Limited Arbitrage and Pricing Discrepancies in Credit Markets

Kasing Man, Junbo Wang, and Chunchi Wu*

November 10, 2013

Abstract

In this paper we investigate the roles of nondefault risk factors and impediments to arbitrage in the pricing discrepancies of credit markets. We find that nondefault factors contribute to the unusual price distortions in credit markets and the noise in CDS price signals during the crisis. However, there is ample evidence that impediments to arbitrage play a more important role in turbulent markets. Impediments to arbitrage result in less market integration and more persistent pricing discrepancies. These effects are more severe for riskier and less liquid firms and in times of stress.

JEL classification: G01; G12

Keywords: impediments to arbitrage; pricing discrepancies; default and nondefault risk factors; slow moving capital; search frictions; long memory; cointegration; price discovery

* Kasing Man is at Western Illinois University, Junbo Wang is at City University of Hong Kong, and Chunchi Wu is at State University of New York at Buffalo.

1. Introduction

The arbitrage-free condition has been a building block in development of modern asset pricing theories. This condition however was severely violated during the subprime crisis in various markets (see Duffie, 2010; Mitchell and Pulvino, 2012; Kapadia and Pu, 2012).[1] Particularly the dramatic violations of the arbitrage-based pricing relationship in credit risk markets during the crisis have attracted a lot of attention. The credit default swap (CDS) spread is normally within a small difference from the yield spread of a reference par bond with the same maturity as the CDS. This spread difference (basis) however widened to above 600 basis points for speculative-grade bonds shortly after the collapse of Lehman Brothers in 2009. As Duffie points out in his 2010 American Finance Association presidential address, "The extreme negative CDS basis 'violations' … across broad portfolios of investment-grade bonds and high-yield bonds, respectively, is far too large to be realistically explained by CDS counterparty risk or by other minor technical details."

What might have caused the large pricing discrepancy in credit markets? One possibility is that markets may price different factors for two related assets. If so, pricing discrepancies are not a real anomaly. Instead, it could be due to a misspecification of risk factors in the credit valuation model. For instance, illiquidity can be an important pricing factor for the corporate bond but not for the CDS. So, when there is an aggregate illiquidity shock, corporate bonds experience a price discount or yield jump, leading to a negative CDS basis. Likewise, counterparty credit risk is perceived to be a more important factor for the credit derivatives market. Heightened counterparty credit risk for CDS sellers will make the CDS worth less and hence have a negative impact on the basis.

Another possibility for pricing discrepancies is limits to arbitrage. Significant impediments to

[1] For example, there were serious violations of covered interest rate parity, a negative spread between Treasury bond yields and LIBOR swap rates, and a breakdown of the capital structure arbitrage across equity and credit markets.

arbitrage can cause large and persistent pricing discrepancies between two similar assets. To take the profitable opportunities when the basis becomes significantly negative, one can short a risk-free bond, use the proceeds to invest in the corporate bond, and buy a CDS of the bond.[2] However, arbitrage is not without costs or constraints. Search costs, market illiquidity and uncertainty, funding constraints, or slow capital movement can impede the arbitrage. For example, arbitrageurs may not be able to unwind their positions profitably in the short term when the market is illiquid. An attempt to arbitrage pricing discrepancies away can also be risky when the price persistently deviates from its equilibrium value as arbitrageurs typically have short investment horizons and cannot sustain large losses (Shleifer and Vishny, 1997; Pontiff, 2006; Gorton and Metrick, 2012). Limited arbitrage of this nature can cause pricing discrepancies to persist over a sustained period of time.

Understanding the causes for pricing discrepancies in two similar markets is important for development of general asset pricing theory. The subprime crisis provides an excellent opportunity to understand the market function and price dynamics in times of stress. A unique feature of this crisis is the drastic deterioration in liquidity and credit quality in financial markets. Many large financial institutions incurred substantial portfolio losses and liquidity suddenly dried up in the midst of the crisis. Failure to regain capital promptly impaired the ability of financial intermediaries to absorb supply shocks. Several studies have ascribed the unusual price distortions to this problem (see, for example, Mitchell, Pedersen and Pulvino, 2007; Duffie, 2010; Mitchell and Pulvino, 2012). As explained by these studies, impediments to capital movement, such as time required to raise capital and inefficiency in search for trading counterparties, prevent arbitrageurs from exploiting the profitable opportunities and cause extreme pricing discrepancies.

In this paper, we examine different hypotheses for the pricing discrepancies between the

[2] The profit of this strategy is the principal debt position times the absolute magnitude of the basis.

CDS and corporate bond and the channels through which this problem occur. In particular, we investigate the possibility that the CDS and corporate bond markets may price different factors as well as the role of limits-to-arbitrage in explaining the pricing anomaly in credit markets. In pursuing these investigations, we address a number of important issues related to the pricing of CDS and corporate bonds and the relationship between the two markets. Do bond and CDS spreads contain different nondefault pricing factors which contribute to pricing discrepancies? Are the CDS and corporate bond markets integrated? If not, is it due to differences in pricing factors or impediments to arbitrage? Does the CDS market lead the bond market in price discovery in the short term and provide credible signals for credit risk? Do impediments to arbitrage lead to more persistent pricing discrepancies between the CDS and corporate bond markets during the subprime crisis? By addressing these issues, we attempt to shed more light on the causes of extreme price distortions in credit markets and improve understanding on asset price dynamics.

We find that nondefault risk factors contribute to the negative CDS basis because bond spreads are more sensitive to these factors. However, nondefault factors can only explain some of the pricing discrepancies between the CDS and corporate bond markets. Empirical evidence suggests that impediments to arbitrage are the fundamental cause for pricing discrepancies and lack of integration in the CDS and corporate bond markets. Firms with high idiosyncratic risk and trading cost and low liquidity face greater pricing discrepancies and less market integration. Pricing discrepancies are more severe for speculative-grade firms and during the subprime crisis. Both the level and volatility of the basis become more persistent during the crisis period and exhibit long memory, supporting Duffie's (2010) hypothesis that impediments to arbitrage cause persistence in pricing discrepancies over longer horizons.

Our focus on the relationship between the CDS and corporate bond markets is related to several recent important papers on this issue (Blanco, Brennan, and Marsh, 2005; Duffie, 2010;

Nashikkar, Subrahmanyam, and Mahanti, 2011; Bai and Collin-Dufresne, 2013; Das, Kalimipalli, and Nayak, 2013). Our work differs from these studies in several aspects. First, we explore the roles of both impediments to arbitrage and differential nondefault pricing factors in explaining CDS-bond pricing discrepancies. Second, we look into the channels through which pricing discrepancies may occur. Third, we investigate whether firm-level impediments to arbitrage can explain the price divergence in the CDS and bond markets. Lastly, we test Duffie's (2010) hypothesis of slow capital movement and persistent pricing discrepancies using long memory time-series models.

The remainder of this paper is organized as follows. Section 2 discusses the research issues and empirical methodology. Section 3 describes the data and presents empirical results and Section 4 examines the persistence of pricing discrepancies and volatility in the credit markets. Finally, Section 5 summarizes our major findings and concludes the paper.

2. Methodology

In this section, we explore pricing factors in the CDS and corporate bond markets and the relation between these markets, and present methodologies for empirical tests.

2.1 The relation between CDS and bond yield spreads

CDS and bond yield spreads both reflect the default risk of corporate bonds. In addition, the literature has suggested that these spreads contain nondefault components associated with liquidity, counterparty risk and bond characteristics. To the extent that the importance of these factors differs between the two markets, CDS and bond spreads can deviate. Denote the CDS and bond yield spreads as

$$CDS_{it} = \lambda_{it} + L_{it}^{c} + \eta_{it}^{c} + F_{it}^{c} + \varepsilon_{it}^{c}, \tag{1}$$

$$BYS_{it} = \lambda_{it} + L_{it}^{b} + F_{it}^{b} + \varepsilon_{it}^{b} \tag{2}$$

where CDS_{it} and BYS_{it} are credit default swap rates and corporate bond yield spreads for entity i

at time t, λ_{it} is the default premium, L_{it}^{j} is the liquidity premium, η_{it}^{c} is the counterparty risk premium, F^{j} represents effects of other factors such as frictions and aggregate shocks, ε_{i}^{j} is the noise term and the superscript $j = c$, b denotes the CDS and bond, respectively.

In this specification, CDS and the reference bond spreads share a common default risk component. In an efficient market, default risk should be priced equally across markets to give the same default premium λ_{it}. Besides default risk, the literature has shown that liquidity is an important pricing factor in credit markets (see, for example, Bongaerts, de Jong and Driessen, 2011; Lin, Wang, and Wu, 2011; Friewald, Jankowitsch, Subrahmanyam, 2012; Dick-Nielsen, Feldhutter, and Lando, 2012). However, the magnitude of the liquidity component can differ between the two securities. For one, the CDS market is more liquid than the corporate bond market. In addition, sensitivity to liquidity shocks can differ between the two securities. For counterparty risk, as it is perceived to be more relevant for the derivatives market (Jarrow and Yu, 2001; Arora, Gandhi and Longstaff, 2012), we add this risk component in the CDS spread. Finally, F_{it}^{j} represents other factors such as search frictions, bond characteristics and aggregate shocks that can affect the pricing of the CDS and corporate bonds.

The basis is the difference between the CDS spread and the bond yield spread (BYS),

$$Basis_{it} = CDS_{it} - BYS_{it} \tag{3}$$

If both CDS and bond spreads contain only the common default component, the no-arbitrage condition implies a zero basis. Even in this simplified case, the arbitrage can only be perfect if the spread on a par risky floating-rate bond over a risk-free floating rate bond equals the CDS spread or if the payment dates on the bond and the CDS are identical (see Duffie, 1999; Houweling and Vorst, 2005; Hull, Predescu and White, 2004). Cheapest-to-delivery options and costs of short-selling bonds can also derail the arbitrage-based pricing relationship.

An important issue is whether CDS and bond spreads contain different nondefault components. If one market prices a factor that is not priced in the other market, the basis will by nature not converge to zero. For instance, if counterparty risk is important for the CDS but is trivial for the corporate bond, the basis will reflect this risk premium for the CDS. Similarly, if the liquidity premium component is more important for corporate bonds, it can lead to a negative basis. Also, firm/bond characteristics and supply/demand shocks can have different effects on CDS and bond prices. For example, selling pressure and deleveraging by dealer banks is likely to have a larger impact on the bond price than the CDS rate. Also, bond-specific liquidity characteristics would be less relevant to the CDS pricing. We can express CDS basis as a function of these nondefault factors:

$$Basis_{it} = f(L_{it}^{j}, \eta_{it}^{c}, F_{it}^{j}), \qquad j = c, b \tag{3a}$$

where the default risk premium is netted out.

