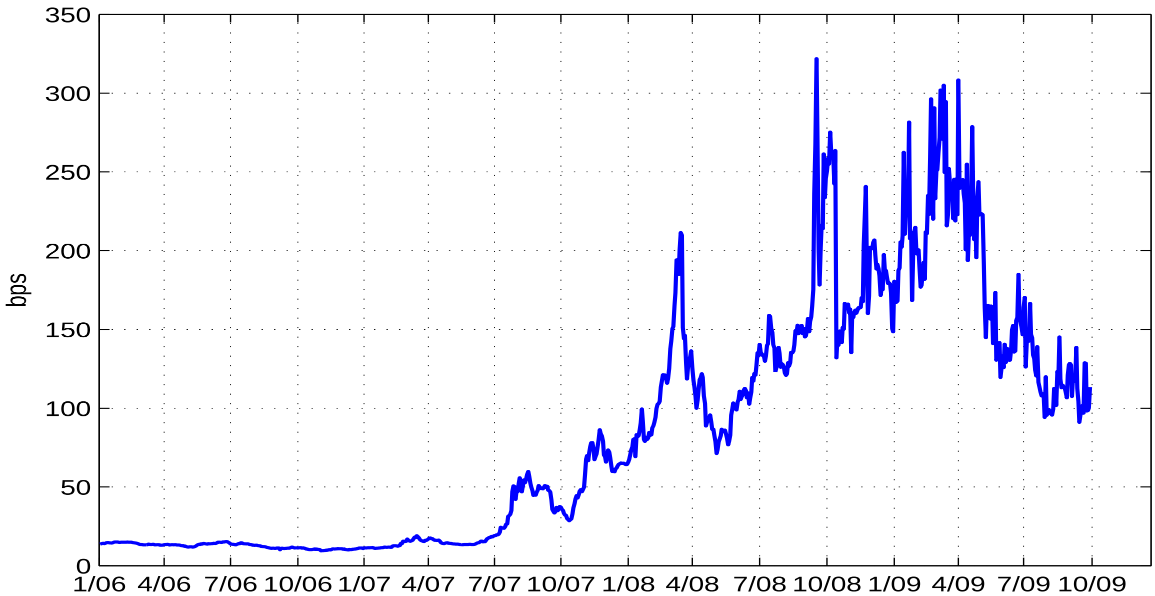
Source: Federal Reserve Bank of New York.

the fairly valued CDS, due to the lack of available 'arbitrage risk capital.'

A different explanation for the negative basis focuses on the CDS side of the trade. In a basis trade, the protection is typically bought from a broker dealer such as J.P. Morgan, Goldman Sachs, or Lehman Brothers. Clearly, the counterparty risk of these protection sellers increased considerably during the crisis. Figure 3 plots the value-weighted credit default spread of the primary broker-dealers in the U.S. market. We see a striking widening in the default risk of the average broker-dealers. A direct implication is that the insurance sold by these broker-dealers should be less valuable. So increasing counterparty risk of the broker-dealers should directly lead to lower CDS spreads, and therefore could explain the observed negative CDS-Bond basis.

Our empirical investigation seeks to identify what were the main drivers of the basis during the crisis. First, we analyze the time-series determinants of the average (IG and HY) basis during the crisis to uncover which factors have predictive impact on the basis. We find that important predictors are

Figure 3: The Average Five-Year CDS Spread for the Primary Broker-Dealers



Source: Markit Inc. and Federal Reserve Bank of New York.

related to funding costs (and counterparty risk) of financial intermediaries in the sense that an increase in financial intermediaries funding costs (as measured by OIS-LIBOR or primary dealer CDS) leads to a more negative average basis. But, interestingly, we find significant differences in the time series behavior of IG and HY basis. Specifically, deleveraging as measured by the change in the bond position of primary dealers (PD) mainly affected the HY basis (a lower PD-bond position lowers the HY-basis). For the IG basis, a more important determinant was the collateral-quality-funding spread as measured by the difference in repo rates using MBS versus Treasury as collateral. The wider the spread the more negative the basis. This suggests that the level of the individual bond basis may depend in a complex manner on individual characteristics such as risk, collateral quality, and aggregate market conditions such as dealers' financial health, availability of collateralized and uncollateralized funding, and selling pressure.

We confirm this by investigating the impact of individual firm/bond characteristics on the cross-sectional (within rating) variations of the CDS-bond basis. Specifically, we construct measures (i.e., 'betas') of market risk, funding cost risk, flight to quality risk, collateral quality and counterparty risk for each firm, and run Fama-McBeth style cross-sectional regressions of the individual firm basis on these (funding, liquidity, collateral and counterparty) betas. We then plot the resulting time-series of regression coefficients. Our main results are that unconditionally all risk measures are statistically significant in explaining the cross-sectional variation in the basis, as one would expect if the marginal investor were a leveraged hedge-fund trading off risk and return when allocating scarce risk-capital to these different basis-investment opportunities. Overall, the empirical model is reasonably successful at explaining cross-sectional variation in the basis during the post-Lehman phase. Interestingly, we find that IG and HY basis behave quite differently, with the former more driven by our proxies for counterparty risk and flight to quality and the latter more by counterparty risk, funding costs and collateral quality.

Finally, we conduct additional tests at the individual bond level to investigate the role of selling-pressure. Specifically, we look at the average level and the range of the post-crisis individual bond trading volume (relative to its pre-crisis level). We find that only for HY bonds is this measure statistically significant in explaining the bond basis (confirming our time-series result for the average basis indexes). We also investigate lead-lag effects between price-discovery in the CDS and bond market, following Blanco, Brennan, Marsh (2005). One would expect that if deleveraging was a big factor for the basis, then bond spreads would lead CDS, and more so for bonds with higher price pressure, and more risk.[3] Indeed, we find that the share of price-discovery occurring in the CDS market falls significantly during the crisis. The drop is much more significant during the post-lehman phase and more pronounced for HY firms. For the latter the share falls even below 50% indicating that by that metric bond price innovations lead the CDS market and thereby lending some support to the deleveraging story for the HY market.

[3]Instead, if counterparty risk was driving the basis, then we would expect only the CDS component to be affected with not much effect on price discovery across markets.

The negative basis has been subject of considerable attention in the practitioner literature (DE Shaw 'The basis monster that ate wall street' (2009), JP Morgan 'The bond-CDS basis handbook' (2009), Mitchell and Pulvino (2010)). These papers emphasize the role of financing risk in generating the negative basis, as well as the deleveraging of key leveraged investors in generating downward price pressure on cash-bonds. In the academic literature Garleanu and Pedersen (2011) provide a theoretical model, where leverage constraints can generate a pricing difference between two otherwise identical financial securities that differ in terms of their margin requirements or hair-cuts. Specifically, their theory predicts that the difference between two basis should be related to the difference in margin requirements (i.e., haircuts) times the difference between the collateralized and uncollateralized borrowing rate. They find support for their model in explaining the average basis difference between high grade and high-yield bonds by the average difference in hair-cuts times a proxy for the collateral borrowing spread as proxied by LIBOR-OIS.[4] Our study differs from these previous papers in that we focus on the cross-sectional variation in individual firms' basis (rather than on the average basis level) during the crisis and try to relate it to firm, bond and CDS characteristics. As in Garleanu and Pedersen (2011) we find that collateral quality (our proxy for hair-cut margins) is an important determinant of the basis, especially in the post Lehman phase. However, we also find substantial cross-sectional variation in the basis that is hard to attribute solely to differences in margins.

In section 2 we discuss some practical issues regarding an actual basis trade and isolate the various sources of risk in such a trade. In section 3, we discuss our data sources, and various proxies for liquidity risk, funding cost, price pressure, and collateral quality. In Section 4 we present evidence from predictive regression on factors driving the average levels of IG and HY basis. In section 5 we show evidence on cross-sectional risk-factors driving individual bond basis from Fama-McBeth style regressions. In section 6 we present some evidence about lead-lag effects of the basis for CDS and

[4]Below we argue that a better proxy for the collateral spread is the OIS-GC Repo spread. Indeed, LIBOR-OIS contains a pure bank-credit-term-spread component since LIBOR is a 3-month rate and OIS is based on overnight borrowing, which may somewhat muddle the pure collateral effect.

credit spread. We conclude in section 7.

2 The CDS-Bond Basis

A credit default swap is essentially an insurance contract against a credit event of a specific reference entity. It is an over-the-counter transaction between two parties in which the protection buyer makes periodic coupon payments to the protection seller until maturity or until some credit event happens. When a credit event occurs,[5] typically the protection buyer delivers a bond from a pool of eligible bonds to the protection seller in exchange for its par value.[6]

The contract is designed so that the owner of a particular bond can hedge her credit risk exposure to the issuer of that bond by buying CDS protection on that counterparty. As a result we would expect CDS spreads to be similar to credit spreads observed on corporate bonds that are deliverable into the CDS contract. In fact, under some conditions, an exact arbitrage relation exists which implies that the CDS spread should equal the credit spread on the deliverable corporate bond.[7] This leads to the theoretical definition of the CDS-bond basis as the CDS spread minus the corporate bond credit spread.

While the CDS spread is observable in the market, it is not obvious how to compute the appropriate corporate bond spread. As discussed by Duffie (1999) the ideal corporate bond spread would be the spread over libor of a floating rate note with the same maturity as the CDS referenced on the same firm. In practice, this spread is often not observable as firms rarely issue floating rate notes. Instead, we have to rely on other available fixed rate corporate bond prices. Several methodologies have been proposed in the literature. Following Elisade, Doctor, and Saltuk (2009) we adopt the Par Equivalent CDS (PECDS) methodology developed by J.P. Morgan. This method, which we present for completeness

[5]In the 2003 definition, the International Swap and Derivative Association (ISDA) lists six items as credit events: (1) bankruptcy, (2) failure to pay, (3) repudiation/moratorium, (4) obligation acceleration, (5) obligation default, and (6) restructuring. For more detail, see "2003 ISDA Credit Derivatives Definitions," released on 11 February 2003.

[6]See Duffie and Singleton (2003) for a detailed description.

[7]Duffie (1999) discusses the specific conditions and shows why this relation might not exactly hold in practice.

in the appendix, essentially amounts to extracting the default intensity consistent with the prices of the corporate bonds observed in the market and using the libor swap curve as the risk-free benchmark curve. Then one can calculate the fair CDS spread consistent with the bond implied default intensity and the risk-free benchmark curve (given a standard recovery assumption). It is this theoretical bond-implied CDS spread, called the PECDS spread, that we compare to the quoted CDS spread on the same reference entity to define the CDS-bond basis:

$$Basis_i(\tau) = CDS_i(\tau) - PECDS_i(\tau), \tag{1}$$

where τ is the maturity and i indicates the reference entity. This methodology has several advantages, reviewed in Elisade, Doctor and Saltuk (2009). It has also been used by previous academic studies such as Subramanyam et al. (2009).

Another important issue for the measurement of the basis is the funding or 'risk-free' rate benchmark (Hull, Pedrescu and White (2004)). Several authors have argued that the Treasury curve is not the appropriate risk-free benchmark and, indeed, that it is lower than the typical funding cost an investor can achieve via collateralized borrowing.[8] In fact, Hull, Predescu and White (2004) use the basis package (a portfolio long several corporate bonds and long CDS protection) to define a risk-free asset available to any investor. They argue that since the average CDS-bond basis is zero when measuring funding cost using swap rate minus 10 bps and the CDS-bond basis exhibits little cross-sectional variation, this is evidence that the 'true' shadow risk-free rate for a typical investor is around swap minus 10 bps (or approximately Treasury plus 50 bps). We note that the very large cross-sectional variation in the basis (across rating categories) documented in Figure 1 allows us to immediately dismiss the fact that mis-measurement of the risk-free rate benchmark is the explanation for the puzzling behavior of the CDS-bond basis during the crisis. If we were simply mis-measuring

[8]Studies that document the special status of the US Treasury curve, –presumably due to its greater liquidity– include Longstaff (2004), Feldhutter and Lando (2008) among others.

the risk-free benchmark we would observe an approximately constant CDS-Bond basis across firms reflecting the spread between our benchmark risk-free curve and the true (unobserved) risk-free curve. Let us stress, however, that since we do not observe the true risk-free benchmark curve, it is important to focus on the cross-sectional variation in the basis, rather than focusing on the average level, which could be affected by the 'flight-to-quality' effects documented in the benchmark Treasury and Swap yield curves.

When the basis is positive, the credit default swap spread is greater than the bond spread. An investor could then short the bond and sell CDS protection to capture the basis. When the basis is negative, the credit default swap spread is lower than the bond spread. By buying the bond and buying protection, investors could "lock-in" a risk-free annuity equal to the (absolute value of the) basis.

As discussed in the introduction, during normal times the CDS-bond basis tends to be very small and, if anything, slightly positive when measured relative to the libor-swap benchmark. This has been studied extensively by Blanco, Brennan, and Marsh (2005) and Subramanyam et al. (2009). However, Figure 1, which shows the time-series pattern of the CDS-bond basis for the overall U.S. IG and HY bonds over the past four years, reveals that the CDS-bond basis was significantly and persistently negative during the recent financial crisis. Furthermore, there was substantial cross-sectional variation in the negative basis as we can see from the conspicuous difference in basis between IG bonds in Figure 1A and HY bonds in Figure 1B.

While a positive basis can often be traced back to some inability to implement the 'arbitrage' trade because either bonds are difficult to short, or there exists a cheapest-to-deliver option (see Blanco, Brennan, and Marsh (2005)), a negative basis is harder to explain. Indeed, in the negative basis case, the 'arbitrage' trade requires buying the bond, financing its purchase, and buying protection to hedge against the default event. Figure 1 suggests that the return to the 'negative basis' trade would have been between 250 bps and 650 bps for IG and HY bonds respectively. These seem like very high arbitrage profits. So it is important to review the details of such a basis trade implementation to better understand where the 'limits to arbitrage' may arise.

2.1 Negative Basis Trade

In practice, there are several reasons why a negative basis trade is not a pure arbitrage. These risks are discussed in detail in Elisade, Doctor, Saltuk (2009) (see, in particular, their table 2 on page 23). The main issues when implementing a negative basis trade have to do with funding risk, sizing the long CDS position, and counterparty risk.

Suppose we find a bond with negative basis that trades at a price B below its notional of N. A negative basis trade requires buying the bond. The purchase is funded via the repo market where investors face a haircut h. This effectively implies that arbitrageurs will have to provide hB dollars of 'risk-capital' funded at $Libor + f$ where f is the funding spread over libor faced by the arbitrageur. The repo contract is typically over-night (up to a few months at most) with an agreed upon repo rate and needs to be rolled over repeatedly until the maturity of the basis trade which is the lesser of default and maturity (e.g., 5 years).

At the same time, to offset the risk of default, the investor buys protection in the CDS market. A question arises as to how to size the CDS position. A conservative approach from a point of view of minimizing exposure to 'jump to default' is to buy protection on the full notional N of the bond.

Market participants typically prefer to buy less protection to improve the carry profile of the trade (pay less in insurance premium). The justification is that the maximum capital at risk in the transaction is the initial purchase price of B.[9] In fact, a customary approach is to make an assumption about recovery (for example, assume that in case of bankruptcy a fraction R of the notional of the bond is recovered) and buy protection on a CDS notional of N_{CDS} so as to cover the loss in capital, i.e., such that $B - N\,R = N_{CDS}(1-R)$. This will increase the carry of the trade (since the CDS premia

[9]For bonds that trade at a premium one may in fact buy more protection!

are now reduced), but expose the investor to a jump to default in case the recovery is smaller than expected. An alternative approach is to choose the notional of the CDS position to match the spread duration on the risky bond (this approach tries to minimize mark-to-market differences between the bond and CDS position over the life of the bond as opposed to thinking about jump to default risk). As explained in Duffie (1999) there is no perfect arbitrage when the underlying bond is not a floating rate note with the same maturity as the CDS contract.

For illustration, suppose the investor buys protection on a notional N_{CDS}. This requires a margin payment of M and periodic mark-to-market margin calls. The margin has to be funded at $Libor + f$.

After one day the profit or loss (P&L) on the trade can be written as:

$$
\begin{aligned}
P\&L(t+1) &= B_{t+1} - B_t + N_{CDS} D_{CDS} * (CDS_{t+1} - CDS_t) \\
&\quad - B_t * [h(libor + f) + (1-h) * (repo)] - M_t(libor + f)
\end{aligned}
$$

where D_{CDS} is the duration of the CDS (such that the P&L on the CDS is the product of the duration with the change in CDS rate; note that if CDS increases the short-credit/long-protection position makes money). For illustration, suppose we size our position in the CDS to match the libor-spread duration on the corporate bond, then we can rewrite the P&L as:[10]

$$
\begin{aligned}
P\&L(t+1) &\approx D_B * (Basis_{t+1} - Basis_t) \\
&\quad - B_t * [h(libor + f) + (1-h) * (repo)] - M_t(libor + f)
\end{aligned}
$$

Specifically, this relation shows that the typical basis trade, when rolled over repeatedly, is exposed to:

- The basis becoming more negative,

[10] We use the approximation $\Delta B \approx -D_D \Delta libor$ and size the position in the CDS so that $N_{CDS} D_{CDS} = D_B$.

- An increase in liquidity as measured by the benchmark libor rate.

- An increase in the arbitrageurs own credit risk, which would lead to a larger markup (f). We note that if the arbitrageur has a large position in basis trades then this could be tied to the basis becoming more negative (i.e., the trade running away from him).

- A worsening of collateral quality of the bond (funding liquidity), which would lead to an increase in the haircut (h) and the repo rate.

- An increase in the margin requirements on the CDS position (M_t).

Last but not least, the trade is also affected by counterparty risk in the sense that if a default on bond occurs at time τ_B, then the P&L will be:

$$P\&L(\tau_B) = R\,N + N_{CDS}(1 - R)\mathbf{1}_{\tau_C > \tau_B}$$

where τ_C denotes the default time of the counterparty selling protection and R denotes the realized recovery on the bond. Specifically, if the counterparty defaults (or has defaulted) when the underlying firm defaults then the CDS protection expires worthless. This highlights the fact that from an ex ante perspective counterparty risk depends on the correlation between the default risk of the underlying name and the counterparty selling the protection, which is typically a large bank such as J.P. Morgan, Lehman Brothers, Bear Stearns, or Goldman Sachs. Now, it is important to stress that, in general, counterparty risk is viewed as likely to be small, since if the counterparty defaults prior to the default event (i.e., $\tau_C < \tau_B$) and if mark to market were perfect, then the investor could reopen a new position at no cost with another counterparty. Thus, in theory, counterparty risk only affects the investor if the counterparty defaults on the exact same day as the underlying bond ($\tau_C = \tau_B$). In practice however, it is likely that the failure of the counterparty, especially during an extraordinary period like the financial crisis, would be associated with substantial costs and risks for the investor. These losses would typically be related to the likely mark-to-marking loss in the position on the day of the counterparty default as well as more technical considerations, which have to do with the specific bankruptcy provisions in the ISDA covering the CDS trade (e.g., if the mark-to-market limits were insufficient, or if the collateral posted with the counterparty was rehypothecated, or if the cash settlement done upon bankruptcy of the counterparty is based on mid-market quotes).

Below we try to use the cross-sectional variation in individual bond basis to disentangle the effects of various risks outlined above that affect the risk-return trade-off of a basis trade. Our working hypothesis is that an arbitrageur having limited access to capital will try to exploit the basis trade opportunities that offer the best expected return per unit of risk-capital. So he will choose basis trades that have the most negative basis (highest expected return) but controlling for ex ante measures of exposure to market and funding liquidity. All else equal he will prefer basis trades on bonds with low haircuts, low exposure to funding cost (in the sense that for two bonds with equally negative basis, the one which correlates more with funding costs is more attractive, since the basis trade converges when funding costs rise), low counterparty risk (in the sense that the probability of the underlying firm defaulting at the same time as the counterparty in the CDS is lower). If this hypothesis is correct then we expect that the risk characteristics of the basis trade (counterparty risk, funding liquidity risk, collateral quality) should be related to the level of the basis in the cross-section.[11] We first describe the data sources and time-series behavior of the basis.

3 Data

The data used to study the CDS-bond basis come from several sources. We start with the universe of firms whose single-name CDS is traded in the derivative market and transactions are recorded in the Markit database. Then we collect these firms' corporate bond information from the Mergent Fixed

[11]A more sophisticated analysis would be to solve the optimal capital allocation decision of the arbitrageur to the available basis-trades and test his first order condition.

Income database. Finally we match each firm's credit default swap and bond spread to corresponding equity returns in the Center for Research in Security Prices (CRSP). All data are in daily frequency from January 1, 2006 through September 30, 2009. The whole sample is further partitioned into three phases: Phase 1 is the period before the subprime credit crisis, named 'Before Crisis' (1/2/2006 - 6/30/2007);[12] Phase 2 is the period between the subprime credit crisis and the bankruptcy of Lehman Brothers, called 'Crisis I' (7/1/2007 - 8/31/2008); and Phase 3 is the period after Lehman Brothers' failure, 'Crisis II' (9/1/2008 - 9/30/2009).

3.1 Credit Default Swap

We download single-name credit default swap data from Markit Inc. for U.S. firms. The prices are quoted in basis points per annum for a notional value of \$10 million and are based on the standard ISDA contract for physical settlement. The original dataset provides daily market CDS prices in various currencies and different types of restructuring documentation clauses. Following a conventional rule, we choose the CDS price in US dollar and the documentation clause type as 'Modified Restructuring' (MR).[13]

The original dataset also provides a CDS spread term structure incorporating maturities of 3m, 6m, 1y, 2y, 3y, 4y, 5y, 7y, and 10y. We use all maturities in conjunction with matching interest rate swaps to calculate a term structure of default probability, which is an integral component in deriving the bond-implied CDS spread (PECDS) and hence the CDS-bond basis (see Appendix A). In the end we focus on the CDS-bond basis with a maturity of five years because the 5-year CDS is by far the most liquid in the credit derivative market and for the convenience of comparison, because the 5-year

[12] There is not a unanimously agreed day for the beginning of the subprime crisis. Popular opinion is that the subprime crisis started in August 2007 for a series of credit crunch events. Here we take a conservative stance by starting the crisis period in July.

[13] Under the 2003 Credit Definitions by the International Swap and Derivative Association (ISDA), there are four types of restructuring clauses: Cumulative Restructuring (CR), Modified Restructuring (MR), Modified-Modified Restructuring (MM), and No Restructuring (XR). 'Modified Restructuring' is used by most broker-dealers in the U.S. market. This convention holds till April 8, 2009. Afterwards the U.S. market adopts the 'No Restructuring' convention. For consistency, we choose the MR documentation clause throughout our sample.

CDS is widely used in the literature.

3.2 Corporate Bond

We get corporate bond data from the Mergent Fixed Income Databases. This database contains information on virtually all publicly-traded bonds issued in the United States since 1980. For each firm in the Markit dataset, we search Mergent datascope for all bonds which have 3 to 7 years remaining to maturity measured each day during the sample period. We find that quite a few firms such as Warren Buffet's Berkshire Hathaway Inc. don't issue mid-term bonds less than 7 years in the sample period, then we further expand the bond sample to include firms which issue bonds with 7 to 10 years left to maturity also measured at each day during the sample period. In line with Blanco, Brennan and Marsh (2005), we exclude floating-rate securities and all bonds that have embedded options, step-up coupons, sinking funds, or any special feature that would result in differential pricing.

For each bond, we collect bond price, coupon rate, annual payment frequency, issuing date and maturity date. We then apply the methodology described in Appendix A to calculate the bond price implied CDS spread and further to calculate the CDS-bond basis. Since we target the 5-year CDS contract, we prefer bonds with maturities as close to five years as possible for better maturity matching. Therefore, if an underlying firm issues bonds with $3 \sim 7$ years left to maturity, we only use these mid-term bonds to calculate the basis. If an underlying firm like Berkshire doesn't have bonds with $3 \sim 7$ years remaining to maturity in the sample period, we then calculate the basis from the firm's bonds with $7 \sim 10$ years left to maturity.

The method we use to calculate the CDS-bond basis is quite different from Blanco, Brennan and Marsh (2005). They choose bonds with $3 \sim 5$ year to maturity at the beginning of their sample period, and use a linear interpolation method to estimate a 5-year bond yield to match the 5-year CDS spread. In terms of CDS data, Blanco et al. (2005) only need the five-year CDS spread. Yet we need to use the complete CDS term structure to get more accurate measures of default intensity and hence a better fit of the bond-implied CDS spread.

Finally we match the combined Markit-Mergent data to CRSP to gather information on stock prices and outstanding shares. All together we get 484 firms throughout the whole sample period.

3.3 Reference Rate

We use U.S. dollar interest rates swaps as reference rates. The reference rate is used to proxy the risk-free interest rate when credit spreads are calculated. The natural choice is a government bond yield. As Blanco, Brennan and Marsh (2005) point out, "government bonds are no longer an ideal proxy for the unobservable risk-free rate" due to tax treatment, repo specialness, legal constraints, and other factors. Importantly, the libor-swap rate represents a better indicator of the funding cost for financial intermediaries and typical basis swap traders than the Treasury curve. Therefore we use it as our benchmark funding curve for the basis calculations.[14] As discussed above, we choose not to focus on absolute levels for the CDS-bond basis to be more immune to the reference rate issue.

3.4 Firm Characteristics

To construct the risk factors introduced in Section 3, we download firm characteristics from Capital IQ and Mergent. For each firm in the merged CDS-bond-Equity dataset, we collect and calculate the following variables at quarterly frequency from 2006:Q1 to 2009:Q3: *SIZE*, the logarithm of total assets; *LEVERAGE*, the ratio of total debt to market capitalization; *TANGIBLE RATIO*, the percentage of tangible asset in total asset; *RATING*, the firm's long-term credit rating provided by Standard & Poor's; and *SECTOR*, including eight subsectors for industrial firms and six subsectors for financial firms.

[14]See also the Swap-Treasury spread discussions in Hull, Pedrescu and White (2004), Collin-Dufresne and Solnik (2001).