In empirical investigation, we examine the roles of nondefault factors in explaining the CDS-bond pricing discrepancies by running regressions of the basis, CDS spreads and bond spreads, respectively, against these factors. The sensitivity of CDS and bond spreads to each factor provides important information for the sources of pricing discrepancies and the relative contribution of each factor to the negative CDS spread. For example, if bond spreads are more sensitive to illiquidity and supply shocks than CDS spreads do, then the greater effects of these risk factors on bonds contribute to the negative CDS spread. The coefficients in the spread and basis regressions allow us to infer the role of each nondefault factor in affecting the CDS basis.

2.2. Market integration and price discovery

2.2.1. Cointegration tests

If default is the only risk factor for the CDS and corporate bond, the two markets should be integrated under rationality. When there are nondefault factors, the cointegration hypothesis can be rejected for two reasons. First, the CDS and corporate bond markets price different factors.

Pricing discrepancies are therefore not real anomalies if the CDS and bond prices are evaluated against the true credit pricing model. Second, there are impediments to arbitrage. If so, the cointegration hypothesis can still be rejected even if we account for the effects of nondefault risk factors on the CDS and bond prices using the correct valuation model.

To examine whether the CDS and corporate bond markets are cointegrated, we perform two tests: one is based on the observed (raw) spreads and the other based on the spreads adjusted for the nondefault components. These tests allow us to assess the role of nondefault factors in the long-term relation between the two markets. The adjusted spreads are the CDS and bond spreads adjusted for the effects of nondefault factors. These adjusted CDS and bond spreads can be viewed as pure default spreads, which should be equal if the market is integrated. If nondefault risk factors are the reason for rejecting the hypothesis, the two series of adjusted spreads should be cointegrated. Otherwise, limits-to-arbitrage is likely to be the cause for violation of market integration.

To perform the cointegration test, we estimate the vector error-correction model (VECM) of CDS and bond spreads. Denote $Y_t = (p_t, q_t)'$, where p_t and q_t are CDS and bond spreads, respectively, unadjusted or adjusted for nondefault components. The VECM model can be written as

$$\Delta Y_t = c + \lambda b' Y_{t-1} + \sum_{i=1}^{r-1} \Psi_i \Delta Y_{t-i} + e_t, \tag{4}$$

where c is the constant term, e_t's are serially uncorrelated innovations with mean zero and covariance matrix $Var(e_t)$ with diagonal elements σ_1^2 and σ_2^2 and off-diagonal elements $\rho\sigma_1\sigma_2$, $b = (1, \beta)'$ is the cointegration vector with the first element normalized to one, $\lambda = (\lambda_1, \lambda_2)'$ is the vector of responses for the error-correction term, and $\Delta = 1 - B$ is the difference operator with B being the back-shift operator. We apply Johansen's trace test to the VECM to determine the number of cointegrated vectors. Details of this test procedure are described in Appendix A.

Blanco, Brennan, and Marsh (2005) examine the long-run equilibrium relation between the CDS and corporate bond markets using the pre-crisis data. By contrast, we examine the relations between the two markets in the normal and crisis periods. More importantly, we investigate whether the rejection of the cointegration hypothesis is due to nondefault risk factors or impediments to the arbitrage.

2.2.2 Nonparametric tests

Besides the cointegration test, we carry out a nonparametric test for market integration.[3] When the CDS basis is significantly negative, the bond spread should move down and the CDS spread should move up to close the gap if markets are integrated. If instead the CDS and bond spreads move in the same direction, a pair of CDS and bond prices can remain divergent and present an arbitrage opportunity. Thus, we can perform a nonparametric test for market integration based on the frequency of observations for such arbitrage opportunities. For a given period with $k = 1, 2, \ldots, T$ observations, we define γ_i for firm i as

$$\gamma_i = \sum_{\tau=1}^{T-1} \sum_{k=1}^{T-\tau} 1_{[\Delta CDS_{i,k}^{\tau} \Delta BYS_{i,k}^{\tau} > 0]} \tag{5}$$

where $\Delta CDS_{i,k}^{\tau} = CDS_i(k+\tau) - CDS_i(k)$ and $\Delta BYS_{i,k} = BYS_i(k+\tau) - BYS_i(k)$, $k \le T - \tau$, $1 \le \tau \le T - 1$, τ indicates a non-overlapping time interval and T is the number of observations. For a given T, firm i's bond and CDS markets are more integrated than those of firm j, if $\gamma_i < \gamma_j$. γ is related to the Kendall correlation κ in that $\kappa = \frac{4\gamma}{T(T-1)} - 1$. In the absence of mispricing, $\kappa = -1$. More generally, a larger κ corresponds to less integrated markets.

There are advantages for this nonparametric test on market integration. First, the nonparametric measure is not model-dependent and is thus robust to potential nonlinearities in the CDS and bond spread relation. Additionally, the measure accounts for all possible pairs from

[3] Bakshi, Cao and Chen (2000) use a similar approach to study the relation between the stock and option markets.

T observations and is independent of the horizon over which spreads are observed. For robustness, we compare the result of this test with the time-series test for market cointegration.

2.3 Price discovery

Even if credit risk prices in CDS and bond markets converge to a common efficient price in the long run, they can deviate from each other in the short run due to different speeds of adjusting to new information or frictions. From the microstructure point of view, it is important to evaluate the information content of prices and to know which market provides more timely information for credit risk. When similar securities are traded in a single centralized market, price discovery is solely produced by that market. Conversely, when trades of similar securities take place in multiple trading venues, questions naturally arise as to what is the relative contribution of each venue to price discovery of the whole market. The CDS market is perceived to be more liquid than the corporate bond market. If the information is impounded in a liquid market faster, credit risk prices in the CDS market will lead prices in the corporate bond market and the former will assume the price leadership.

We employ two price discovery measures suggested by Hasbrouck (1995) and Gonzalo-Granger (1995) to assess the price leadership in the credit risk market. These are standard price discovery measures in market microstructure literature. In brief, the Gonzalo-Granger method decomposes the price into permanent and transitory components, and associates the permanent component with the long run price. This price discovery measure depends on the speed of adjustment of the preceding disequilibrium in prices in the two markets. By contrast, the Hasbrouck price discovery measure takes into consideration the innovations in the two markets.

The parameters estimated from the VECM in (4) can be used to construct the price discovery measures. The Gonzalo-Granger (G) measure for p_t and q_t are defined as

$$G_1 = \frac{-\lambda_2}{\lambda_1 - \lambda_2}, \text{ and } \quad G_2 = \frac{\lambda_1}{\lambda_1 - \lambda_2}. \tag{6}$$

By construction, the G measure is based on the speed (λ) of the error-correction term, or how price in each market changes in response to the price disequilibrium in the preceding period.

Hasbrouck's information share (S) measures are defined as

$$S_1(u) = \frac{(-\lambda_2\sigma_1 + \lambda_1\rho\sigma_2)^2}{(-\lambda_2\sigma_1 + \lambda_1\rho\sigma_2)^2 + (\lambda_1\sigma_2\sqrt{1-\rho^2})^2},$$

$$S_2(l) = \frac{(\lambda_1\sigma_2\sqrt{1-\rho^2})^2}{(-\lambda_2\sigma_1 + \lambda_1\rho\sigma_2)^2 + (\lambda_1\sigma_2\sqrt{1-\rho^2})^2}, \tag{7}$$

where u indicates the upper bound and l is the lower bound. In addition to the speed of adjustment, Hasbrouck's information share measure incorporates the innovations of the two markets through their covariance structure.

Note that Hasbrouck's measures depend on the ordering of the price series. For $Y_t = (p_t, q_t)'$, the measures above give the upper bound (maximum) for the first price series p_t and the lower bound (minimum) for the second price series q_t. Reversing the order in the vector of the price series $(q_t, p_t)'$ gives the upper bound $S_2(u)$ for q_t and the lower bound $S_1(l)$ for p_t. For small correlation ρ between innovations in the two markets, the upper and lower bounds will be close. In practice, the average of the two bounds is used as a summary measure of information share.

We use these price discovery measures to assess the price leadership role of the CDS and corporate bond markets in the pre-crisis and the subprime crisis periods. This analysis focuses on the dynamic behavior of CDS and bond yield spreads with lead-lag relations. It contrasts the cointegration test which deals with the long-run equilibrium relation between the two markets.

2.4 Persistence in pricing discrepancies and volatility

Duffie (2010) argues that slow movement in investment capital to trading opportunities is a fundamental cause for the unusual negative basis during the subprime crisis. His model suggests that slow capital movement leads to persistent pricing discrepancies. The slower the movement in investment capital or the longer it takes for financial intermediaries to regain capital, the lower is the supply of capital to support arbitrage trading and therefore, the more persistent will be the pricing discrepancies between the CDS and bond spreads. We test this hypothesis based on the level and changes in the CDS basis.

2.4.1. Time-series tests for the persistence of pricing discrepancies

We employ two approaches to study price persistence. The first one is the impulse response analysis. The impulse response analysis provides a direct diagnosis for price persistence after an exogenous shock, which can be easily visualized. The second approach involves estimating persistence or a long memory parameter commonly used in the literature of financial time-series.

We use the impulse response function (IRF) to examine the speed and dynamic responses of the CDS and bond spreads to an external shock (see Appendix B for the detail of the estimation procedure). If capital movement is slow, it will take longer time for the spreads of the CDS and reference bond to converge after an exogenous shock. Also, the initial impact of the shock on spreads will be stronger in a less liquid market. Thus, we can compare the results in the normal period and in the crisis period with slow capital movement to see if there are significant differences in impulse responses.

In addition, we can measure the persistence of the pricing discrepancy between the CDS and bond prices using time-series models. Persistence behavior of the CDS basis can be best studied through the long-range dependency or long memory. Using this approach, we study pricing discrepancy persistence by estimating the long memory parameter d. For a price series with long memory, the autocorrelation between two observations k period apart decays in a slower hyperbolic rate of k^{2d-1} as opposed to the faster exponential rate of a^k for a short memory time series. A persistent time series does not have summable autocorrelations, and it is the slow declining rate of autocorrelations that generates the persistence behavior.[4]

There are a number of ways to estimate the long memory parameter *d*. Here we employ the rescaled range R/S method which is widely used in the literature. The R/S statistic is originally proposed by Hurst (1951) and modified by Lo (1991). The R/S statistic is defined as

$$Q_N = \frac{1}{s_N}[M - m] \tag{8}$$

where $M = \max_{1 \le k \le N} \sum_{j=1}^{k} (y_j - \bar{y})$ is the cumulative maximum, $m = \min_{1 \le k \le N} \sum_{j=1}^{k} (y_j - \bar{y})$ is the cumulative minimum, $s_N^2 = \frac{1}{N} \sum_{j=1}^{N} (y_j - \bar{y})$ is the sample variance, and *N* is the sample size.

Intuitively, consider a series of gains or losses of an investment over a period of time of length *N*. Within the period, *M* is the highest net cumulative gain, while *m* is the lowest net position. If there are persistent gains or losses (i.e., the series tends to be consistently above or below the mean over a sustained period), the cumulative max *M* minus cumulative min *m* will tend to be large. On the other hand, if there are short gains or losses (i.e., the series tends to move above and below the mean quickly), then *M* minus *m* would tend to be small. Thus, a larger R/S statistic suggests a persistent behavior. In essence, R/S is simply a suitably adjusted range statistic,[5] where the range is the difference between the cumulative high and low positions.

The range scaled by the standard deviation will converge to a random variable at the rate of $N^{0.5}$ if there is no long memory, and at a faster rate $N^{d+0.5}$ if there is long memory. Thus, the

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[4]Consider a simple long memory time series model $(1-B)^d x_t = e_t$ where *B* is the back-shift operator, e_t is a stationary ARMA process and *x* in the time series, where *d* is a real number between -0.5 and 0.5. This fractional difference series exhibits persistent behavior can be seen as follows. Taking a binomial expansion of $(1-B)^d x_t$ gives: $\sum_{j=0}^{\infty} b_j x_{t-j} = e_t$ where $b_0 = 1$ and $b_j = \frac{\Gamma(j-d)}{\Gamma(-d)\Gamma(j+1)}$ is the binomial coefficient, and $b_j \approx \frac{j^{-d-1}}{\Gamma(-d)}$ for large *j*. Thus, the model can be considered as an AR model of an infinite order with slow decaying coefficients. Such dependency of the series on its infinite past is the basis for its persistence behavior. Furthermore, it can be shown that the lag *k* autocorrelation of x_t decays in an hyperbolic rate, $\rho_k = O(k^{2d-1})$, and that the autocorrelations are not summable (see Hosking, 1981). For a time series which follows a fractionally integrated ARFIMA (*p, d, q*) model, the time series is stationary when *d* is between -0.5 and 0.5.

[5] Lo's (1991) modified R/S statistic replaces the standard deviation by the square root of Newey-West estimate of the long-run variance.

slope in the log-log plot of R/S statistic versus N gives the Hurst parameter $H = d + 0.5$.[6] We use the R/S statistic to measure persistence in the CDS basis in the normal and crisis periods. A higher d estimate signifies a more persistent behavior that a higher basis level tends to accompany with another higher level, and low by low.

2.4.2. Tests of volatility persistence

Similarly, we can test whether the change of the pricing discrepancy or volatility is persistent. If there is slow capital movement or significant impediments to arbitrage, changes in the CDS basis will be more persistent. A simple way to capture this phenomenon is by the absolute daily basis change and for this we can study the persistence behavior using the R/S statistic discussed above. But a more formal way is to analyze volatility persistence in the GARCH setting as basis changes exhibit pronounced volatility clustering. This approach studies volatility persistence within the GARCH framework.

We employ a long memory GARCH model called the frictionally integrated GARCH model (FIGARCH) proposed by Baillie, Bollerslev and Mikkelsen (1996) to measure volatility persistence through the long memory parameter d. Consider an MA(1)-GARCH(1,1) model for the basis change:

$$\Delta basis_t = c + e_t - \theta_1 e_{t-1} \tag{9}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{10}$$

where the conditional variance of the error term e_t is σ_t^2. Let $v_t = e_t^2 - \sigma_t^2$; then we can rewrite the conditional variance equation as

$$[1-(\alpha_1+\beta_1)B]e_t^2 = \alpha_0 + (1-\beta_1 B)v_t$$

where B is the back-shift operator. The FIGARCH model introduces a long memory parameter d into the squared residuals equation:

[6] For details, see Zivot and Wang (2006, chapter 8).

$$[1-(\alpha_1+\beta_1)B](1-B)^d e_t^2 = \alpha_0 + (1-\beta_1 B)v_t \tag{11}$$

or,

$$\beta(B)\sigma_t^2 = \alpha_0 + [\beta(B) - \phi(B)(1-B)^d]\varepsilon_t^2 \tag{12}$$

where $\phi(B) = 1-(\alpha_1+\beta_1)B$ and $\beta(B) = 1-\beta_1 B$. The parameter d captures the persistence behavior of volatility. Baillie et al (1996) show that the model is strictly stationary when d is between 0 and 1.[7] We perform the persistence tests using daily CDS basis data.

3. Data and empirical results

3.1. Data

Our sample includes data from the CDS, bond and stock markets. Daily credit default swap (CDS) data are provided by the Markit Group. Bond transaction data are from the Trade Reporting and Compliance Engine (TRACE), and bond characteristic information is from the Fixed Investment Securities Database (FISD). Daily stock returns are from the Center for Research in Security Prices (CRSP). To compare the behavior of the CDS basis before and after the onset of the subprime crisis, we set our sample period from January 2005 to December 2009.

CDSs are over-the-counter derivatives, and their rates are quoted typically in basis points. Markit Group constructs the daily composite CDS spread by aggregating dealer quotes. For each reference entity, a large number of CDS contracts can exist with differences in maturity, currency denomination, seniority of reference bonds, and treatment of restructuring in credit event definition. We choose the US dollar-denominated 5-year CDS contracts on senior unsecured debts with modified restructuring (MR). Also, because of the need to match CDS data with other databases, we focus on the US reference entities.

TRACE provides prices, yields, par value of a transaction and other trading information of corporate bonds. The FISD database contains issue- and issuer-specific information, such as

[7] Note that this is unlike the stationary region of -0.5 and 0.5 for an ARFIMA model.

coupon rate and frequency, maturity date, issue amount, provisions and credit rating history, for all US corporate bonds maturing in 1990 or later.

We match the 5-year CDS contract with reference bonds of the same maturity. We obtain the yield of the 5-year bond from a set of bonds with maturities that bracket the 5-year horizon. For each reference entity, we search TRACE for a set of bonds with 3 to 5 years left to maturity, and another set of bonds with maturity longer than 6 years at the start of each year. By regressing the yields of these bonds against maturities, we obtain the yield to maturity for a five-year bond to match the CDS. To calculate yield spreads of bonds, we use the five-year swap rate as the reference rate. Swap rates are collected from the Federal Reserve Board.

We use several variables related to counterparty risk, liquidity, market uncertainty and aggregate shocks to explain the CDS basis behavior. We use the Libor-OIS spread (LOIS) as a counterparty risk measure, which is the difference between the 3-month Libor rate and the overnight index swap rate. This spread has been shown to be an effective measure of counterparty credit risk of financial intermediaries (see Gorton and Metrick, 2012). Libor and OIS are from Bloomberg. In addition, we use average CDS rates for primary dealers to measure the credit risk of market makers.

We consider broad liquidity measures to capture the effect of illiquidity in financial markets. These include Amihud and Pastor-Stambaugh bond and stock market liquidity measures, on/off-the-run spreads, money market fund flow (MMFF) and the liquidity factor constructed by Hu, Pan and Wang (2012) from the Treasury market. The Pastor-Stambaugh stock market liquidity index is downloaded from WRDS. The Pastor-Stambaugh bond market liquidity index is constructed using the same method as in Pastor and Stambaugh (2003). The Amihud stock and bond market liquidity indices are constructed using the procedure suggested by Amihud (2002).[8]

[8] The Amihud illiquidity measures are scaled by the ratio of capitalizations of stocks and bonds to obtain the innovations using a procedure similar to Lin et al. (2011).

The data for money market fund flow and on-the-run bond yield are from Bloomberg and off-the-run bond yields are from the Federal Reserve Board (see Gurkaynak, Sack, and Wright, 2007). Moreover, we use liquidity characteristics such as the amount of issuance and age as proxies for bond-specific illiquidity. The age variable is the average age of bonds that we use to construct the 5-year bond yield. Additionally, we use the CDS bid-ask spreads as a proxy for liquidity. Bond liquidity characteristics are obtained from the FISD and CDS bid-ask spreads are from Bloomberg.

Aggregate supply or demand shocks can cause deleveraging and market uncertainty. We use VIX (volatility index) provided by the Chicago Board Options Exchange (CBOE) as a proxy for market uncertainty. To capture the effect of selling and pricing pressure, we calculate the change in the primary dealer position in long-term corporate securities and use it as a measure of deleveraging. The data are obtained from the Federal Reserve Bank of New York.

We keep only the reference entities for which CDS, stock and bond data are available over the sample period. Our sample includes 138,518 daily observations for 453 firm/year reference entities from 198 firms. The data sample includes firms from 11 industries and the sample size is much larger than that employed by Blanco et al. (2005) and Longstaff et al. (2005).

Table 1 provides a summary of the data sample. Over the whole sample period, average basis is negative (-.35%), which is largely due to the reverse relation between CDS and bond spreads during the financial crisis. We use July 1, 2007 as the cutoff for the normal and crisis periods (see also Friewald et al., 2012; Dick-Nielsen et al., 2012). During the normal period (January 2005 to June 2007), average basis is slightly positive. It then becomes quite negative (-.82%) during the crisis period (July 2007 to December 2009). Much of this reversion is because bond spreads increase more rapidly than CDS rates during the financial crisis. Volatility of the basis also increases considerably during the crisis period, about 10 times of the magnitude during the normal period. Bond volatility is higher than CDS volatility. Both yield spreads and CDS rates become much more volatile during the crisis with the volatility of the former being higher than the latter.

[Insert Table 1 Here]

The patterns of the negative basis and high volatility are more pronounced for speculative-grade bonds. Average CDS basis is -1.18% for speculative-grade bonds and -.72% for investment-grade bonds during the crisis period. Average yield spread for speculative-grade bonds is about four times that of the investment-grade bonds. CDS rates are also much higher for speculative-grade bonds than for investment-grade bonds. Moreover, yield spreads and CDS rates are more volatile for speculative-grade bonds than for investment-grade bonds.

Panel B provides a detailed summary of the basis and CDS and bond spreads by rating. During the crisis period, the CDS basis becomes increasingly more negative as the rating decreases. The bond spread increases faster than that the CDS spread during the crisis period and more so for low-grade bonds. Volatility of the basis also increases as the rating decreases.

3.2. Regression results

We select variables related to liquidity, counterparty risk, market uncertainty and supply shocks to explain the temporal behavior of the CDS basis and the underlying bond and CDS spreads. These include NOISE, VIX, PSB, PDCDS, LOIS, DPDPL, and three security-specific liquidity measures: Amihud individual bond liquidity, Zero and CDS bid-ask spreads. The NOISE index captures the deviation of observed Treasury prices from equilibrium prices. Hu et al. (2012) show that this index contains information for marketwide illiquidity. Besides this variable, we use the Pastor-Stambaugh corporate bond market liquidity index (PSB) as a direct measure of bond marketwide liquidity. VIX captures the effect of market uncertainty and PDCDS is the average rate of the CDS contracts written against primary dealers, which is used as a measure of the credit risk of market makers. LOIS is the yield spread between Libor and OIS. DPDPL is the change in the long-term security holdings by primary dealers, which captures the deleveraging effect and selling pressure in the corporate bond market during the subprime crisis when dealers dumped long-term bonds to reduce their risk exposure.