3.5 Interest Rate Benchmarks

Finally we download the libor rate, interest rate swap rates, repo rates, Treasury note rates from the Federal Reserve Board, and download the overnight indexed swap (OIS) from Bloomberg. We present in Figure 4 the time series of various interest rate proxies. As is apparent there are a number of interesting spreads that can be constructed from these series. In particular, we will focus on the following spreads:

- LIBOR-OIS: The difference between uncollateralized interbank 3-month borrowing and overnight borrowing rates. We consider it a proxy for short term banking credit risk as well as interbank liquidity risk.
- OIS-RepoGC: The difference between an uncollateralized overnight rate and the rate obtained for borrowing against general collateral (e.g., Treasury Bonds). This is the 'collateral spread'
- RepoMBS-RepoTsy: the difference between the rate obtained for borrowing against collateral using MBS versus against collateral using Treasury bonds. This is the 'collateral quality spread.'
- RepoGC-Treasury: The difference between collateralized lending rate and the 3-month T-Bill rate. This captures a flight-to-quality liquidity component[15] in that a widening of the spread captures episodes where investor would rather own a 3-month Treasury-Bill paying a lower yield than an overnight loan fully collateralized by that same Treasury!

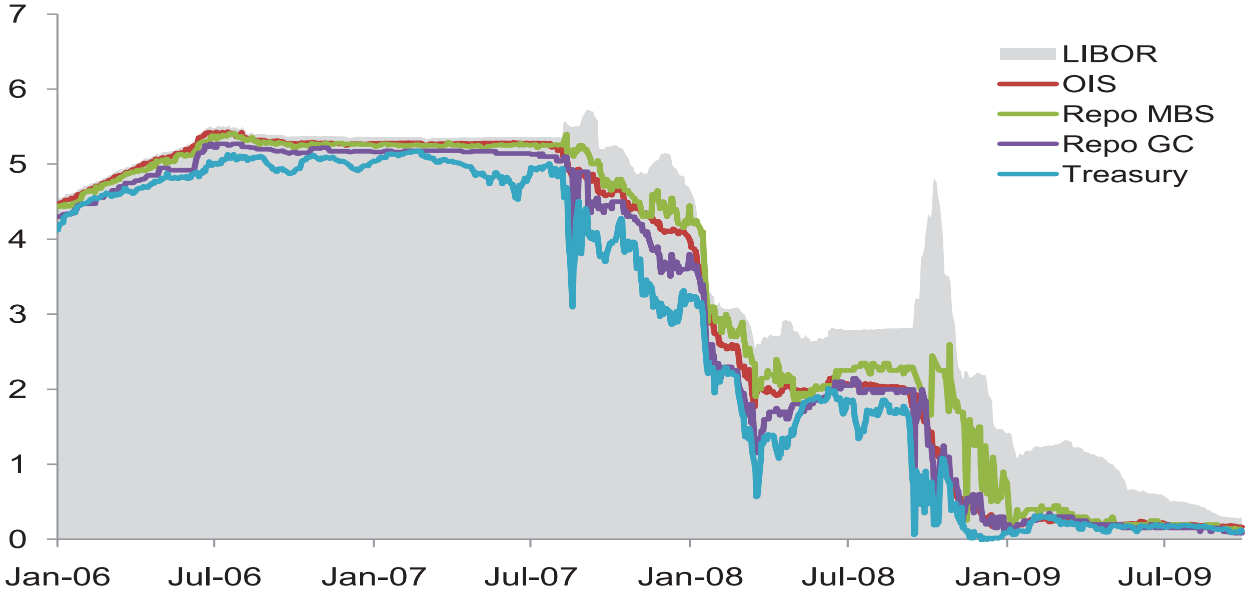
We provide some evidence on the correlation matrix of our various interest rate spread measures in Table 2.

3.6 Other Data Sources

We also collect the following variables:

[15] Note that there is also a small term premium component to that spread, since the repo is typically overnight and has to be rolled over.

Figure 4: The Time-series Evolution of various Interest Rates



Note: All interest rates are in the three-month maturity.

- The Volatility index (VIX) from the Chicago Board Options Exchange (CBOE): This index captures both expected volatility as well as a volatility risk-premium.

- Stock market index from the Center for Research in Security Prices (CRSP);

- The noise factor from Hu, Pan and Wang (2011): This measure captures the extent to which Treasury yields deviate from a smooth curve, and can be interpreted as an indirect measure of the availability of risk-capital, since in periods of easy access to capital, fixed income relative value strategies will be less costly to implement, and therefore fixed income convergence trades will be less abundant.

- Corporate bond trading volume from the Trade Reporting and Compliance Engine (TRACE). We will use this to build a measure of selling pressure. We refine this measure, when available, by making use of the 'sell' indicator, reflecting a seller initiated transaction.

- Primary dealer position in long-term corporate securities from the Federal Reserve Bank of New York. We use it as the proxy of deleveraging pressure in the bond market.

3.7 Summary Statistics

Table 1 presents summary statistics of the CDS-bond basis. The basis across all firms was slightly negative before the crisis, -3bps on average between 1/2/2006 to 6/30/2007, but fell to -21bps in the first phase of the financial crisis (7/1/2007 - 8/31/2008) and further fell to -171bps after the bankruptcy of Lehman Brothers (9/1/2008 - 9/30/2009). Meanwhile the volatility of the basis kept increasing for all types of firms, on average from 9bps before the crisis to 22bps and further to 46bps during the turmoil of the financial crisis.

Panel A also shows that firms with the IG rating share the same pattern as firms overall, whose bases become more and more negative and volatile as the financial crisis progresses. However, firms with HY ratings have strikingly different basis dynamics. Before the crisis these HY firms have positive bases, as high as 83 bps on average. These firms' bases began to narrow at the start of the subprime mortgage crisis in the summer of 2007, yet they were still positive on average and higher than the bases of IG firms in the first phase of the crisis. Only after the collapse of Lehman Brothers, did HY firms' bases plunge to an average -322 bps. Further the bases of HY firms is always much more volatile than those of IG firms.

Panel B provides additional evidence to the different basis patterns between IG and HY firms. We refine the rating to subcategories from AAA, AA to CCC and NR (no rating). Here each rating category includes both its + and - notch, for example, AA group contains firms with ratings of AA+, AA and AA-. We find consistent patterns as in Panel A that firms with lower credit rating tend to have more negative and more volatile bases, suggesting a monotonic relationship between a firm's rating and the discrepancy between the CDS and cash-bond credit spread of the same firm. However such a relationship only holds in the second phase of the crisis, i.e. after the Lehman Brothers failure.

The basis displays a right-skewed 'smile' from AAA to CCC during the pre-Lehman period.

Figure 1A and 1B provide an illustration of the basis dynamics for IG and HY firms respectively. The solid red line is the average CDS-bond basis for firms in each rating category, weighted by firms' market capitalization. In addition to echoing numbers in Table 1, these plots suggest that credit conditions for firms in both rating category, though improved, are still far below their pre-crisis levels. By the end of September 2009, the IG firms still had an average -140 bps basis and the HY firms a -170 bps basis. In contrast, the negativeness of libor-ois spread illustrated by the dotted blue line, had already come back to its pre-crisis level (12 bps on September 30, 2009 compared with 9 bps on January 3, 2006), indicating that the international bank financing system had significantly recovered by then.

In Panel A we also notice that financial firms have more negative and volatile bases than non-financial firms during the crisis. Such a pattern is well illustrated in Figure 3. Panel C reports detailed results for 14 sectors. Unlike the rating-categorized results in Panel B, we cannot find clear patterns across industry sectors except that (i) manufacturing firms tend to have positive CDS-bond basis before the crisis, (ii) the credit/financing sector was the most hit in the crisis with the largest discrepancy between CDS and the cash-bond spread, (iii) the leasing and manufacturing sectors have relatively small discrepancies in the crisis. Though no clear pattern emerges, Panel C provides strong evidence for the existence of heterogeneity across firms. To illustrate this further we select a few interesting examples.

3.8 Evidence on the Cross-sectional Variation in the Basis.

Garleanu and Pedersen (2011) make the point that haircuts are typically around 25% for IG firms (and very similar across firms rated from AAA-BBB) and of the order of 55% for HY bonds (rated BB or lower). In their model, to first order, the basis differential between IG and HY bonds should be equal to the difference between haircut margins multiplied by the collateral funding spread (i.e., the difference between the collateralized rate and the uncollateralized funding rate). While indeed an important plausible determinant of the basis, our data suggests that there may be additional important factors. Indeed, as clearly apparent from Panel B in Table 1 there is tremendous amount of variation in the basis within a credit-rating category, and certainly a lot of differences in the basis within the IG and the HY category.[16]

To illustrate this point even more dramatically, we present the basis in the following table for (twelve) firms which in our sample have positive basis for more than 100 days during post-Lehman Crisis II (9/1/2008 - 9/30/2009, with 271 days) period. These firms have diverse credit ratings, ranging from B (Las Vegas Sands Corp and Penn Natl Gaming Inc) to AAA (Berkshire Hathaway, and GE), and belong to six separate industries! This is clearly at variance with a model that would have a single factor, such as haircuts or margins, explaining the basis.[17] Clearly, the haircuts and margin requirement on Las Vegas Sands were much larger than for Berkshire bonds, and yet both display a positive basis (when the bulk of both IG and HY bonds displayed strongly negative bases at the time).

We will focus more systematically on the cross-sectional variation in the CDS-bond basis below. We begin by first investigating the time series determinants of the basis.

4 Time Series Determinants of the Average Basis

We seek to identify the main drivers of the basis during the crisis. We first analyze the time-series determinants of the average (IG and HY) basis during the crisis to uncover which factors had predictive impact on the basis. To that effect, we perform predictive regressions of the average (equity market cap weighted) basis of all firms, and of only IG and HY firms respectively. The candidate explanatory

[16]Overtime there is also a lot of variation in the basis in a way that cannot solely be explained by the variation in the collateral funding spread, and as we argue below is unlikely to be explained solely by changes in haircuts, though the latter are not directly observable.

[17]Indeed, Garleanu and Pedersen (2011)'s general model predicts that other factors (such as the covariance of the underlying cash-flows with aggregate consumption) in addition to the margin differential should predict the difference in the basis. It is only for the specific application to the CDS basis that they focus on the margin difference. Our data suggests it is important to look for additional factors.

ShortName	Crisis I	Crisis II	Credit Rating	Industry
Newmont Mng Corp	286	250	BBB	Basic Materials
Berkshire Hathaway	127	244	AAA	Financials
Amern Tower Corp	237	226	BB	Technology
Emc Corp	259	188	BBB	Technology
MetLife Insurance Co	12	178	A	Financials
Boyd Gaming Corp	253	163	BB	Consumer Services
General Electric Co	89	154	AAA	Industrials
Windstream Corp	54	131	BB	Telecommunications
Penn Natl Gaming Inc	134	130	B	Consumer Services
Mylan Inc	204	122	BB	Health Care
AutoNation Inc	1	117	BB	Consumer Services
Las Vegas Sands Corp	108	106	B	Consumer Services

Note: Ratings are based on September 2008.

variables (Z_t) include

1. the 5-year CDS spread of the primary dealer index, where the constituent primary dealers are banks and security broker-dealers that trade in the U.S. government securities with the Federal Reserve System.
2. the stock return of the primary dealer index,[18]
3. the CBOE volatility index,
4. the primary dealers' position in corporate bonds with remaining maturity larger than one year,
5. the 3-month libor-ois spread,
6. the 3-month repo-Tbill spread,
7. the 3-month repo spread between MBS collateral and Treasury collateral,
8. the 3-month ois-repo spread,

[18] A current list of primary dealers can be found at the Federal Reserve Bank's website: http://www.newyorkfed.org/markets/primarydealers.html.

9. the noise factor for illiquidity in Hu, Pan and Wang (2010).

We test the impact of contemporaneous and up to three biweekly lagged explanatory variables in the following regression:

$$\Delta \text{Basis}_t^J = \alpha_0 \Delta Z_t + \alpha_1 \Delta Z_{t-1} + \alpha_2 \Delta Z_{t-2} + \alpha_2 \Delta Z_{t-3} + \varepsilon_t, \qquad J \in \{All, IG, HY\}$$

The results are reported in Table 3. The t-statistics are reported in the parentheses and estimated using Newey-West standard errors with a lag of two. The data are biweekly spanning from January 2006 to September 2009. We then investigate a more succinct multi-variate model by selecting different predictors from our previous univariate regressions investigation, to see how robust these initial results are. The results of the multi-variate regressions are given in Table 4.

4.1 Results

We find that important predictors are related to funding costs (and counterparty risk) of financial intermediaries in the sense that an increase in financial intermediaries funding costs (as measured by libor-ois or primary dealer CDS) leads to a more negative average basis. But, interestingly, we find significant differences in the time series behavior of IG and HY basis. Specifically, deleveraging as measured by the change in the bond position of primary dealers (PD) mainly affected the HY basis (a lower PD-bond position lowers the HY-basis). For the IG basis, a more important determinant was the collateral-quality-funding spread as measured by the difference in repo rates using MBS versus Treasury as collateral. The wider the spread the more negative the basis. This suggests that the level of the individual bond basis may depend in a complex manner on individual characteristics such as risk, collateral quality, and aggregate market conditions such as dealers' financial health, availability of collateralized and uncollateralized funding, and selling pressure.