For security-specific liquidity variables, “Amihud” is the Amihud liquidity measure constructed for an individual bond with a maturity closest to the maturity of the CDS reference bond. We add a negative sign to the original Amihud measure to convert it into a liquidity measure for the ease of comparison with the Pastor-Stambaugh marketwide liquidity measure. Zero is proportion of days with no CDS price changes and Askbid is the bid-ask spread for the CDS. These three variables are included to capture the effect of idiosyncratic illiquidity.

Table 2 reports the results of regressions for the basis, CDS spreads and corporate bond yield spreads, respectively. Panel A shows the results of basis regressions for the whole sample and two subsamples: investment and speculative grades. The coefficients and *t*-values are averages of individual regressions. Most explanatory variables are more significant for the crisis period. In addition, the coefficients in absolute terms are much larger for the crisis period than for the normal period, suggesting that these variables become more important during the crisis. There is evidence that nondefault variables play significant roles (in terms of *t* statistics) in explaining the difference in CDS and bond spreads during the crisis.

[Insert Table 2 Here]

The sign of coefficients for NOISE, VIX, LOIS and DPDPL is negative whereas that of PSB and PDCDS is positive. Results show that factors related to market uncertainty and liquidity and supply pressure have contributed significantly to the negative basis during the subprime crisis. A more negative CDS basis is associated with higher market uncertainty, market illiquidity, counterparty risk, funding liquidity and dealers’ selling pressure (deleveraging). Note that PSB is a corporate bond market liquidity measure. The positive coefficient of PSB indicates that when bond market liquidity is low, the basis is low (or more negative). On the other hand, when primary dealers’ credit risk is high, the basis is high (or less negative), implying that when the credit risk for market makers increases, its (positive) impact on CDS rates is greater than that on bond spreads. This finding suggests that credit risk of primary dealers is more important for the CDS market. The three idiosyncratic liquidity variables, Amihud, Zero and Askbid, are mostly insignificant except for a few cases. Although these variables often have significant effects on yield spreads or CDS rates (see Panels B and C), their effects tend to net out in the basis regression.

When the whole sample is divided into subsamples for investment and speculative grades, an interesting pattern emerges. The magnitude of regression coefficients in the CDS basis regression is much larger for speculative-grade bonds, indicating that explanatory variables have much stronger effects on the basis for risker bonds. This explains the more negative basis for speculative-grade bonds and suggests that the selected risk factors play a more important role for low-grade bonds.

Panels B and C report results of regressions for yield spreads and CDS rates, respectively. These results reveal important information for the channels through which the negative basis occurs. All variables except PDCDS, Zero and Askbid have larger coefficients (in absolute terms) for bond spreads than for CDS rates, indicating that these variables have stronger effects on yield spreads than on CDS spreads. Results show that the larger impacts of these variables on bond yields are primarily responsible for the occurrence of the negative basis. The effects of these variables are only partially offset by the effect of PDCDS which has a larger impact on CDS spreads than on bond spreads. Furthermore, these patterns are stronger for speculative-grade bonds and during the crisis period. This explains why the basis is more negative for speculative-grade bonds and for the crisis period. Libor-OIS is more significant for the CDS spread and this variable is not significant for corporate bonds in the normal period.

For robustness, we also consider other liquidity variables such as the Pastor-Stambaugh and Amihud stock market liquidity measures, money market fund flow (MMFF) and bond age.

Results (omitted for brevity) show that including these variables does not increase the explanatory power of the regression model in terms of adjusted R^2. Thus, the liquidity effect is largely captured by the liquidity variables in Table 2.

In summary, we find that bond spreads are more sensitive to both marketwide and bond-specific liquidity, market uncertainty and dealers' deleveraging. On the other hand, CDS spreads are more sensitive to the primary dealers' credit risk and counterparty risk is more significant for the CDS. The former effects dominate the latter effects, leading to the negative basis during the crisis. Results show that part of pricing discrepancies can be explained by differences in the nondefault components of the corporate bond and CDS.

3.3. Cointegration tests

Two markets are cointegrated if they exhibit a long-term equilibrium relation. From the econometric point of view, cointegration implies that a linear combination of two non-stationary series is stationary. The underlying idea is that the two series share a common non-stationary component that can be netted out when they are properly scaled.

The first step to conduct tests of cointegration between CDS and the corporate bond spreads is to check if they are each I(1) non-stationary. We use the augmented Dickey-Fuller (ADF) unit root test for the two spread series and the null hypothesis is that each series has a unit root. After confirming that a unit root exists in each spread series, we set up a VAR model for the bivariate series and use the BIC criterion to determine the AR order in the model. This in turn determines the AR order in the VECM model. We use Johansen's trace statistic to determine the number of cointegration vectors in the spread series. Details for the testing procedure are described in Appendix A.

We perform the cointegration tests for the observed (unadjusted) data and the data adjusted for the effects of nondefault factors. As indicated above, nondefault factors can affect CDS and bond spreads in different ways. If these spreads contain different nondefault components, the

CDS and bond markets will not be integrated. If so, we can adjust the observed spreads for the effects of nondefault factors and see if the adjusted spreads will be cointegrated. The adjusted spreads are the unexplained CDS and bond spreads from the regressions (residuals plus intercept) in Panels B and C of Table 2. If the nondefault components of spreads are primarily responsible for the rejection of the null hypothesis based on the raw data, we expect the tests based on the adjusted spreads to reject the cointegration hypothesis less frequently.

Before performing the cointegration test, we plot the residuals from the CDS and bond spread regressions and the raw (unadjusted) spreads in Figure 1. As shown, the basis adjusted for the effects of nondefault components is closer to zero. Results suggest that nondefault factors play an important role in the negative basis during the crisis period.

Table 3 reports results of cointegration tests at the 1% significance level for both normal and crisis periods. The upper rows show test results based on observed (raw) spreads. We find that 79% of the firms support the cointegration hypothesis for the normal period and 65% of the firms support the hypothesis for the crisis period. Results show that the CDS and corporate bond markets are less integrated during the crisis period.

[Insert Table 3 and Figure 1 Here]

The bottom rows of Table 3 report the results of cointegration tests based on the adjusted spreads. The percentage of firms supporting the cointegration hypothesis increases quite a bit. There are 89% of the firms that support the cointegration hypothesis for the normal period and 75% for the crisis period. Results suggest that nondefault factors are part of the reasons causing the rejection of the cointegration hypothesis. However, there are still a sizable portion of firms rejecting the cointegration hypothesis in the crisis period.

To see whether the rejection is due to missing nondefault variables in the CDS and bond regressions, we include additional variables in the regressions and obtain the adjusted spreads from the regression residuals using the same procedure. The additional variables are intended to capture the effects of possible missing variables for the pricing of CDS and bonds. These include all structural variables used in Collin-Dufresne, Goldstein and Martin (2001),[9] trading volume, coupon, and issuance amount of corporate bonds, the number of quote providers for the CDS, volatility of the CDS rate, number of primary dealers, repo rates (e.g., repoGC, repoMBS), on- and off-the-run spreads, and interest rate volatility in the Treasury market. We then re-conduct the cointegration tests using these finer adjusted spreads. However, we find that the percentage of firms/bonds rejecting the cointegration hypothesis remains almost unchanged. Results cast doubt that missing variables are the reason for rejecting the cointegration. Instead, it points to the possibility that the limited arbitrage is the likely cause for the rejection of the cointegration hypothesis.

3.4. Price discovery

We next examine the issue of price leadership in credit risk markets. Panel A of Table 4 reports the distribution of the information share measures of Hasbrouck (S) and Gonzalo-Granger (G) for individual CDS and bond pairs. These information share measures are estimated from observed CDS and bond spreads. There is clear evidence that the CDS market assumes the dominating price leadership in the credit risk market before the onset of the financial crisis. The information share of the CDS market ranges from 0.92 to 0.95 for the Hasbrouck measure and averages 0.97 for the GG measure during the normal period.

[Insert Table 4 Here]

However, the information share of the CDS market drops significantly during the crisis period though the CDS market remains as the price leader. The mean Hasbrouck measures are 0.67 (lower bound) and 0.73 (upper bound) and the mean G measure is 0.86 for the CDS market. Results suggest that CDS rates become less informative for credit risk during the subprime crisis.

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[9] These include leverage, firm value, return volatility, spot rates, distance to default calculated from the KMV model, expected recovery rates, and term spreads.

One possible reason that CDS rates are less informative is the heightened counterparty risk and credit risk of CDS market makers during the subprime crisis, so that CDS rates reflect not just the credit risk of the reference bond but also other risk factors. This may be why CDS rates become a noisier signal for bond default risk during the subprime crisis. To check this possibility, we re-estimate the information shares using the adjusted spreads, which are the observed spreads adjusted for the effects of nondefault factors.

Panel B of Table 4 reports the results based on the CDS and bond spreads adjusted for the effects of nondefault risk factors. Results suggest that nondefault factors are a main cause for noisy CDS signals during the crisis period. The median Hasbrouck information share measures for the CDS increase substantially to 0.97 (upper bound) and 0.94 (lower bound) for the crisis period after purging the influence of nondefault factors. Results reveal that CDS rates convey important information for credit risk. It is the effects of nondefault factors that induce noise to the CDS signal and make the picture murky. By contrast, using the adjusted spreads has little effect on the information share estimates for the normal period. This result makes sense too. In the tranquil period, counterparty risk and liquidity factors become less important. Therefore, accounting for the effects of nondefault factors has little help for enhancing the signals of CDS rates because the disturbance from these factors is already low.

In summary, we find that the credit risk information is impounded in CDS rates much faster than in corporate bond yields. Results confirm that the CDS market assumes the price leadership in the credit risk markets. The noisy signals of the CDS during the crisis period are largely due to the disturbances of nondefault factors such as counterparty risk and illiquidity. When the effects of these nondefault factors are isolated, the purified CDS rates provide very good signals for credit risk even during the turbulent time. A practical implication from this finding is that to obtain high-quality credit signals, one must account for the effects of nondefault factors on CDS rates.

3.5. Nonparametric tests for market integration

The cointegration tests suggest that limited arbitrage is a likely reason for rejecting the hypothesis of market integration particularly during the crisis period. To further examine this issue, we perform the nonparametric tests based on the direction of price changes and the likelihood of price convergence. Table 5 reports the results of nonparametric tests for pricing discrepancies. As shown, the proportion of pricing discrepancies ($\Delta CDS*\Delta BYS>0$) to total observations ranges from 47.81% at the five-day interval to 46.92% at the 50-day interval during the normal period. Results show that pricing discrepancies can persist over a fairly long period of time as there are still about 47% of co-movements represent arbitrage opportunities at a horizon of 50 days. By contrast, the proportion of co-movements of spreads in the right direction is 41.53% at the five-day interval and increases to 52.05% at the 50-day interval.

[Insert Table 5 here]

The proportion of pricing discrepancies increases during the crisis period. It ranges from 50.46% to 57.10% over different horizons for the whole sample during the financial crisis. The proportion of pricing discrepancies is higher for speculative-grade bonds, ranging from 53.09% to 60%. Consistent with the finding of cointegration tests, results show that markets are less integrated during the subprime crisis. This finding suggests that impediments of arbitrage during the crisis have resulted in more serious distortions in the relationship between CDS rates and bond yield spreads. In addition, pricing discrepancies are more frequent and persistent for riskier bonds. This could be due to higher risk of speculative-grade bonds that makes arbitrage riskier or higher funding constraints (e.g., haircuts) for riskier assets that reduce the capital available for undertaking the arbitrage to eliminate pricing discrepancies.

3.6. Firm-specific impediments and market integration

To understand what have contributed to the persistence in pricing discrepancies, we examine firm characteristics in each CDS/bond pair. If limited arbitrage is a major reason for pricing discrepancies, firms with characteristics related to impediments to arbitrage will be more likely to violate the arbitrage-free condition. The literature has suggested that firm-specific risk, volatility, trading cost and illiquidity are important factors associated with limits to arbitrage. We select these variables for this test. Volatility is the firm's stock return volatility and leverage is the ratio of the book value of debt to the sum of book value of debt and market value of equity. The expected default rate (EDF) calculated by the KMV model is used to measure the default risk of the firm. These three variables are related to firm-specific risk. Arbitrage is riskier for high-risk firms. For the liquidity variable, we choose the Amihud individual bond liquidity measure. To be consistent with the regression results in Table 2, we convert the original Amihud illiquidity measure into the liquidity measure by adding a negative sign. We use the CDS bid-ask spread as the trading cost variable as bid-ask spreads for bonds are unavailable in TRACE during most of our sample period. The Amihud measure and CDS bid-ask spreads measure the liquidity in the corporate bond and credit derivatives markets.

We first calculate the mean of each characteristic variable for the firms that reject or accept the cointegration test and conduct two-sample mean difference tests for these two groups of firms. Panel A of Table 6 provides test results for the whole sample period. Results show that firms which reject the cointegration hypothesis tend to have high stock return volatility, default risk (EDF), leverage, CDS bid-ask spread, and low bond liquidity. Test statistics are all significant at least at the ten percent level for the full sample. When dividing the sample period into the normal and crisis periods, an interesting pattern emerges. All firm-specific impediment variables are significantly different for the crisis period whereas for the normal period, most variables are insignificant except leverage. Results suggest that impediments to arbitrage are more severe and their effects become more important during the financial crisis.

[Insert Table 6 Here]

We next examine the relation between the nonparametric pricing discrepancy measure

(Kendall κ ratios) and firm-specific impediment characteristics. Table 7 summarizes the estimation of simple regressions of κ against each impediment variable over different intervals τ. For the whole sample period, all variables are mostly significant and of the predicted sign and the average adjusted R^2 is 10%. Results show that market integration increases with liquidity and decreases with firm-specific risk and return volatility. For the crisis period, we find a similar pattern in the regressions and much stronger results. The coefficients of explanatory variables are more significant in the crisis period and the adjusted R^2 averages 15%. By contrast, these variables are less significant and average adjusted R^2 is only about 4% for the normal period.

[Insert Table 7 Here]

In summary, we find that firms with greater impediments to arbitrage (e.g., higher risk and trading cost and lower liquidity) are more likely to experience pricing discrepancies. Moreover, pricing discrepancies are more serious and markets are less integrated during the subprime crisis. These findings strongly support the hypothesis that pricing discrepancies are caused by impediments to arbitrage.

4. Persistence in pricing discrepancies

The analysis above suggests that market disintegration is associated with impediments to arbitrage, which become more serious during the crisis period. Impediments can be due to search frictions and slow capital movement. Duffie (2010) suggests that impediments to arbitrage lead to persistent pricing discrepancies over longer horizons. In this section, we investigate this implication for persistence behaviors in pricing discrepancies. We first examine the speed of impulse response in the CDS and corporate bond markets. Following this, we study the persistence of the basis and its volatility using long memory models.

4.1. Impulse response in the CDS and bond markets

The impulse response function provides important information for the speed and dynamic response to a unit shock in the CDS and bond markets. The manner in which the response function tapers off sheds light on how "persistent" prices are. Although this information can be extracted from observed prices, daily prices are typically quite noisy with fairly large fluctuations, particularly for corporate bonds. In such a case, time aggregation can help reduce noise and enhance information signal. We experiment a few options and find that a low level of 3-day aggregation provides the most satisfactory result. We therefore construct the 3-days data series, which are non-overlapping averages of every 3 consecutive daily observations, to perform the impulse analysis. We find that this gives a more telling picture of price response to shocks than the unsmoothed raw data.

The impulse response function IRF is depicted in Figure 2, which plots the price response up to 200 steps.[10] The response functions in the two markets are labeled as CDS_N, CDS_C, BYS_N, and BYS_C, where N and C denote the normal and crisis periods, respectively. The IRFs show the dynamic response to a unit shock in each market.[11]

The response patterns for investment-grade (IG) bonds and speculative-grade (SG) bonds are portrayed in Figures 2a and 2b, each shows the IRFs for the two markets in two subperiods. Corresponding to Figure 2, Table 8 reports the peak IRF values and the steps it takes for the IRF to go down to 0.75, 0.5 and 0.25 of its peak, labeled as 3Q, 2Q and 1Q, respectively, which capture the speed that the IRF tapers off. The longer it takes to reach these quartile marks, the slower is the response to die down to zero and the greater is price persistence.

[Insert Figure 2 Here]

We first look at the IRFs for investment-grade bonds. Figure 2a shows that as expected, the magnitude of the response from a unit shock during the normal period is much smaller in comparison to the crisis period, and the peak response value is about 0.02 in comparison to 0.1. Interestingly, the CDS and bond markets for the investment grade show a fairly similar response

[10] Each step represents three days.
[11] The impulse response analysis requires constructing the orthogonal IRF. The procedure is given in Appendix B.

pattern in both periods with CDS rates somewhat more persistent during the crisis period.

For speculative-grade bonds, Figure 2b gives the impression that the CDS is much more persistent than the bond market. Looking more closely reveals that there is a sharp initial jump for the corporate bond spread during the crisis period, which drops rapidly and after that the IRF tapers off slowly. To better reflect the speed of decay, we ignore the first IRF jump and report the 3Q, 2Q and 1Q without it in Table 8. The resulting quartile marks for corporate bonds become quite comparable to those of the CDS during the crisis period. For investment-grade bonds, the quartile marks for the CDS require 14, 31 and 65 steps to reach and 13, 28 and 61 steps for bonds during the crisis. A similar pattern is found for speculative-grade bonds.

[Insert Table 8 Here]

Results in Figure 2 clearly show that the magnitude of the impulse response is much higher for speculative-grade bonds than investment-grade bonds. During the normal period, the peak IRF is around 0.02 for IG bonds and 0.09 for SG bonds. During the crisis period, it is 0.12 for IG bonds and 0.63 for SG bonds. From Figure 2, it can also be visualized that the speed of CDS spread adjustment to a shock depends on the riskiness of the reference bond and the condition of the financial market. The speed of adjustment is somewhat higher for the CDS of IG bonds. As shown in Table 8, it takes 8, 15 and 25 steps to drop to the quartile marks of the peak response value for the CDS of SG bonds but it only takes 7, 12, 19 steps for the CDS of IG bonds during the normal period.

Controlling for the riskiness of the security, the speed of price adjustment is slower when the market is more uncertain as it is during the crisis period. For example, it takes 31 steps for the CDS of investment-grade bonds to drop down to the half of the peak response value during the crisis period, compared to only 12 steps during the normal period. Similarly, for the CDS of speculatively-grade bonds, it takes 22 steps to drop down to the half of the peak response during the crisis period, as opposed to 15 steps during the normal period.

The response to a shock in the bond market exhibits a somewhat different pattern. When there is a shock in the bond market, bond yield spreads respond almost instantly, then drops and decays slowly. Ignoring the first sharp jump, the peak IRF is about 0.02 (IG bonds) and 0.06 (SG bonds) during the normal period, and a much larger response of 0.10 (IG bonds) and 0.40 (SG bonds) during the crisis period. After that, it takes about 8 to 10 steps during the normal period for the response to reduce to half of the peak value and about 21 to 28 steps during the crisis period.

Overall, results of the impulse response analysis are consistent with the hypothesis of impediments to arbitrage. Price jump is larger and recovery is slower for riskier securities and in a less liquid market. Results show that it takes longer time to converge to a new equilibrium for a riskier security after an exogenous shock. Moreover, the convergence speed is much lower during the crisis period.

4.2. Persistence of basis, absolute basis and absolute basis changes

While the impulse response analysis above provides a nice picture for the adjustment of CDS and bond prices which is easy to visualize, it does not give a precise measure for persistence of pricing discrepancies. To this end, we measure the persistence of pricing discrepancies using the long memory parameter d. Table 9 reports estimates of the persistence measure d based on the R/S statistic by bond quality, period (normal versus crisis) and by both quality and period. We estimate the long memory parameter for the CDS basis, the absolute value of the basis, and the absolute value of basis changes. Details of estimation procedure are described in Appendix C.

Impediments to arbitrage cause persistence in the pricing discrepancy and this effect is expected to be stronger for riskier bonds (Duffie, 2010). To see if this is the case, we estimate the long memory parameter d for the CDS basis over the whole sample period and then average them across bonds of different grades.

[Insert Table 9 Here]

Panel A of Table 9 reports estimates of the long memory parameter *d* for the full sample, and tests of the differences of *d'*s between speculative- and investment-grade bonds. As indicated, all three persistence measures are higher (ranging from 0.025 to 0.05, for the basis, |basis| and |Δbasis|) for *Difference*. The bottom row reports the *p*-value for the test of the difference in mean *d* estimates of SG and IG bonds. The null hypothesis is that the two groups have the same mean of *d*, against a one-sided alternative that the mean of *d* for SG bonds is greater than that for IG bonds. Results show that the null hypothesis is rejected at the 5% significance level for all cases, supporting the hypothesis that the CDS basis is more persistent in both level and changes for speculative-grade bonds.

An important question is whether the basis (or |basis|, |Δbasis|) is more persistent during the crisis period. Pricing discrepancies should be more persistent when there are greater impediments to arbitrage during the crisis period. Panel B of Table 9 reports the estimates for the two subperiods. Results show that all persistence measures for the basis, |basis| and |Δbasis| are higher during the crisis period. The bottom row reports the *p*-value of the two-sample *t*-test on the difference in *d* estimates between the two subperiods. The null hypothesis is that the two subperiods have the same mean of *d*, against a one-sided alternative that the mean of *d* during the crisis period is greater than that during the normal period. Panel B shows that the null hypothesis is easily rejected with *p*-values all close to 0. Results strongly support the hypothesis that the basis is more persistent in both level and change during the crisis period.