5 Cross Sectional Determinants of Individual Firm Basis

We now investigate the cross-sectional variation in the bond basis, by first constructing individual measures of exposure to funding cost risk, collateral quality, market risk, and countparty risk. Then we run cross-sectional Fama-McBeth style regression of the basis on these beta measures.

5.1 Constructing Measures of Risk Exposures

5.1.1 Counterparty Risk

Counterparty risk is the risk that the seller of protection, typically an investment bank, cannot make good on its commitment to the protection buyer in case of default. Counterparty risk should therefore make the insurance less valuable and lower the CDS spread, possibly contributing to the negative basis. As explained previously, counterparty risk is bigger, the higher the correlation between the default events of the underlying entity and the protection seller.[19] The challenge is how to measure the correlation between the default risk of the underlying name and the counterparty selling the protection.

The CDS market is over-the-counter and the exact nature of counterparties is not known. Further, the process of netting makes it difficult to establish an aggregate measure of counterparty risk for individual reference entity.[20] Instead, we construct a counterparty risk measure for a representative CDS issuer using the list of primary dealers designated by the Federal Reserve Bank of New York. These

[19] That counterparty risk is not irrelevant, can be seen from the Lehman Brothers experience. Suppose an investor had bought protection on Washington Mutual from Lehman Brothers. Washington Mutual defaulted only a few days after Lehman. Without marking to market, the investor would be a regular claimant in bankruptcy for the protection purchased from Lehman, leading to at best a partial loss. Of course, if ISDA agreements were well enforced, and provided the investor had negotiated full-two-way mark to market with Lehman, then the risk would be further mitigated. However, in practice, it is likely that most funds would have ended with a at least some partial loss as a result of this double default.

[20] In September 2008 the bankruptcy of Lehman Brothers caused almost $400 billion to become payable to the buyers of CDS protection referenced against the insolvent bank. However the net amount that changed hands was around $7.2 billion This difference is due to the process of “netting”. Market participants cooperated so that CDS sellers were allowed to deduct from their payouts the funds due to them from their hedging positions. Dealers generally attempt to remain risk-neutral so that their losses and gains after big events will on the whole offset each other.

primary dealers are banks and security broker-dealers that trade in the U.S. government securities with the Federal Reserve System. To become qualified as a primary dealer, a firm must be in compliance with capital standards under the Basel Capital Accord, with at least $100 million of Tier I capital for a bank or above $50 million of regulatory capital for a broker-dealer. As trading partners of the central bank, these primary dealers often are the biggest and most competitive financial institutions who happen to be dominant issuers of credit default swap contracts. As of September 2008, there were 19 primary dealers such as Citigroup, Goldman, J.P. Morgan Chase and Morgan Stanley. The list changes over time since some primary dealers may fail to meet required capital standards. Accordingly, we update the components of the primary dealer index. For example, the index includes Lehman Brothers' Holdings before its bankruptcy on September 15, 2008, but exclude it afterwards and adds Nomura Securities International, Inc. starting from July 27, 2009.

For the primary dealer index, we calculate its stock return (R_{index})and CDS spread (CDS^{index}) weighted by each constituent's market capitalization. Appendix B lists the current component in our primary dealer index. We then measure an underlying entity's counterparty risk as the beta coefficient of its stock return (R_i) with respect to the primary dealer index stock return (R_{index}) :

$$\beta_{i,cp} = \frac{cov(R_i, (R_{index} - R_{mkt}))}{var(R_{index} - R_{mkt})} \tag{2}$$

or by the beta coefficient of the one-day change in the CDS spread (ΔCDS_i) on change in the primary dealer CDS index (ΔCDS_{index}):

$$\beta_{i,cp} = \frac{cov(\Delta CDS_i, \Delta CDS_{index})}{var(\Delta CDS_{index})} \tag{3}$$

The higher the β_{cp} the larger the likelihood of a joint default and the less valuable we expect the protection to be when purchased from that counterparty. So we expect a negative coefficient in the cross-sectional regression of bases on counterparty betas.

5.1.2 Funding Cost Risk

For an arbitrageur entering a basis trade, the risk is that the basis becomes more negative at the same time as her funding costs widen. So a measure of the funding cost risk should be obtained from the regression coefficient of the change in the basis on a measure of the change in funding costs. We consider several measures of funding costs. The libor-ois spread which proxies at least partially for the uncollateralized funding cost of financial intermediaries (unfortunately it also contains a credit risk component). Alternative measures of funding cost that we also considered is the ois-repoGC spread and the repoMBS-repoTsy, which as we describe previously measures respectively the 'collateral spreads' and the 'collateral quality spreads'. We report the results with only libor-ois beta in the current paper, since we found the others to be highly correlated. (see table 2 for the correlation).

We thus measure an underlying entity's funding cost risk as the regression coefficient of credit default spread changes on changes in the libor-ois spread:[21]

$$\beta_f^i = \frac{cov(\Delta CDS_i, \Delta(libor - ois))}{var(\Delta(libor - ois))} \tag{4}$$

The higher the funding cost beta, the less aggressively an arbitrageur would invest in that basis trade, as the basis will become more negative in trades where his funding cost increases. So we expect a negative coefficient in the cross-sectional regression the basis of firm i on their funding cost beta.

A caveat on the libor-ois spread is that this spread contains not only liquidity risk but also financial intermediary credit (and therefore counterparty) risk during the financial crisis of 2007-2009. This effect will go in the same direction for the expected coefficient.

[21] We also considered to construct the beta by regressing the change in the basis on the change in the libor-ois spread. Since our betas are estimated from daily data, using the cleaner CDS data seems preferable. This is also partially justified, by the fact that most price discovery occurs in the CDS market, as we document in the next section.

5.1.3 Liquidity Risk

We also include a measure of liquidity risk, the repo spread, which is calculated as the 3-month general collateral repo rate minus the 3-month Treasury bill. The difference between these two rates reflects a flight-to-quality liquidity component as we discussed above. Our estimate of the liquidity risk beta is therefore:

$$\beta_l^i = \frac{cov(\Delta CDS^i, \Delta repospread)}{var(\Delta repospread)} \tag{5}$$

The higher the liquidity beta, the less aggressively an arbitrageur would invest in that basis trade, since the basis will become more negative in states where liquidity becomes more valuable. So we expect a negative coefficient in the cross-sectional regression of the bases on liquidity betas.

5.1.4 Collateral Quality

A fourth risk factor that affects the CDS-bond basis is the quality of bonds issued by the reference entity in a CDS contract. To do the negative basis trade, an arbitrageur needs to buy bonds which are funded via the repo market using the same bonds as collateral. The haircut imposed on that transaction reduces the amount of leverage available to the arbitrageur. Higher hair-cuts imply higher funding costs and therefore less profitable basis trade. All else equal we expect bonds with higher haircuts to have more negative basis. We also expect bonds whose haircuts are more likely to increase in the future to be less attractive for a basis trade. Unfortunately, haircuts are not observed for individual bonds. Instead, we build a collateral quality index, from firm characteristics that is likely correlated (in cross-section) with lower contemporaneous and future expected haircuts.

Specifically, we expect a firm with more total assets, more tangible assets, higher rating, lower leverage, lower credit default swap spread, lower CDS volatility, to have bonds with higher collateral quality.[22] Therefore, for each firm we construct a collateral index in the similar way as Altman's Z-score (Altman (1968)). For each phase (Before Crisis, Crisis I and Crisis II), we collect and calculate

[22]See also Ashcraft and Santos (2009).

firms' size(+), leverage(-), tangible ratio(+), rating(+), average CDS spread(-) and CDS volatility(-), standardize them cross-sectionally and add up the values according to the sign in the parentheses. The resulting value defines our collateral index which reflects the collateral quality of bonds for each reference entity.

The lower the collateral quality, the less profitable a basis trade is, measured per unit of expected risk-capital usage. Indeed, we view collateral quality as a measure of the current (and expected future) level of the haircut, with higher collateral quality meaning lower current and expected future haircut. Thus, the lower the collateral quality the more negative the basis to equalize expected returns on a per unit of risk-capital basis. So we expect a positive coefficient in cross-sectional regressions of the basis of firm i on its collateral quality.

5.1.5 Additional Controls

It may be useful to add other factors in the cross-sectional regression to control for other sources of risk that might affect how an arbitrageur would allocate risk capital to the basis trade. The obvious candidate, in a CAPM spirit, is a 'market beta' factor, a proxy for how the particular basis covaries with the arbitrageur's portfolio. We tried two definitions of market beta: a standard beta defined with respect to the equity market and a beta defined with respect to the CDS market (depending on whether the arbitrageur holds a diversified portfolio or is specialized in fixed income markets, either could be relevant). The results below are presented using the equity market beta as a control, since we found little difference between the two and, in fact, the equity market factor seemed marginally more significant.

5.2 Empirical Results

We study the cross-sectional determination of the CDS-bond basis with the following regression:

$$Basis^i = \alpha^i + \gamma_{cp}\beta^i_{cp} + \gamma_f\beta^i_f + \gamma_l\beta^i_l + \gamma_{coll}\text{Collateral}^i + \gamma_k\beta^i_{Controls} + \epsilon_i \tag{6}$$

Table 6 shows the correlation between various estimated betas. Since some of them display fairly high correlation, we present different specifications of the multivariate regression. This table is also to bear in mind when we seek to interpret the results economically. Obviously, the correlation makes these interpretations somewhat ambiguous.

In Table 7 we present several specifications of the multivariate cross-sectional regressions of individual firm bases on proxies for counterparty risk, funding cost risk, liquidity risk and collateral quality.

The full sample regressions presented in Panel A show that for the whole sample, all coefficients are statistically significant, and most have the expected signs: negative for counterparty risk, negative for funding cost risk, and positive for collateral quality. Unexpectedly the liquidity beta comes in with a positive sign. However, focusing on subsamples and subsets of investment-grade or high-yield firms, we see that the picture is somewhat more complex. Before the crisis, and during the early part of the crisis, the explanatory power of the regressions (measure by adjusted R^2) is fairly low (typically less than 5 percent). It becomes much higher during the post-Lehman Crisis II phase: The R^2 are around 20 percent for HY firms and 10 percent for IG firms. The main (statistically and economically significant) drivers of IG firms basis during the Crisis II period are counterparty risk and flight to quality risk, both entering with a negative sign, and also significant but smaller in magnitude the collateral quality variable entering with the positive sign. Instead, funding cost is not statistically significant. On the other hand for HY firms during the Crisis II period, we find that the most important variables (statistically and economically) are counterparty risk, collateral quality, and funding risk. Now, liquidity risk is not statistically significant (even though it enters with the expected 'negative' sign).

Figure 6 shows the time series of the dynamic γ_j coefficients in the Fama-Macbeth regressions. We see that counterparty risk becomes significant in the second half of 2008 and in the first quarter of 2009. Interestingly these two periods correspond precisely to the bankruptcy filing for Lehman Brothers Inc.(September 2008) and the stock market hitting bottom (March 2009) respectively. Outside these periods, the cross-sectional regressions do not find significant coefficient loading on the counterparty risk beta. Funding cost risk as measured by the libor-ois spread becomes statistically and economically most significant during the post-Lehman period, achieving its largest negative loading in March 2009. Similarly, collateral quality matters most during this post-Lehman period.

The graph refines our understanding of why the regression on flight-to-liquidity risk as measured by the GCRepo-TBill spread is not of the expected 'negative' sign unconditionally. During the crisis II phase it becomes statistically significant (negative) only during the two short periods of the second half of 2008 and March 2009. However, before that (during 2007-2008) it tends to have a positive loading.

Figure 7 shows a 'naive'[23] variance decomposition of the cross-sectional variance in the basis explained by each beta. The picture is interesting because it provides again a richer perspective than the unconditional results. In particular, we see that the flight-to-liquidity beta, while in general only a minor component of the cross-sectional variation, became very important relative to the other factors during the second half of 2008 at the same time when it became statistically significantly negative. We also see that during the early part (Crisis I) the main explanatory power comes from funding cost risk and counterparty risk, whereas in the post Lehman phase, funding cost risk and collateral quality become dominant and the role of counterparty risk diminishes.

Of course, there is a general caveat with the interpretation we provide for our results, since it is

[23]We decompose the total explained variance into separate components explained by individual regressors, but ignoring the correlation between them.

difficult to account for the endogenous correlation between the various risk-factors we have labeled funding cost risk, market liquidity, counterparty risk and collateral quality. For example, what we have interpreted as funding cost risk could be due to counterparty risk, as libor-ois also reflects bank credit risk.[24]

Overall, the empirical model is reasonably successful at explaining cross-sectional variation in the basis during the post-Lehman phase. Our main results are that unconditionally all four types of risk measures are statistically significant in explaining the cross-sectional variation in the basis, as one would expect if the marginal investor were a leveraged hedge-fund trading off risk and return when allocating scarce risk-capital to these different basis-investment opportunities. Further, we find that these betas become economically more important after the Lehman bankruptcy. Interestingly, we find that IG and HY basis behave quite differently, with the former more driven by our proxies for counterparty risk and flight to quality and the latter more by counterparty risk funding costs and collateral quality.