Panel C of Table 9 reports results by both bond grade and period. As shown, persistence of the basis is the lowest (0.34) for IG bonds during the normal period and the highest (0.40) for SG bonds during the crisis period. In between, persistence measure is about 0.36 for SG bonds during the normal period and is 0.39 for IG bond during the crisis period. Results show that for both IG and SG bonds, the basis is more persistent during the crisis period and the difference is 0.042 for the former and 0.043 for the latter, both are highly significant. The basis for SG bonds is more persistent than that for IG bonds, both in the crisis and normal periods. The difference is 0.015 (crisis period) and 0.014 (normal period) but the *p* values are only 0.15 to 0.22.

Summarizing, our results show that the basis becomes significantly more persistent during the crisis period and speculative-grade bonds are more persistent than investment-grade bonds. Comparatively speaking, the basis for SG bonds during the crisis period has the highest persistence whereas that for IG bonds during the normal period has the lowest.

Results for the absolute basis (|Basis|) and absolute basis changes (|ΔBasis|) also show significantly higher *d* values during the crisis period. For the absolute basis, the difference between SG and IG bonds in the normal period is significant at the one percent level. Similar results are found for the difference in the persistence of absolute basis changes.

Overall, results strongly support the hypothesis that pricing discrepancies become more persistent during the financial crisis. This finding is consistent with the contention that frictions to capital movement and arbitrage lead to more persistent pricing discrepancies during the crisis period. Results show that pricing discrepancies between the CDS and reference bond can persist over a long period of time, and are more persistent in times of stress. Moreover, pricing discrepancies are more persistent for riskier bonds.

4.3. Volatility persistence of the basis

The above results for absolute basis changes suggest that volatility of the basis is persistent. There is a large literature on volatility persistence and this issue can be explored in a more formal setting. As basis changes exhibit clustering, it is particularly suitable to analyze volatility persistence in the GARCH framework. In this section, we estimate the long memory FIGARCH model which admits a long memory structure in conditional volatility. Specifically, we estimate the MA(1)-FIGARCH(1,1) for basis changes: $\Delta basis_t = c + e_t - \theta_1 e_{t-1}$ where $(1-(\alpha_1+\beta_1)B)(1-B)^d e_t^2 = \alpha_0 + (1-\beta_1 B)v_t$ with $v_t = e_t^2 - \sigma_t^2$ (see (9) and (10)). We fit this model to the basis series for investment- and speculative-grade bonds.

Table 10 reports estimates of the MA(1)-FIGARCH(1,1) model of basis changes for IG and SG bonds for the normal and crisis periods. We observe that in normal times, the CDS basis for both investment- and speculative-grade bonds does not show very significant volatility persistent behavior. The *d* estimate is a little over 0.1 and *p*-value is about 9% to 10%. In contrast, during the crisis period the CDS basis shows highly significant volatility persistence, particularly for speculative-grade bonds. The *d* estimates are 0.74 and 0.97 for the basis of investment- and speculative-grade bonds, respectively, with *p*-values close to 0.

[Insert Table 10 Here]

These results are consistent with the findings in Table 9 and support the hypothesis that impediments to arbitrage lead to persistent pricing discrepancies during the subprime crisis. Volatility persistence becomes significantly higher during the crisis period. Moreover, the basis and its volatility for SG bonds are more persistent than for IG bonds in both normal and crisis periods. The basis and its volatility for SG bonds during the crisis period are most persistent whereas those for IG bonds during normal period are least persistent.

5. Conclusion

How can two closely related markets have exceedingly large pricing discrepancies? This important question bears on equilibrium asset pricing and market integration. Our paper examines this issue using the data of credit markets, which exhibited an extremely negative CDS basis during the financial crisis. We investigate roles of nondefault risk factors and impediments to arbitrage in the unusual pricing discrepancies of the CDS and corporate bond markets.

We find that price discrepancies can be explained partly by nondefault risk factors in the CDS and bond markets. Bond spreads are more sensitive to nondefault factors such as liquidity, market uncertainty and supply shocks. This contributes to the negative basis during the subprime crisis. However, we also find that nondefault risk factors can only explain some of the pricing discrepancies between the CDS and corporate bond markets. Empirical evidence suggests that impediments to arbitrage are the root cause for pricing discrepancies and lack of integration in the CDS and corporate bond markets.

Our results show that a significant portion of firms reject the hypothesis of cointegration. Accounting for the effects of nondefault factors reduces the cases of violations in normal market conditions but the percentage of firms rejecting the hypothesis remains high during the crisis. Similar findings are obtained by the nonparametric test. Results point to limits-to-arbitrage as the cause for disintegration between the CDS and the bond markets.

Consistent with the hypothesis of limited arbitrage, we find that firms with high risk and trading cost and low liquidity are more likely to experience pricing discrepancies in credit markets. Pricing discrepancies are more persistent for speculative-grade bonds and are more severe during the subprime crisis. Both the level and volatility of the basis become more persistent during the crisis period and exhibit long memory. This finding supports Duffie's (2010) hypothesis that slow-moving capital and other impediments to arbitrage cause persistence in pricing discrepancies over longer horizons.

Appendix

A. Cointegration Analysis

The cointegration analysis is conducted at the firm's level for the observed CDS and BYS series as well as their adjusted spreads based on the regression of spreads on the nondefault factors such as liquidity, counterparty risk and deleveraging. For the cointegration analysis to be meaningful, we first need to check if the two spread series are each I(1) non-stationary. Thus, we first conduct an augmented Dickey-Fuller (ADF) test on each series. If both series accept the null hypothesis of unit root, we move forward to the cointegration analysis; otherwise, the case will be left out. In empirical analysis, the ADF test conducted at the 5% and 10% level give similar results.

We follow Johansen's methodology to perform the cointegration test. Detailed description about this method can be found, for example, in Zivot and Wang (2006, Chapter 12) and we briefly describe the methodology below. Let $Y_t = (p_t, q_t)'$, where p_t and q_t are CDS and the bond yield spreads, respectively, unadjusted or adjusted for the nondefault components. We first consider a VECM model of the following form:

$$\Delta Y_t = c + \Pi Y_{t-1} + \sum_{i=1}^{r-1} \Psi_i \Delta Y_{t-i} + e_t$$

Based on the rank of the long-run impact matrix Π, the number of cointegration vector is determined. Specifically, there are three possibilities: 1) the case of no cointegration vector with the rank of Π = 0, in which both series are non-stationary I(1) but they are not cointegrated since a cointegration vector cannot be found; 2) the case of two cointegration vectors with the rank of Π = 2 in which both CDS and BYS are stationary series; 3) the relevant case of one cointegration vector with the rank of Π = 1. In the last case, both series are non-stationary I(1) but a linear combination of them is stationary; therefore $\Pi = \lambda b'$, and $b = (1, \beta)'$ is the normalized cointegration vector.

We use Johansen's trace test to draw the inference. The methodology is a sequential test procedure. Step 1 tests Ho: no cointegration vector versus Ha: at least 1 cointegration vector. If Ho is not rejected, then no cointegration vector is concluded. If Ho is rejected, step 2 further tests if there are one or two cointegration vectors; i.e., Ho: 1 cointegration vector versus Ha: 2 cointegration vector. Thus, to conclude one cointegration vector, the trace test statistic has to be significantly large in step 1 and is significantly small in step 2. Details and critical values are discussed in Zivot and Wang (2006, Chapter 12).

B. Impulse Response Analysis

For the impulse response analysis, we use the orthogonal impulse response function (IRF) to study the speed of dynamic response to a unit shock in each market. The approach is briefly described as follows.[12] Let $Y_t = (p_t, q_t)'$ be a vector of bivariate price series which follows a VAR model: $Y_t = c + \sum_{i=1}^{r} \Phi_i Y_{t-i} + e_t$. The error e_t is a zero-mean vector of serially uncorrelated innovations with a covariance matrix Ω, which is not necessarily diagonal. In our estimation, the order of the VAR model use is two. To study the impulse response, a unit shock is introduced to the system. Specifically, let e_t = (1,0)′ or (0,1)′ be a unit shock occurred in the CDS or the bond market. The impulse response can be computed based on the estimated VAR model. However, the impulse response computed this way has the right interpretation only when the covariance matrix Ω is diagonal, a condition which in practice is seldom met. In the literature, a common practice is to first diagonalize Ω and then use the transformed VAR model to compute the (orthogonal) impulse response.

For the two series that we analyze, the CDS has a much higher information share and so we put it as the first series p_t and the BYS as the second series q_t. Note that the impulse response pattern depends on the imposed ordering. The series is then transformed using a lower triangular

[12] See Zivot and Wang (2006, Chapter 11) for details.

matrix B with a unit diagonal: $BY_t = d + \sum_{i=1}^{r} \Gamma_i Y_{t-i} + \eta_t$ such that the error term η_t is orthogonal and has a diagonal covariance matrix. This triangular structural VAR model can be re-expressed in an infinite VMA based on the orthogonal error η_t as $Y_t = a + \Theta_0 \eta_t + \Theta_1 \eta_{t-1} + \Theta_2 \eta_{t-2} + \ldots$, where the diagonal *ii*th element of Θ_s can be regarded as the orthogonal impulse response function (IRF) of the price with respect to the orthogonal error η_t in the *i*th market, which represents the effect on the price *s*th period later for a unit shock in η_t.

C. The Procedure for Estimating the Long memory Parameter

We take the following approach to estimate persistence and perform significance tests. In the time-series literature, it is well known that the persistence behavior, i.e., the long memory parameter *d*, is preserved upon time aggregation[13] (see for example, Tschernig, 1995; Chambers, 1998; Tsai and Chan, 2005; Man and Tiao, 2006). Time aggregates refer to the non-overlapping sums (or averages which we use here to maintain the magnitude) of the underlying data. For instance, weekly and monthly data are time aggregates of daily data, with the level of aggregation 7 and 30, respectively. Theoretically, they all share the same persistence behavior *d*. We utilize this important property to construct our persistence estimate. Specifically, we use the R/S method to estimate *d* for each bond rating portfolio based on the underlying daily data, and its time aggregates from 2 to 10 days. For each rating portfolio, we obtain ten *d* estimates and the average of these *d* values is used as the persistence measure. We find that this approach yields a more stable persistence estimate. Results are then summarized into speculative- and investment-grade bond groups. We use this procedure to obtain the persistence measure for the whole sample period and the normal and crisis periods, respectively.

[13] Ohanissian, Russell and Tsay (2008) use this invariance property to propose a statistical test to distinguish between true long memory and spurious long memory.