6 Evidence on Deleveraging and Limits to Arbitrage.

As mentioned in the introduction, there was substantial discussion in the popular press and also some empirical evidence (see Figure 2) that financial institutions were forced to off-load risky assets to reduce their leverage, resulting in fire-sale prices for risky bonds. Combined with limits to arbitrage, one would expect to see significant drops in bond prices as a result of the price pressure and only a slow lagged reaction of the CDS spread as arbitrageurs step in and equilibrate markets. Our time-series regression suggest that deleveraging may have played a role for the average basis of HY firms. To further test this hypothesis we perform two additional experiments.

First, we look at the average level and the range of the post-crisis individual bond trading volume

[24]If unwilling to give an economic interpretation to the variables, then at a minimum, our results provide an interesting statistical description of the cross-sectional determinants of the basis in terms of observable covariates.

(relative to its pre-crisis level). We find that only for HY bonds is this measure statistically significant in explaining the bond basis (confirming our time-series result for the average basis). Second, we investigate lead-lag effects between price-discovery in the CDS and bond market, following Blanco, Brennan and Marsh (2005). One would expect that if deleveraging was a big factor for the basis, then bond spreads would lead CDS, and more so for bonds with higher price pressure, and more risk.[25] Indeed, we find that the share of price-discovery occurring in the CDS market falls significantly during the crisis. The drop is much more significant during the post-Lehman phase and more pronounced for HY firms. For the latter the share falls even below 50% indicating that by that metric bond price innovations lead the CDS market and thereby lending some support to the deleveraging story for the HY market.

6.1 Price Pressure in Bond Market

To test whether bond selling pressure is one determinant of the CDS-bond basis, we use bond volume percentage change as a proxy of bond selling pressure. For each firm in the sample we first calculate its average monthly dollar trading volume in the before-crisis period as the benchmark. We then record the average monthly dollar volume in the post-Lehman period.[26] The bond selling pressure is then approximated by the percentage change in volume with respect to the pre-crisis level. Here we use average monthly volume in order to reduce the noise in the daily bond volume measure. Further, we construct another bond selling pressure measure by using the volatility of trading volume change.

We report our test results for the impact of deleveraging in Table 8. This table shows the influence of the change of bond trading volume on the change of basis between the post-Lehman period and the

[25] Instead, if counterparty risk was driving the basis, then we would expect only the CDS component to be affected with not much effect on price discovery across markets.

[26] An accurate measure should use bond trading volume indicated as *Sell*. However, the buy/sell indicator only becomes available since the late 2008 in the TRACE dataset. We do a robustness check using bond trading volume indexed as sell for a much shorter sample period and find similar impact compared with the result using bond trading volume without a sell indicator.

before-crisis period, using the following regression:

$$\Delta Basis_i^J = \beta_1(\frac{\Delta Vol}{Vol})_i^J + \beta_2(\frac{\Delta(High - Low)}{Mean})_i^J + \varepsilon_i^J, \quad J \in [IG, HY, Fin, NF], \tag{7}$$

where $\Delta Basis \equiv Basis_2 - Basis_0$; $\Delta Vol/Vol \equiv (Vol_2 - Vol_0)/Vol_0$ is the percentage change of corporate bond trading volume; *High* is the maximum monthly trading volume in a specific phase, and *Low* is the minimum monthly trading volume in the same phase, *Mean* is the average monthly volume in the same phase. The second independent variable is a measure of the volatility of trading volume change. Our intuition is that a very wide volume range may be a better proxy of price pressure during the period than simply a change in average volume (though admittedly both are crude). The subscript '2' refers to the post-Lehman phase (9/1/2008 - 9/30/2009) and the subscript '0' refers to the before-crisis phase (1/2/2006 - 6/30/2007). We observe negative regression coefficients for the volume percentage change consistently across all types of firms. However none of them is statistically significant at the 10% critical value. We also observe consistent negative coefficients for trading volume range, and find statistical significance for HY as well as non-financial firms. Overall, the explanatory power of volume change and its volatility is marginally small in explaining the change of the basis. The highest R-square is six percent.

Overall these results offer little evidence of the price pressure hypothesis driving the basis of investmeng-grade or financial firms. There is marginal evidence that deleveraging might have contributed to the negative basis for high-yield and non-financial firms, which is consistent with our time-series regression results. We turn to lead-lag price-discovery for additional evidence next.

6.2 Price Discovery across Markets

Another channel to explore the determinant of CDS and cash-bond arbitrage is to evaluate the information content in each market and to study which market provides more timely information over various phases of the crisis. In line with Blanco, Brennan and Marsh (2005), we test the CDS market's contribution to price discovery in the following vector error-correction models:[27]

$$\begin{aligned}
\Delta CDS_t &= \lambda_1(CDS_{t-1} - PECDS_{t-1}) + \beta_1 \sum_{i=1}^{p} \Delta CDS_{t-i} + \gamma_1 \sum_{i=1}^{p} \Delta PECDS_{t-i} + \varepsilon_{1,t} \\
\Delta PECDS_t &= \lambda_2(CDS_{t-1} - PECDS_{t-1}) + \beta_2 \sum_{i=1}^{p} \Delta CDS_{t-i} + \gamma_2 \sum_{i=1}^{p} \Delta PECDS_{t-i} + \varepsilon_{2,t} \qquad (8)
\end{aligned}$$

where $PECDS$ is the par-equivalent CDS calculated in section 2.

The contribution of the CDS market to the price discovery of common credit risk is defined by the permanent factor in Gonzalo and Granger (1995). [28] The Gonzalo and Granger measure ignores the correlation between the two markets and attributes superior price discovery to the market that adjusts the least to price movements in the other market, defined as

$$GG = \frac{\lambda_2}{\lambda_2 - \lambda_1}, \qquad (9)$$

where the λ coefficients reveal which of the two market leads in price discovery.

We do the price discovery test for each firm and summarize the mean, median, and standard error in Table 9 for all firms, investment-grade, high-yield, financial, and non-financial firms during each phase of the financial crisis, – Pre-Crisis (1/2/2006 - 6/30/2007), Crisis I (7/1/2007 - 8/30/2008), and Crisis II (9/1/2008 - 9/30/2009). In addition to confirming the previous results in the literature that the CDS market leads the bond market (indicated by a GG factor larger than 50%), we also find that the information content captured by the CDS spread is almost monotonically declining as the financial crisis worsens. When averaged across all firms, the CDS market contribution reduces from 92% before the crisis to 74% in the post-Lehman period. Similarly, the CDS market contribution drops 5% for investment-grade firms, 80% for high-yield firms, 18% for non-financial firms, and 16% for financial firms.

[27] Blanco, Brennan, and Marsh (2005) adopt a general form for the error term, allowing for flexible cointegration relationship. In our case, PECDS is designed to match CDS and hence their difference, the basis, is a more direct and accurate measure of the error term.

[28] We have also calculated alternative measure using Hasbrouck "information share." Given that Hasbrouck's approach can only provide upper and lower bounds on the information shares of each market, it is not suitable to report the evolution of information content over the phases of the crisis. The range of lower and upper bounds are not small and overlapping across phases, making it hard to distinguish the nuance over time.

Summarizing, we find that the share of price-discovery occurring in the CDS market falls significantly during the crisis. The drop is much more significant during the post-Lehman phase and more pronounced for HY firms. For the latter the share falls even below 50% indicating that by that metric bond price innovations lead the CDS market and thereby supports the deleveraging story for high-yield bonds.

7 Conclusion

We have analyzed the cross-sectional variation in the CDS-bond basis during the crisis. Focusing on the cross section of the CDS-bond basis is interesting as it provides a natural testing ground for the literature that models 'limits to arbitrage,' and specifically the behavior of arbitrageurs with limited capital facing multiple 'arbitrage' opportunities (Gromb and Vayanos (2010)). We find that, especially during the post-Lehman phase, some risk-factors can 'explain' the basis (in Fama-MacBeth-style regressions). Factors, which we interpret as proxying for counterparty risk, collateral quality, and funding risk have significant impact on the cross-sectional differences in the levels of the basis for high-yield firms. Instead, for investment-grade firms, the overall explanatory power of the regressions is lower. We find that the IG-basis are mostly driven by counterparty and flight to quality risk. Further analysis of the relation between the basis and bond trading volume, and of cross-market price-innovations gives some support to the widespread story that deleveraging of corporate bonds led to significant price 'concessions' in HY-bonds, not matched by contemporaneous increases in CDS spreads. We find that the previously documented result that the CDS market tends to lead the bond market (Blanco-Brennan and Marsh) changed dramatically during the crisis, especially for HY bonds. These results seem at least qualitatively consistent with some of the implications of the 'limits to arbitrage' literature. Much work remains to be done to test these more formally.

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A The Par-Equivalent CDS Methodology

We present the Par Equivalent CDS methodology developed by J.P. Morgan to calculate the CDS-bond basis in Section 2. This survival-based valuation approach provides an apple-to-apple measure across the cash-bond spread and the credit default swap spread.

The fair value of the coupon on a CDS is set so that the expected present value of the premium leg is equal to the expected present value of the contingent payment (see Duffie (1999)). Assuming that we have a zero-coupon discount curve $Z(t)$ extracted from swap spreads and assuming a constant intensity survival probability $S(t)$, the expected present value of the premium leg is given by:

$$\mathrm{PV}_{premium}(C) = \sum_{i=1}^{n} Z(t_i)S(t_i)\, C * dt + \sum_{i=1}^{n} Z(\frac{t_i + t_{i-1}}{2})[S(t_{i-1}) - S(t_i)]\, C * dt/2, \tag{10}$$

where the second component is the present value of the accrued interest upon default (assumed to occur halfway between t_{i-1} and t_i). The expected present value of the contingent leg is:

$$\mathrm{PV}_{contingent} = (1-R)\sum_{i=1}^{n} Z(\frac{t_i + t_{i-1}}{2})[S(t_{i-1}) - S(t_i)], \tag{11}$$

where R stands for the recovery rate. The fair credit default swap spread is the number C that sets

$$\mathrm{PV}_{premium}(C) = \mathrm{PV}_{contingent} \tag{12}$$

The par-equivalent CDS uses the market price of a bond to calculate a spread based on CDS-implied default probabilities. First, we need to get a CDS-implied default probability curve. We plug in the market CDS price with 3-month maturity ($C_{0.25}$) to get the 3-month survival probability, $S_{0.25}$. Then we plug in the CDS price with 6-month maturity ($C_{0.5}$) and the calculated 3-month survival probability ($S_{0.25}$) to get the 6-month survival probability, $S_{0.5}$. Sequentially plugging in CDS spread with longer maturity from 1-year to 10-year, we can get a curve of the survival probability $S_{CDS}(t_i)$.

Second we need to get a bond-implied survival probability curve $S_{bond}(t_i)$. Using the CDS-implied survival probability as a prior, we calculate the bond-implied survival probability curve as the one that minimize the pricing error between the market price and derived bond price:

$$S_{bond}(t_i) = S_{CDS}(t_i) + \varepsilon. \tag{13}$$

s.t.

$$\varepsilon = \arg\min \left(PV(S_{bond}) - \text{Market Price of Bond}\right)^2. \tag{14}$$

Then the bond-implied CDS spread term structure is defined by substituting the survival probability term structure fitted from bond prices, $S_{bond}(t)$, into the following equation for par equivalent CDS spreads, denoted as PECDS:

$$PECDS = \frac{(1-R)\sum_{i=1}^{n} Z(\frac{t_i+t_{i-1}}{2})[S_{bond}(t_{i-1}) - S_{bond}(t_i)]}{\sum_{i=1}^{n} \left[Z(t_i)S_{bond}(t_i) \ * dt + Z(\frac{t_i+t_{i-1}}{2})[S_{bond}(t_{i-1}) - S_{bond}(t_i)] \ * \frac{dt}{2}\right]} \tag{15}$$

B The Primary Dealers List

Effective since July 27, 2009. The list is downloaded from the website of the Federal Reserve Bank of New York: `http://www.newyorkfed.org/markets/pridealers_current.html`.

BNP Paribas Securities Corp.

Banc of America Securities LLC

Barclays Capital Inc.

Cantor Fitzgerald & Co.

Citigroup Global Markets Inc.

Credit Suisse Securities (USA) LLC

Daiwa Securities America Inc.

Deutsche Bank Securities Inc.

Goldman, Sachs & Co.

HSBC Securities (USA) Inc.

Jefferies & Company, Inc.

J. P. Morgan Securities Inc.

Mizuho Securities USA Inc.