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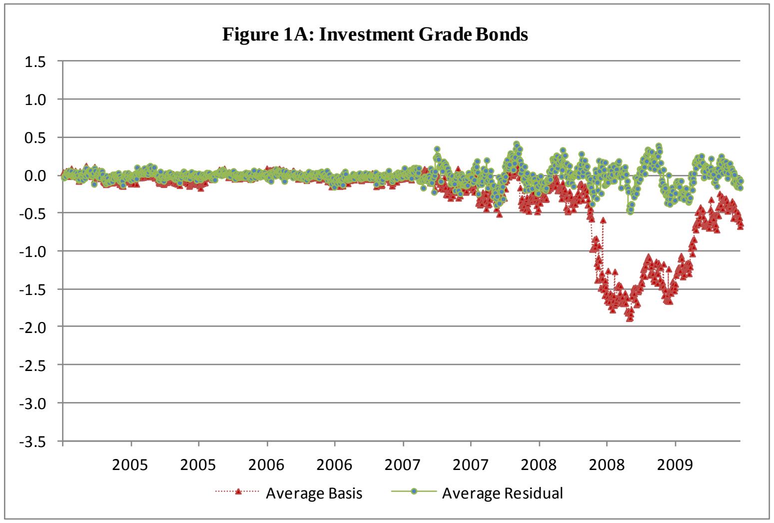
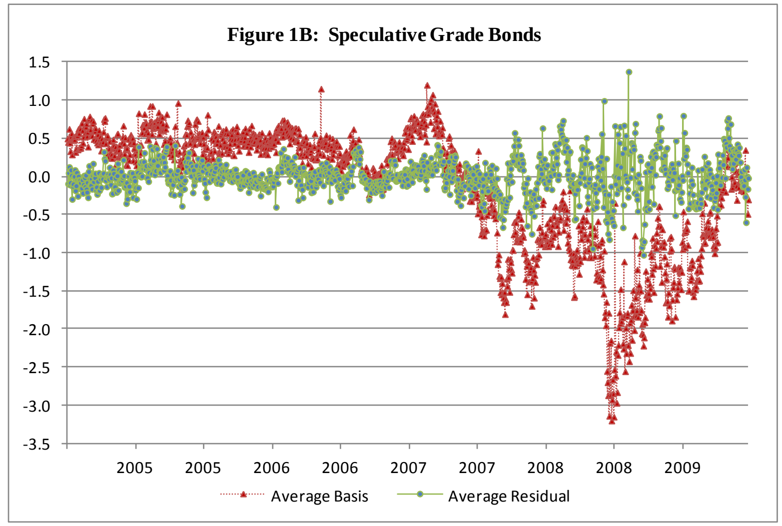
Figure 1: Average basis and residuals (risk-adjusted basis) from 2005 to 2009.

This figure plots mean observed basis and the basis adjusted for the effects of nondefault factors in percentage. Figure 1a is for the investment-grade firms, figure 1b is for the speculative-grade firms, and figure 1c is for all firms.





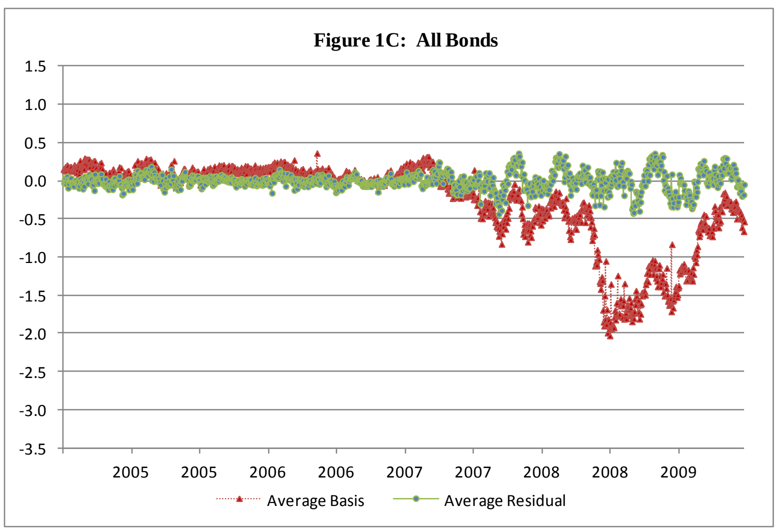
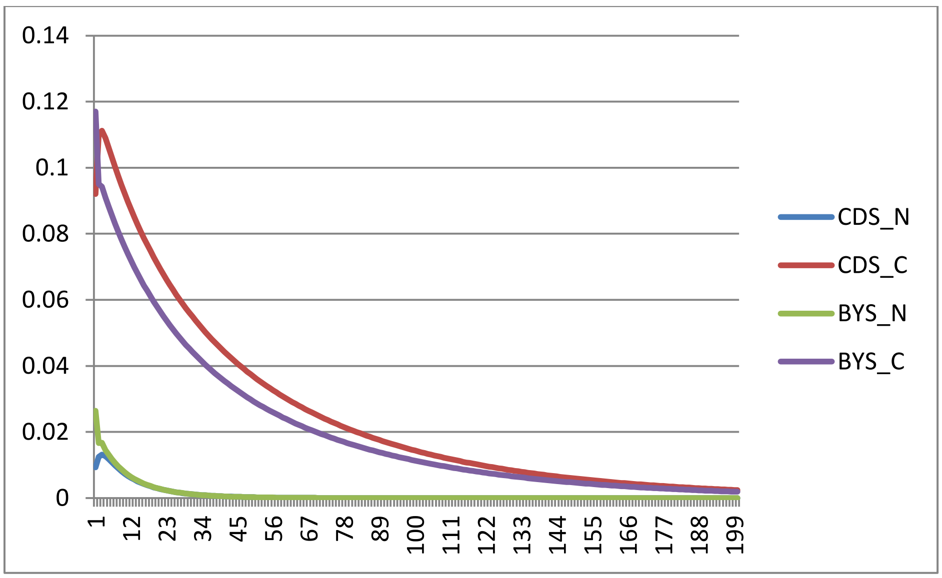


Figure 2. Impulse Response

The graphs show the speed and dynamic responses to a unit shock in the CDS and bond markets during the normal and crisis periods. We plot the orthogonal IRF (vertical axis) up to 200 steps (horizontal axis) based on 3-day data, each step represents three days. The graph shows the orthogonal IRF of CDS during normal period (CDS_N) and crisis period (CDS_C), and similarly for bond yield spreads BYS_N and BYS_C, resulting from a unit shock in their own market. The IRF is computed based on the estimates of the VAR model. Figure 2a is for investment-grade bonds, while Figure 2b is for speculative-grade bonds. The two higher response curves correspond to the crisis period.

2a. Investment-grade bonds



2b. Speculative-grade bonds

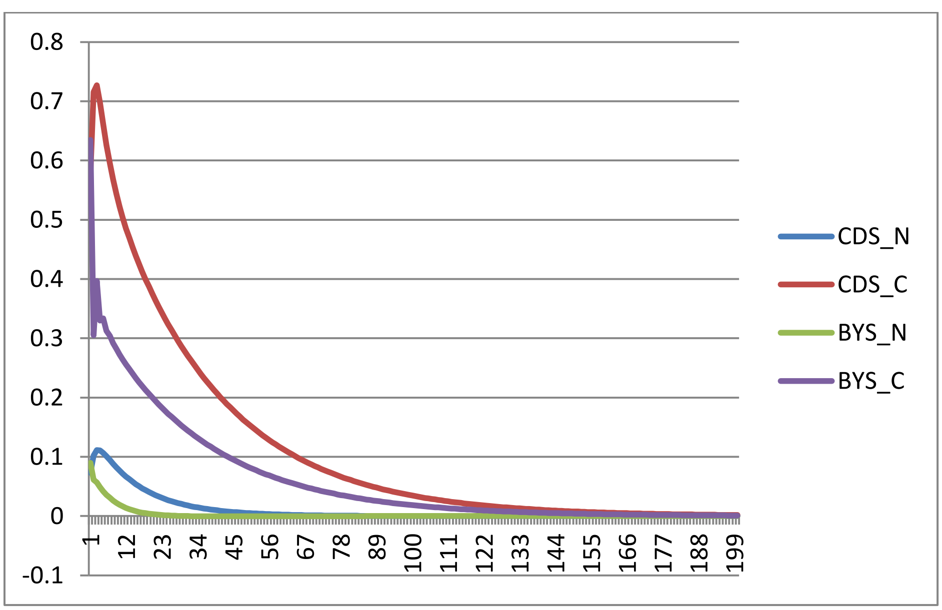


Table 1. Summary statistics

This table summarizes the bond yield, CDS spread and basis. The sample period is from January 2005 to December 2009. The whole sample is further divided into two subperiods where the normal period is from January 2005 to June 2007 and the crisis period is from July 2007 to December 2009. Panel A provides the summary for all bonds, investment-grade bonds and speculative-grade bonds, Panel B provides the summary for bonds in each rating category.

Panel A: Summary of spreads and basis

		Basis			Bond			CDS		
	Period	Mean	Median	Std.	Mean	Median	Std.	Mean	Median	Std.
All bonds	Normal	0.075	0.084	0.071	0.816	0.808	0.139	0.891	0.886	0.127
	Crisis	-0.823	-0.535	0.745	3.518	3.123	1.722	2.695	2.381	1.065
	Whole	-0.351	-0.021	0.683	2.148	1.042	1.845	1.796	1.176	1.179
Investment Grade	Normal	-0.020	-0.017	0.053	0.308	0.299	0.068	0.288	0.295	0.039
	Crisis	-0.724	-0.378	0.719	2.299	1.884	1.483	1.576	1.383	0.762
	Whole	-0.354	-0.077	0.608	1.288	0.421	1.450	0.934	0.370	0.841
Speculative Grade	Normal	0.323	0.350	0.193	2.132	2.203	0.317	2.455	2.513	0.337
	Crisis	-1.181	-1.073	1.143	8.329	7.639	4.035	7.147	6.119	3.161
	Whole	-0.433	-0.068	0.969	5.199	2.595	4.260	4.766	3.237	3.219

Panel B: by rating

		Basis			Bond			CDS		
	Period	Mean	Median	Std.	Mean	Median	Std.	Mean	Median	Std.
AAA/AA	Normal	0.054	0.059	0.063	0.123	0.115	0.059	0.177	0.115	0.027
	Crisis	-0.173	-0.077	0.353	1.274	1.073	0.746	1.101	0.968	0.419
	Whole	-0.054	0.036	0.272	0.670	0.210	0.772	0.616	0.245	0.521
A	Normal	0.018	0.023	0.055	0.209	0.199	0.061	0.227	0.210	0.039
	Crisis	-0.581	-0.281	0.651	2.154	1.640	1.457	1.573	1.337	0.791
	Whole	-0.267	-0.327	0.541	1.133	0.304	1.397	0.866	0.295	0.852
BBB	Normal	-0.143	-0.123	0.121	0.626	0.596	0.145	0.483	0.487	0.066
	Crisis	-1.248	-0.802	1.032	3.348	2.934	1.849	2.100	1.883	0.886
	Whole	-0.667	-0.287	0.904	1.917	0.855	1.865	1.250	0.607	0.974
BB	Normal	0.125	0.131	0.221	1.585	1.576	0.310	1.710	1.701	0.275
	Crisis	-1.467	-1.616	1.343	6.510	6.151	3.559	5.043	4.191	2.671
	Whole	-0.631	-0.118	1.230	3.922	2.000	3.480	3.291	2.257	2.494
B	Normal	0.160	0.068	0.407	2.953	3.020	0.472	3.113	3.686	0.674
	Crisis	-1.938	-1.561	1.314	10.108	8.909	4.602	8.170	7.663	3.591
	Whole	-0.986	-0.699	1.242	6.345	3.604	4.788	5.359	4.694	3.639