Morgan Stanley & Co. Incorporated

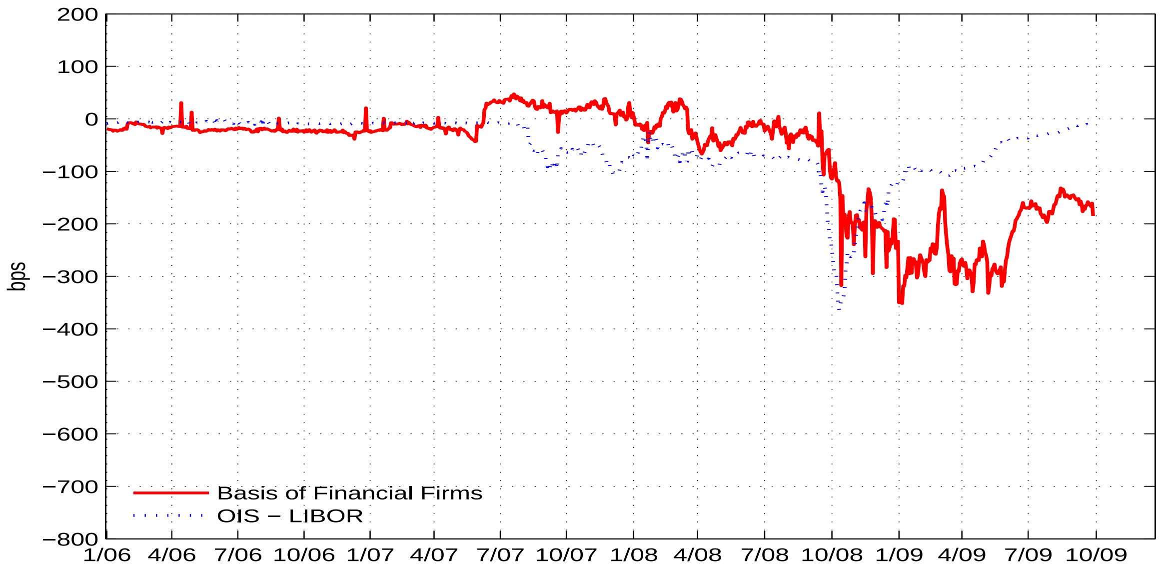
Nomura Securities International, Inc.

RBC Capital Markets Corporation

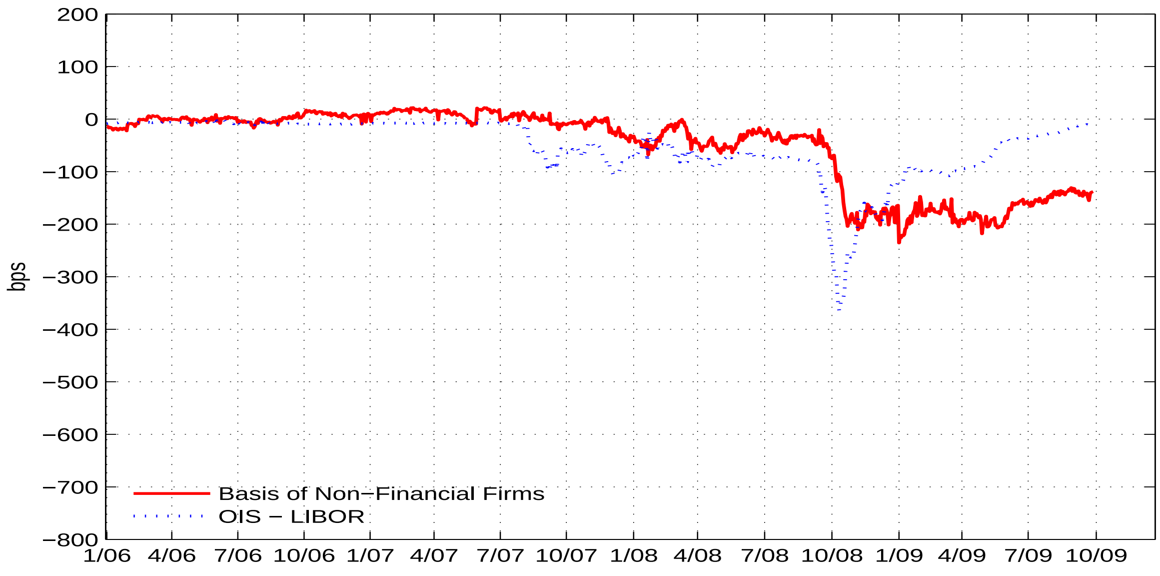
RBS Securities Inc.

UBS Securities LLC.

Figure 5: A. The CDS-Bond Basis of Financial Firms vs OIS-LIBOR spreads



B. The CDS-Bond Basis of Non-Financial Firms vs OIS-LIBOR spreads



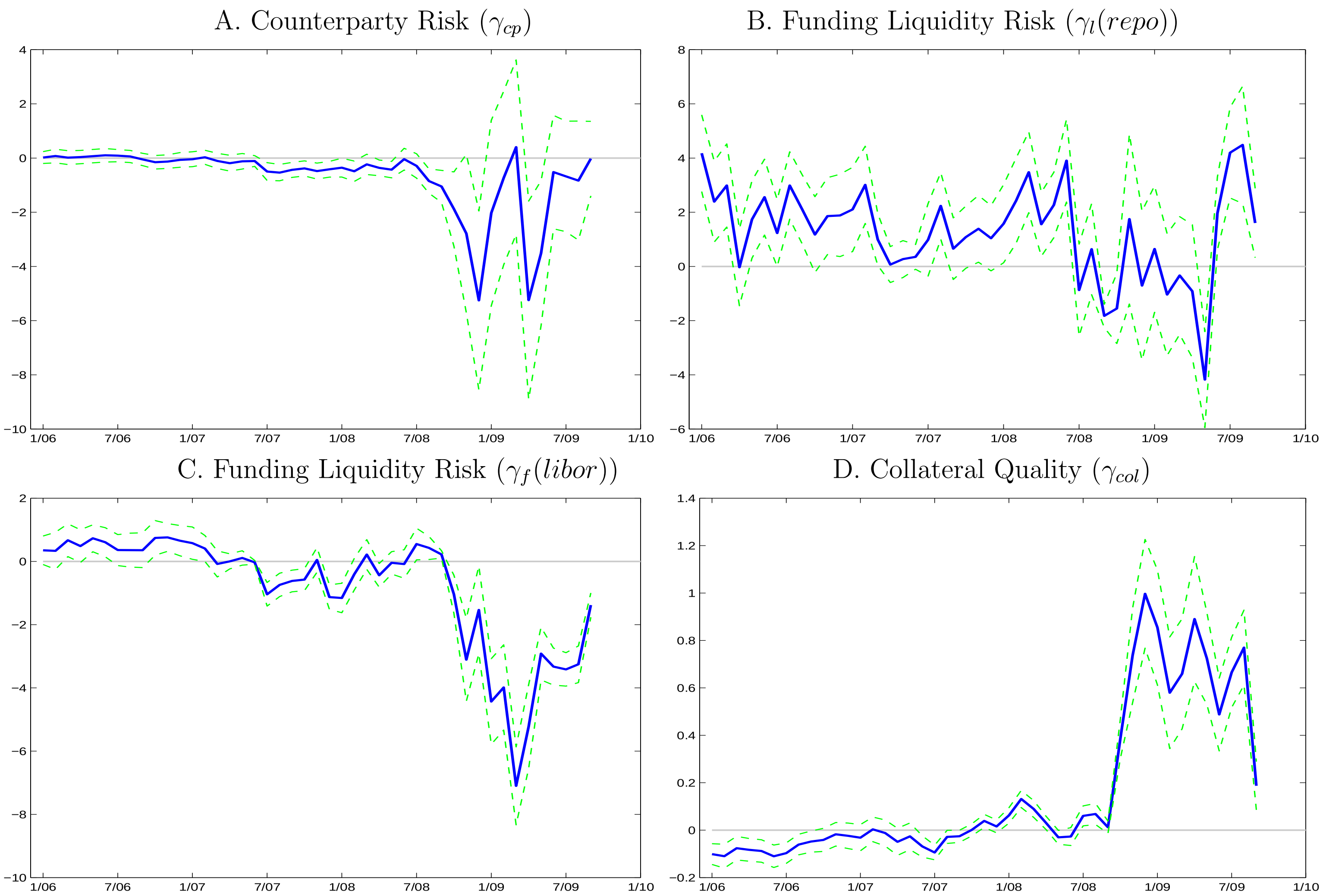


Figure 6: Dynamic Coefficients in the Cross-Sectional Regression: $Basis_t^i = \gamma_{t,cp}\beta_{cp}^i + \gamma_{t,l}(repo)\beta_l^i + \gamma_{t,f}(libor)\beta_f^i \gamma_{t,coll}\text{Collateral}^i + \gamma_k \beta_{control}^i + \varepsilon_t^i$, where β_l^i is measured by the change of the repo spread (3m repo rate with general collateral of Treasury bill minus the 3m Treasury bill rate) and β_f^i is measured by the change of the libor-ois spread.

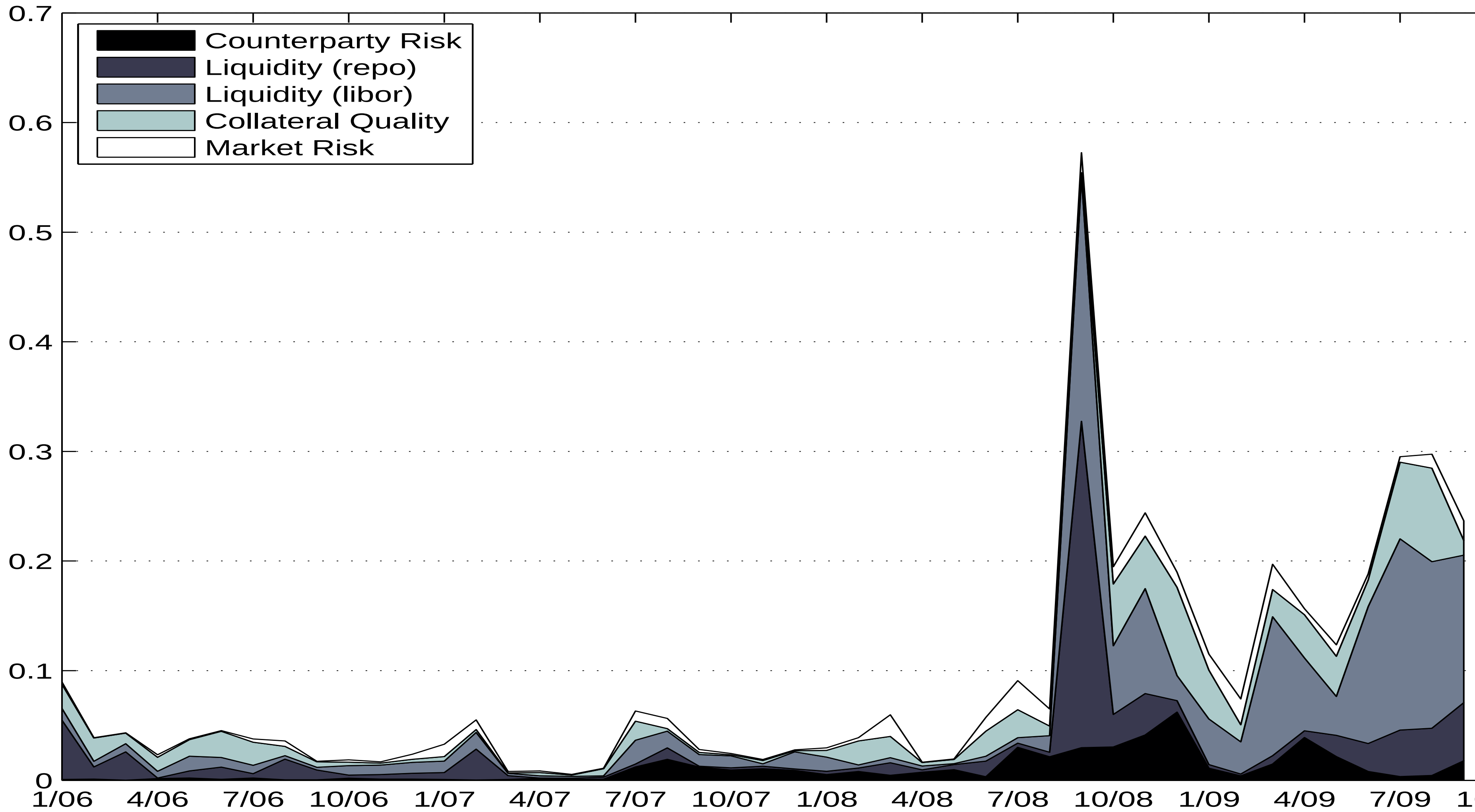


Figure 7: Dynamics of Variance Decomposition in the Cross-Sectional Regression: $Basis_t^i = \gamma_{t,cp}\beta_{cp}^i + \gamma_{t,l}(repo)\beta_l^i + \gamma_{t,f}(libor)\beta_f^i + \gamma_{t,coll}\text{Collateral}^i + \gamma_k\beta_{control}^i + \varepsilon_t^i$, where β_l^i is measured by the change of the repo spread (3m repo rate with general collateral of Treasury bill minus the 3m Treasury bill rate) and β_f^i is measured by the change of the libor-ois spread.

Table 1: **Summary Statistics of Discrepancies in CDS and Cash Bond Markets**

This table provides descriptive statistics for the CDS-bond basis in three phases: Phase 1 is the period before the subprime credit crisis, named "Before Crisis" (1/2/2006 - 6/30/2007), Phase 2 is the period between the subprime credit crisis and the bankruptcy of Lehman Brothers, called "Crisis I" (7/1/2007 - 8/31/2008), and Phase 3 is the period after Lehman Brothers' failure, called "Crisis II" (9/1/2008 - 9/30/2009). The basis is calculated as the difference between the CDS spread and the par-equivalent corporate bond spread, using the methodology in Appendix A. Panel A presents the average results across investmeng-grade and high-yield firms, financial and non-financial firms; Panel B provides further results according to firm credit rating; and Panel C reports the results by firm's industry sector. All numbers are in basis points.

Panel A

		All	IG	HY	Financial	Non-Financial
Before Crisis	Mean	-3	-7	83	-17	4
(T=375 days)	Std.Err	9	8	30	12	10
	Min	-22	-26	-9	-43	-23
	Max	29	19	163	36	22
Crisis I	Mean	-21	-27	11	-2	-24
(T=295 days)	Std.Err	22	19	53	28	20
	Min	-66	-69	-110	-67	-68
	Max	20	6	136	47	15
Crisis II	Mean	-171	-165	-322	-206	-161
(T=271 days)	Std.Err	46	44	136	73	43
	Min	-258	-252	-653	-352	-236
	Max	-17	-17	-28	11	-20

Panel B: By Credit Rating

		IG				HY			
		AAA	AA	A	BBB	BB	B	CCC	NR
Before Crisis	Mean	-20	18	-7	-31	17	170	440	-17
(1/2/2006 - 6/30/2007)	Std Err.	11	18	10	13	32	54	271	26
	Min	-54	-28	-49	-47	-27	-26	156	-58
	Max	3	68	15	31	100	285	1211	105
Crisis I	Mean	3	4	-35	-50	-22	36	436	32
(7/1/2007 - 8/31/2008)	Std Err.	20	21	17	34	41	91	314	55
	Min	-58	-50	-80	-124	-110	-109	-334	-77
	Max	44	43	-4	8	75	232	1232	135
Crisis II	Mean	14	-83	-176	-267	-262	-431	-1315	-96
(9/1/2008 - 9/30/2009)	Std Err.	47	29	53	76	116	238	1596	260
	Min	-87	-168	-263	-406	-754	-1244	-6099	-289
	Max	188	-11	-1	-87	-41	-3	746	871

Panel C: By Industry Sector

	Before Crisis				Crisis I				Crisis II			
	Mean	Std	Min	Max	Mean	Std	Min	Max	Mean	Std	Min	Max
Industrial Firms												
Manufacturing	14	13	-20	35	-12	19	-56	23	-141	40	-214	71
Media/Commu	135	94	7	386	8	63	-142	100	-240	84	-443	31
Oil & Gas	-22	13	-53	5	-50	17	-105	-12	-196	53	-280	-60
Railroad	-50	17	-96	-19	-70	27	-134	5	-225	96	-494	-30
Retail	-33	10	-70	-14	-52	16	-92	-22	-170	45	-281	-52
Service/Leisure	-33	16	-52	44	-59	26	-112	25	-240	108	-473	-35
Transportation	-13	14	-56	15	-66	35	-144	11	-295	89	-530	-99
Telephone	-42	19	-69	9	-66	45	-160	38	96	652	-902	1104
Financial Firms												
Banking	-30	23	-60	80	26	45	-69	97	-227	84	-339	23
Credit/Financing	-30	17	-63	14	-161	105	-311	108	-678	570	-2253	9
Financial Service	12	16	-29	114	31	36	-59	153	-269	104	-641	36
Insurance	-34	7	-63	-16	-48	25	-114	36	-134	64	-356	26
Real Estate	-24	13	-47	5	0	26	-55	76	-308	215	-1071	100
Leasing	-54	19	-87	12	-32	77	-139	299	-770	970	-4141	64

Table 2: **Correlation Matrix of Interest Rates**

This table shows the correlation values for five interest rates and their spreads. All interest rates have a three-month maturity. The correlation is based on 942 daily observations spanning from January 2006 to September 2009.

Panel A: Level	Libor	OIS	RepoMBS	RepoGC	T-Bill
Libor	1.00				
	(0.00)				
OIS	0.96	1.00			
	(0.00)	(0.00)			
RepoMBS	0.98	0.99	1.00		
	(0.00)	(0.00)	(0.00)		
RepoGC	0.96	0.99	0.99	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)	
T-Bill	0.94	0.99	0.97	0.99	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel B: Spread	Libor - OIS	OIS - RepoGC	RepoMBS - RepoGC	RepoGC - T-Bill
Libor - OIS	1.00			
	(0.00)			
OIS - RepoGC	-0.11	1.00		
	(0.00)	(0.00)		
RepoMBS - RepoGC	0.68	0.45	1.00	
	(0.00)	(0.00)	(0.00)	
Repo GC - T-Bill	0.34	0.07	0.36	1.00
	(0.00)	(0.03)	(0.00)	(0.00)

Panel C: Change of Spread	ΔLibor - OIS	ΔOIS - RepoGC	ΔRepoMBS - RepoGC	ΔRepoGC - T-Bill
ΔLibor - OIS	1.00			
	(0.00)			
ΔOIS - RepoGC	-0.14	1.00		
	(0.30)	(0.00)		
ΔRepoMBS - RepoGC	0.14	0.64	1.00	
	(0.00)	(0.00)	(0.00)	
ΔRepoGC - T-Bill	0.10	-0.76	-0.53	1.00
	(0.00)	(0.03)	(0.00)	(0.00)

Table 3: **The Time-series Determinant of the Average Basis: Univariate Regression**

The basis is value-weighted by market capitalization across all firms, investment-grade firms, and high-yield firms. The candidate explanatory variables include (1) the 5-year CDS spread of the primary dealer index, (2) the 3-month libor-ois spread, (3) the 3-month repo -Tbill spread, (4) the change of primary dealers' position (dollar volume) in long-term corporate bond, (5) the CBOE Volatility Index, (6) the 3-month repo rate spread between MBS collateral and Treasury collateral, (7) the noise factor for illiquidity in Hu, Pan and Wang (2010), (8) the stock return of the primary dealer index, and (9) the 3-month ois-repo spread. We test the impact of contemporaneous and up to three biweekly lagged explanatory variables in the following regression:

$$\Delta \text{Basis}_t^J = \alpha_0 \Delta Z_t + \alpha_1 \Delta Z_{t-1} + \alpha_2 \Delta Z_{t-2} + \alpha_2 \Delta Z_{t-3} + \varepsilon_t, \qquad J \in \{All, IG, HY\}$$

The t-statistics are reported in the parentheses using Newey-West standard errors with a lag of two. Due to the data availability of primary dealer's position on bond, we use biweekly data spanning from January 2006 to September 2009.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔBasis		ΔCDS^{PD}	$\Delta Libor - OIS$	$\Delta RepoSpread$	$\Delta Position^{PD}$	ΔVIX	$\Delta RepoMBS$	$\Delta Noise$	R^{PD}	$\Delta OIS - Repo$
	t	0.33	-0.02	0.17	0.01	0.04	-0.28	-0.03	-1.17	-0.02
		(1.92)	(-0.19)	(1.38)	(0.42)	(0.48)	(-1.47)	(-0.76)	(-0.93)	(-0.27)
	t-1	**-0.53**	**-0.36**	-0.24	-0.04	**-0.24**	-0.07	**-0.15**	2.17	-0.26
		(-2.87)	(-2.25)	(-1.72)	(-1.32)	(-2.66)	(-0.13)	(-2.52)	(0.87)	(-2.37)
$\Delta Basis^{All}$	t-2	-0.02	-0.19	-0.31	0.04	0.00	-0.47	0.06	0.53	0.19
		(-0.08)	(-1.32)	(-1.43)	(1.59)	(0.05)	(-1.59)	(0.97)	(0.27)	(2.57)
	t-3	-0.16	0.18	**-0.27**	0.06	0.09	-0.05	-0.04	-0.56	-0.05
		(-0.86)	(1.40)	(-1.98)	(1.52)	(1.05)	(-0.18)	(-0.90)	(-0.51)	(-0.62)
	R^2_{adj}	0.21	0.10	0.05	0.00	0.17	0.04	0.17	0.03	0.34
	t	0.16	-0.02	0.15	0.01	-0.01	-0.28	-0.03	-0.16	-0.04
		(1.60)	(-0.28)	(1.56)	(0.65)	(-0.24)	(-1.80)	(-1.39)	(-0.21)	(-1.02)
	t-1	**-0.26**	**-0.40**	-0.17	-0.01	**-0.13**	-0.39	**-0.08**	-0.12	-0.02
		(-2.59)	(-6.70)	(-1.57)	(-0.46)	(-2.36)	(-1.50)	(-2.64)	(-0.24)	(-0.80)
$\Delta Basis^{IG}$	t-2	**-0.31**	**-0.16**	**-0.38**	0.01	-0.05	**-0.21**	-0.01	0.81	0.03
		(-3.92)	(-2.00)	(-3.27)	(0.76)	(-1.73)	(-3.10)	(-0.47)	(1.44)	(1.27)
	t-3	-0.09	0.04	**-0.24**	0.02	0.02	0.15	0.01	-0.26	-0.07
		(-1.00)	(0.58)	(-2.73)	(1.37)	(0.60)	(1.38)	(0.29)	(-0.57)	(-1.56)
	R^2_{adj}	0.38	0.39	0.27	-0.02	0.19	0.19	0.17	-0.01	0.06
	t	-0.12	0.01	-0.03	0.01	**-0.32**	-0.41	**-0.25**	3.46	-0.29
		(-0.26)	(0.08)	(-0.08)	(0.42)	(-2.42)	(-0.80)	(-3.15)	(1.36)	(-2.79)
	t-1	**-0.76**	**-1.31**	-0.11	-0.02	**-0.34**	-1.12	-0.08	1.48	-0.04
		(-2.31)	(-5.44)	(-0.35)	(-0.28)	(-3.11)	(-1.54)	(-1.04)	(1.13)	(-0.38)
$\Delta Basis^{HY}$	t-2	**-0.53**	0.22	**-0.94**	**0.10**	-0.14	-0.56	-0.03	**4.11**	0.04
		(-2.15)	(0.82)	(-2.69)	(2.68)	(-1.63)	(-1.13)	(-0.35)	(2.24)	(0.32)
	t-3	-0.02	**-0.51**	0.02	0.02	0.01	-0.21	-0.03	**-3.90**	-0.07
		(-0.08)	(-2.03)	(0.08)	(0.31)	(0.12)	(-0.87)	(-0.45)	(-2.23)	(-0.44)
	R^2_{adj}	0.14	0.34	0.11	-0.01	0.25	0.12	0.21	0.18	0.10

Table 4: **The Time-series Determinant of The Average Basis: Multivariate Regressions**

The basis is value-weighted by market capitalization across all firms, investment-grade firms, and high-yield firms. The candidate explanatory variables include (1) the 5-year CDS spread of the primary dealer index, (2) the 3-month libor-ois spread, (3) the 3-month repo-Tbill spread, (4) the change of primary dealers' position (dollar volume) in long-term corporate bond, (5) the CBOE Volatility Index, (6) the 3-month repo rate spread between MBS collateral and , (7) the noise factor for illiquidity in Hu, Pan and Wang (2010), (8) the stock return of the primary dealer index and (9) the 3-month ois-repo spread. Based on the univariate results in Table 3, we choose the lag of explanatory variables and use them in the multivariate regression. The t-statistics are reported in the parentheses using Newey-West standard errors with a lag of two. Due to the data availability of primary dealer's position on bond, we use biweekly data spanning from January 2006 to September 2009.

	ΔCDS (t-1)	$\Delta Libor - OIS$ (t-1)	ΔVIX (t-1)	$\Delta Noise$ (t-1)	$\Delta OIS - Repo$ (t-1)	$\Delta RepoSpread$ (t-2)	$\Delta Position^{PD}$ (t-2)	$\Delta RepoMBS$ (t-2)	R^{PD} (t-2)	R^2_{adj}
$\Delta Basis_t^{All}$	**-0.45**	-0.11	-0.05	**-0.06**	-0.20	-0.21	0.03	**-0.58**	0.57	
	(-2.85)	(-0.82)	(-1.44)	(-2.14)	(-1.84)	(-1.92)	(1.44)	(-2.48)	(1.05)	0.48
$\Delta Basis_t^{IG}$	**-0.10**	**-0.25**	-0.04	**-0.04**	0.02	-0.16	0.02	**-0.25**	**0.58**	
	(-1.98)	(-2.59)	(-1.76)	(-2.55)	(0.64)	(-1.57)	(1.24)	(-4.09)	2.09	0.50
$\Delta Basis_t^{HY}$	**-0.46**	**-0.67**	-0.11	0.02	0.05	**-0.54**	**0.10**	-0.83	**3.98**	
	(-2.21)	(-2.48)	(-1.05)	(0.44)	(0.68)	(-2.52)	(2.69)	(-1.52)	(3.13)	0.45

Table 5: **Correlation Matrix of Time-Series Risk Factors**

This table shows the correlation values for variables that explain the time-series variation of the average basis, including the CDS spread of primary dealer index, the three-month libor-ois spread, the three-month repo spread, primary dealer's position in corporate bond, volatility index, the three-month repo rate spread between MBS collateral and Treasury collateral, the noise factor for illiquidity in Hu, Pan and Wang (2010), the stock return of the primary dealer index and the ois-repo spread. The p-values are reported in the parentheses below the correlation.

	ΔCDS^{PD}	ΔLibor-OIS	Δ RepoSpread	$\Delta Position^{PD}$	ΔVIX	ΔRepoMBS	ΔNoise	R^{PD}	ΔOIS-Repo
ΔCDS^{PD}	1.00								
	(0.00)								
ΔLibor-OIS	**0.38**	1.00							
	(0.00)	(0.00)							
ΔRepoSpread	**0.29**	0.01	1.00						
	(0.00)	(0.94)	(0.00)						
$\Delta Position^{PD}$	-0.03	0.00	**-0.06**	1.00					
	(0.78)	(0.96)	(0.58)	(0.00)					
ΔVIX	**0.34**	**0.38**	0.01	0.13	1.00				
	(0.00)	(0.00)	(0.91)	(0.21)	(0.00)				
ΔRepoMBS	**0.20**	**0.58**	**-0.33**	-0.02	0.27	1.00			
	(0.05)	(0.00)	(0.00)	(0.84)	(0.01)	(0.00)			
ΔNoise	0.13	**0.23**	0.18	-0.03	**0.30**	0.16	1.00		
	(0.21)	(0.02)	(0.07)	(0.75)	(0.00)	(0.12)	(0.00)		
R^{PD}	-0.15	0.15	0.02	0.00	**-0.37**	0.02	**-0.25**	1.00	
	(0.13)	(0.15)	(0.81)	(1.00)	(0.00)	(0.86)	(0.01)	(0.00)	
ΔOIS-Repo	0.13	-0.04	-0.05	0.01	0.90	**-0.24**	**0.21**	-0.15	1.00
	(0.19)	(0.72)	(0.66)	(0.96)	(0.06)	(0.02)	(0.03)	(0.15)	(0.00)

Table 6: **Correlation Matrix of Cross-sectional Risk Factors**

This table shows the correlation values for betas that capture counterparty risk, liquidity risk, funding cost risk, and collateral quality, which potentially explain the cross-sectional variation of the basis. The correlations are calculated using the whole sample, three subsamples of Before Crisis (1/2/2006 - 6/30/2007), Crisis I (7/1/2007 - 8/31/2008), and Crisis II (9/1/2008 - 9/30/2009).

Full Sample (1/2/2006 - 9/30/2009)

	β_{cp}	$\beta_l(repo)$	$\beta_f(libor)$	Collateral
β_{cp}	1	-	-	-
$\beta_l(repo)$	0.32	1	-	-
$\beta_f(libor)$	0.38	0.62	1	-
Collateral	-0.16	-0.15	-0.33	1

Before Crisis (1/2/2006 - 6/31/2007)

	β_{cp}	$\beta_l(repo)$	$\beta_f(libor)$	Collateral
β_{cp}	1	-	-	-
$\beta_l(repo)$	-0.11	1	-	-
$\beta_f(libor)$	0.07	0.08	1	-
Collateral	-0.01	0.23	-0.19	1

Crisis I (7/1/2007 - 8/31/2008)

	β_{cp}	$\beta_l(repo)$	$\beta_f(libor)$	Collateral
β_{cp}	1	-	-	-
$\beta_l(repo)$	0.37	1	-	-
$\beta_f(libor)$	0.42	0.91	1	-
Collateral	-0.25	-0.19	-0.19	1

Crisis II (9/1/2009 - 9/30/2009)

	β_{cp}	$\beta_l(repo)$	$\beta_f(libor)$	Collateral
β_{cp}	1	-	-	-
$\beta_l(repo)$	0.42	1	-	-
$\beta_f(libor)$	0.48	0.89	1	-
Collateral	-0.11	-0.07	-0.04	1

Table 7: **Cross-Sectional Regression of the CDS-Bond Basis on Risk Factors**

This table shows the Fama-MacBeth cross-sectional regression results of the CDS-bond basis on the following variables:

$$Basis_i^J = \alpha + \gamma_{cp}\beta_{i,cp} + \gamma_l\beta_{i,l_{repo}} + \gamma_f\beta_{i,f_{libor}} + \gamma_{coll}\text{Collateral}_i + \gamma_k\beta_{i,controls} + \varepsilon_i, \quad J \in [All, IG, HY]$$

where

$$\begin{aligned}\beta_{i,cp} &= \frac{cov(R_i,(R_{index}-R_{mkt})}{var(R_{index}-R_{mkt})},\\ \beta_{i,l_{repo}} &= \frac{cov(\Delta CDS_i,\Delta repospread)}{var(\Delta repospread)},\\ \beta_{i,f_{libor}} &= \frac{cov(\Delta CDS_i,\Delta(libor-ois))}{var(\Delta(libor-ois))}.\end{aligned}$$

Collateral is an index measuring the collateral quality of the bond issued by each reference entity, composed of firm size, leverage, rating, tangible ratio, CDS level and CDS volatility. Each day we run the Fama-MacBeth regression using the betas calculated in corresponding periods (Full sample, Before Crisis, Crisis I, and Crisis II). The table reports the average of the cross-sectional regression estimates, and the standard deviations of the estimates in parentheses. The standard deviations are adjusted for the correlations among sampling errors. Estimated coefficients are in bold script if the statistical significance is 5% or below.

Panel A: All Firms

	The Whole Sample (Jan 2006 - Sep 2009)			Before Crisis (Jan 2006 - Jun 2007)			Crisis I (Jul 2007 - Aug 2008)			Crisis II (Sep 2008- Sep 2009)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
γ_{cp}	**-0.86**	**-0.71**	**-1.49**	**0.13**	**0.20**	**0.12**	**-0.57**	**-0.56**	**-0.39**	**-2.55**	**-2.12**	**-4.96**
	(0.27)	(0.25)	(0.47)	(0.02)	(0.03)	(0.02)	(0.06)	(0.06)	(0.04)	(0.77)	(0.72)	(1.21)
$\gamma_{l_{repo}}$	**2.60**		**1.67**	**3.63**		**3.56**	0.30		**1.05**	**3.79**		-0.26
	(0.66)		(0.64)	(1.04)		(1.02)	(0.35)		(0.38)	(1.58)		(1.47)
$\gamma_{f_{libor}}$	**-1.09**	**-1.02**		**0.50**	**0.44**		**0.98**	**1.01**		**-5.64**	**-5.33**	
	(0.51)	(0.49)		(0.10)	(0.09)		(0.18)	(0.17)		(1.79)	(1.70)	
γ_{coll}	**0.19**	**0.18**	**0.28**	**-0.20**	**-0.19**	**-0.19**	-0.01	-0.01	-0.03	**0.97**	**0.90**	**1.28**
	(0.08)	(0.08)	(0.11)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.15)	(0.15)	(0.21)
Adj R^2	0.11	0.09	0.08	0.09	0.06	0.09	0.03	0.03	0.02	0.21	0.19	0.12

Table 7: **Cross-Sectional Regression of the CDS-Bond Basis on Risk Factors (Cont'd)**

Panel B: IG Firms

	The Whole Sample (Jan 2006 - Sep 2009)			Before Crisis (Jan 2006 - Jun 2007)			Crisis I (Jul 2007 - Aug 2008)			Crisis II (Sep 2008- Sep 2009)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
γ_{cp}	**-0.48**	**-0.52**	**-0.44**	**0.08**	**0.07**	**0.08**	**-0.28**	**-0.34**	**-0.21**	**-1.46**	**-1.52**	**-1.40**
	(0.14)	(0.15)	(0.15)	(0.01)	(0.01)	(0.01)	(0.05)	(0.06)	(0.04)	(0.36)	(0.38)	(0.41)
$\gamma_{l_{repo}}$	**-2.49**		**-1.50**	**-2.99**		**-3.06**	**-3.16**		**-0.89**	**-1.09**		-0.08
	(0.41)		(0.47)	(0.36)		(0.32)	(1.09)		(1.15)	(0.43)		(0.50)
$\gamma_{f_{libor}}$	**0.37**	0.08		-0.18	**-0.49**		**0.83**	**0.54**		0.60	0.33	
	(0.15)	(0.15)		(0.10)	(0.09)		(0.15)	(0.17)		(0.42)	(0.40)	
γ_{coll}	**0.10**	**0.10**	**0.10**	**0.06**	**0.06**	**0.06**	**0.09**	**0.09**	**0.09**	**0.16**	**0.18**	**0.16**
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.03)
Adj R^2	0.04	0.03	0.03	0.01	0.01	0.03	0.03	0.03	0.03	0.09	0.08	0.06

Panel C: HY Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
γ_{cp}	**-2.70**	**-2.60**	**-3.00**	**-0.48**	-0.04	**-0.60**	**-1.01**	**-0.97**	**-0.71**	**-7.57**	**-7.86**	**-8.80**
	(0.59)	(0.62)	(0.65)	(0.05)	(0.06)	(0.06)	(0.12)	(0.11)	(0.06)	(1.27)	(1.24)	(1.19)
$\gamma_{l_{repo}}$	**2.36**		**1.98**	**6.27**		**6.09**	0.53		**0.91**	-0.89		-2.36
	(0.93)		(1.04)	(1.38)		(1.36)	(0.31)		(0.31)	(2.05)		(2.51)
$\gamma_{f_{libor}}$	0.30	0.10		**0.64**	**0.56**		**1.20**	**1.20**		-1.15	**-1.74**	
	(0.26)	(0.28)		(0.14)	(0.12)		(0.28)	(0.28)		(0.65)	(0.68)	
γ_{coll}	-0.01	0.02	0.02	**-0.60**	**-0.55**	**-0.61**	**-0.11**	**-0.11**	**-0.14**	**0.90**	**0.92**	**1.05**
	(0.12)	(0.12)	(0.14)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.28)	(0.28)	(0.30)
Adj R^2	0.12	0.09	0.11	0.10	0.04	0.01	0.02	0.03	0.01	0.25	0.21	0.22

Table 8: Test of the Impact of Deleveraging

This table shows the influence of the change of bond trading volume on the the change of basis between the post-Lehman period and the before-subprime period, using the following cross-sectional regression:

$$\Delta Basis_i^J = \beta_1(\Delta Vol/Vol)_i^J + \beta_2(\Delta(High - Low)/Mean)_i^J + \varepsilon_i^J, \quad J \in [IG, HY, F, NF],$$

where $\Delta Basis \equiv Basis_2 - Basis_0$; $\Delta Vol/Vol \equiv (Vol_2 - Vol_0)/Vol_0$ is the percentage change of corporate bond trading volume (source: TRACE); *High* is the maximum monthly trading volume in a specific phase, and *Low* is the minimum monthly trading volume in that phase, *Mean* is the average monthly volume in that phase – this measure shows the volatility of trading volume change. The subscript 2 refers to the phase of Crisis II (9/1/2008 - 9/30/2009) and the subscript 0 refers to the phase of Before Crisis (1/2/2006 - 6/30/2007). The *t*-statistics are reported in the parentheses below the regression coefficients.

$\Delta Basis$	$\frac{\Delta Vol}{Vol}$	$\Delta\frac{High-Low}{Mean}$	R^2
IG	-0.17	-0.53	0.02
	(-1.12)	(-1.58)	
HY	-0.35	**-3.02**	0.06
	(-0.61)	(-2.23)	
Financials	-2.04	-1.02	0.05
	(-1.23)	(-0.87)	
NonFinancials	-0.12	**-0.08**	0.03
	(-0.71)	(-2.55)	

Table 9: **The CDS Market's Contribution to Price Discovery**

This table reports the summary statistics of the contribution to the credit price discovery made by the CDS market. We do the price discovery test for each firm between its CDS spread and bond-implied CDS (PECDS) spread using the daily data. We summarize the mean, median, and standard error for all firms, IG, HY, financial, and non-financial firms during each phase of the financial crisis, – Pre-Crisis (1/2/2006 - 6/30/2007), Crisis I (7/1/2007 - 8/30/2008), Crisis II (9/1/2008 - 9/30/2009). The test is based on the vector error correction model as

$$\begin{aligned}\Delta CDS_t &= \lambda_1(CDS_{t-1} - PECDS_{t-1}) + \beta_1 \sum_{i=1}^{p} \Delta CDS_{t-i} + \gamma_1 \sum_{i=1}^{p} \Delta PECDS_{t-i} + \varepsilon_{1,t} \\ \Delta PECDS_t &= \lambda_2(CDS_{t-1} - PECDS_{t-1}) + \beta_2 \sum_{i=1}^{p} \Delta CDS_{t-i} + \gamma_2 \sum_{i=1}^{p} \Delta PECDS_{t-i} + \varepsilon_{2,t}\end{aligned}$$

We use the Granger-Gonzalo measure $\lambda_2/(\lambda_2 - \lambda_1)$, which indicates the price discovery contribution made by the CDS market for each firm.

	All		
	Pre-Crisis	Crisis I	Crisis II
Mean	0.92	0.84	0.74
Median	0.91	0.93	0.89
Std Err.	0.86	0.78	0.38

	IG				HY		
	Pre-Crisis	Crisis I	Crisis II		Pre-Crisis	Crisis I	Crisis II
Mean	0.84	0.83	0.79	Mean	1.26	0.90	0.46
Median	0.91	0.94	0.92	Median	0.95	0.83	0.60
Std Err.	0.65	0.74	0.32	Std Err.	1.49	0.96	0.50

	Non-Financial				Financial		
	Pre-Crisis	Crisis I	Crisis II		Pre-Crisis	Crisis I	Crisis II
Mean	0.91	0.83	0.73	Mean	0.92	0.94	0.76
Median	0.91	0.93	0.89	Median	0.91	0.93	0.89
Std Err.	0.95	0.84	0.39	Std Err.	0.20	0.34	0.28