Table 2. Regression results

This tables reports the regression results for the basis, bond spreads, and CDS spreads for the whole sample period, and the normal and crisis periods. The normal period is from January 2005 to June 2007 and the crisis period is from July 2007 to December 2009. The regressors include various variables that capture the effects of liquidity, market uncertainty, counterparty risk and deleveraging. *NOISE* is from Hu, Pan and Wang (2012) which measures the deviation of observed Treasury prices from equilibrium prices; *VIX* (volatility index) is from the Chicago Board Options Exchange (CBOE) and is a proxy for risk of arbitrage; *PSB* is Pastor-Stambaugh corporate bond market liquidity index; *PDCDS* is the average rate of the CDS contracts written against primary dealers, which measures the credit risk of primary dealers; LOIS is the yield spread between Libor and OIS, a proxy for counterparty risk; and DPDPL is the change in the long-term security holdings by primary dealers, which measures the selling pressure in the corporate bond market. Beside these variables, we incorporate three other variables in the regressions: Amihud, Zero, and Askibid. Amihud is the Amihud individual bond liquidity measure. We add a negative sign to convert the original illiquidity measure to a liquidity measure to have an easy comparison with the Pastor-Stambaugh liquidity measure. Zero is the proportion of days with no price changes and Askbid is the bid-ask spread for the CDS. For each regression, we report average coefficients *t*-statistics (in parentheses), and adjusted R^2. Panels A, B and C report regression results for basis, bond yield spread, and CDS spread, respectively. *, **, and *** indicate the 10%, 5%, and 1% levels of significance, respectively.

Panel A: Basis regressions

Sample	Period	NOISE	VIX	PSB	PDCDS	LOIS	DPDPL	Amihud	Zero	Askbid	R^2
All bonds	Whole	-1.04***	-0.13**	0.07	0.50*	-0.50*	-7.89*	0.85	-0.45	0.36	0.491
		(-2.53)	(-2.22)	(1.56)	(1.94)	(-1.76)	(-1.68)	(1.12)	(-0.28)	(0.97)	
	Normal	-0.76	-0.06	0.03	0.45*	-0.08	-2.89	0.51	-0.29	0.29	0.182
		(-0.95)	(-0.90)	(1.11)	(1.65)	(-1.36)	(-1.62)	(1.77)	(-0.52)	(0.75)	
	Crisis	-1.20**	-0.19**	0.20*	1.04*	-0.64*	-8.99	1.53	-0.57	0.48	0.548
		(-2.08)	(-2.07)	(1.73)	(1.74)	(-1.78)	(-1.62)	(0.79)	(-1.12)	(0.12)	
Investment grade	Whole	-0.55***	-0.09**	0.03	0.33**	-0.27*	-6.51*	0.78	-0.30	0.27	0.492
		(-2.78)	(-2.33)	(1.57)	(2.12)	(-1.71)	(-1.70)	(1.21)	(-0.25)	(0.66)	
	Normal	-0.41	-0.03	0.02	0.23*	-0.05	-1.63	0.34*	-0.25	0.18	0.152
		(-1.00)	(-0.94)	(1.05)	(1.72)	(-1.03)	(-1.63)	(1.80)	(-0.30)	(0.87)	
	Crisis	-0.65**	-0.16**	0.16	0.62*	-0.50*	-7.27*	0.84	-0.48	0.37	0.552
		(-2.06)	(-2.18)	(1.50)	(1.85)	(-1.65)	(-1.71)	(0.80)	(-0.21)	(0.20)	
Speculative grade	Whole	-2.18*	-0.29*	0.20	1.17**	-0.68**	-13.17*	1.42	-0.68	0.45	0.491
		(-1.79)	(-1.93)	(1.47)	(2.10)	(-2.02)	(-1.79)	(0.56)	(-1.52)	(0.13)	
	Normal	-1.95	-0.15	0.06	0.81	-0.30	-7.19	0.81	-0.31	0.36	0.263
		(-0.76)	(-1.25)	(0.78)	(1.49)	(-1.40)	(-1.57)	(1.05)	(-1.16)	(0.26)	
	Crisis	-2.33	-0.41*	0.52*	1.65*	-0.76**	-17.80	2.06*	-0.78	0.62	0.477
		(-1.64)	(-1.68)	(1.86)	(1.79)	(-2.06)	(-1.50)	(1.81)	(-1.45)	(0.28)	

Panel B: Bond spread regressions

Sample	Period	NOISE	VIX	PSB	PDCDS	LOIS	DPDPL	Amihud	Zero	Askbid	R^2
All bonds	Whole	1.60***	0.29***	-0.22*	0.29***	0.58*	9.14	-2.31	0.27	5.69***	0.681
		(3.10)	(2.98)	(-1.67)	(3.03)	(1.80)	(1.51)	(-1.14)	(0.33)	(4.11)	
	Normal	1.45	0.02	-0.18	0.25	0.35	3.91	-1.98	0.06	1.42**	0.179
		(0.99)	(0.92)	(-1.17)	(1.35)	(1.16)	(1.40)	(-1.40)	(0.25)	(1.99)	
	Crisis	1.99***	0.41***	-0.37	0.38***	0.72*	10.95	-3.12	0.83	5.76***	0.759
		(2.77)	(2.60)	(-1.51)	(2.60)	(1.88)	(1.64)	(-0.83)	(0.46)	(3.62)	
Investment grade	Whole	1.00***	0.20***	-0.07	0.25***	0.41*	5.60	-1.99	0.10	2.31***	0.674
		(3.46)	(3.20)	(-1.52)	(2.76)	(1.81)	(1.52)	(-1.23)	(0.15)	(3.22)	
	Normal	0.77	-0.02	-0.02	0.21	0.26	1.65	-1.24	0.05	0.25	0.135
		(1.14)	(-0.94)	(-1.08)	(1.25)	(1.07)	(1.32)	(-1.49)	(0.30)	(1.17)	
	Crisis	1.24**	0.28***	-0.12	0.27**	0.55**	8.10*	-2.62	0.24	3.85***	0.743
		(2.41)	(2.64)	(-1.44)	(2.35)	(2.23)	(1.72)	(-0.97)	(0.22)	(3.28)	
Speculative grade	Whole	1.78*	0.61**	-0.74**	0.59	0.87*	21.18	-3.39	1.37	5.77***	0.706
		(1.77)	(2.26)	(-2.15)	(1.49)	(1.79)	(1.61)	(-0.82)	(1.07)	(5.22)	
	Normal	1.68	0.03	-0.63	0.25**	0.56**	11.17*	-2.28	0.23	4.31***	0.340
		(1.23)	(0.85)	(-1.45)	(2.12)	(2.02)	(1.70)	(-1.09)	(0.47)	(3.85)	
	Crisis	2.13**	0.99**	-1.74*	0.71*	0.92**	18.71*	-3.69	3.45	6.29***	0.829
		(2.11)	(2.43)	(-1.70)	(1.89)	(2.05)	(1.92)	(-1.07)	(0.73)	(3.48)	

Panel C: CDS spread regressions

Sample	Period	NOISE	VIX	PSB	PDCDS	LOIS	DPDPL	Amihud	Zero	Askbid	R^2
All bonds	Whole	0.55***	0.13***	-0.13	0.97***	0.21**	2.98*	-1.49	0.32	5.33***	0.817
		(4.05)	(3.42)	(-1.53)	(5.79)	(2.27)	(1.84)	(-0.43)	(0.69)	(9.30)	
	Normal	0.41**	0.07***	-0.11**	0.68***	0.16***	1.63*	-0.68	0.20	2.99***	0.562
		(2.22)	(2.52)	(-2.12)	(4.33)	(2.52)	(1.69)	(-0.25)	(1.01)	(3.29)	
	Crisis	0.71***	0.29***	-0.25	1.30***	0.31	3.85**	-2.32	0.39	6.98***	0.862
		(2.83)	(2.99)	(-1.49)	(3.47)	(1.56)	(2.28)	(-0.74)	(0.23)	(8.09)	
Investment grade	Whole	0.44***	0.10***	-0.03*	0.46***	0.10***	2.34***	-0.61	0.05	3.78***	0.842
		(4.35)	(3.84)	(-1.69)	(6.44)	(2.92)	(2.69)	(-0.14)	(0.33)	(7.92)	
	Normal	0.26**	0.03***	-0.01*	0.36***	0.02***	1.15	-0.32	0.03	1.87***	0.549
		(2.34)	(2.78)	(-1.84)	(4.46)	(3.11)	(1.43)	(-0.77)	(0.76)	(3.68)	
	Crisis	0.53***	0.17***	-0.06	0.70***	0.13**	2.59**	-1.46	0.13	4.53***	0.882
		(3.62)	(2.89)	(-1.54)	(3.71)	(1.98)	(2.28)	(-1.41)	(0.29)	(5.76)	
Speculative grade	Whole	0.93***	0.26**	-0.34*	2.08***	0.36**	6.75**	-2.13	0.70*	6.37***	0.730
		(2.50)	(2.15)	(-1.92)	(3.09)	(2.34)	(2.30)	(-1.05)	(1.77)	(5.03)	
	Normal	0.70	0.16**	-0.28	1.33***	0.22*	3.58	-1.29	0.49	3.84***	0.606
		(1.47)	(2.23)	(-1.39)	(3.77)	(1.92)	(1.43)	(-0.90)	(1.33)	(3.62)	
	Crisis	1.41	0.58**	-0.85**	2.43**	0.50**	7.04**	-2.81	0.89*	7.42***	0.773
		(1.64)	(2.13)	(-2.14)	(1.99)	(2.32)	(2.34)	(-1.05)	(1.72)	(4.31)	

Table 3. Cointegration tests

This table summarizes cointegration test results based on both observed (raw) CDS and bond yield spreads, and the spreads adjusted for non-default components for the normal and crisis periods. The normal period is from January 2005 to June 2007 and the crisis period is from July 2007 to December 2009. Reported figures are percentage of firms which do not reject the hypothesis of cointegration with one cointegrating vector at the 1% significance level.

	Period	Percentage of firms with cointegration
Observed Spreads	Normal	79%
	Crisis	65%
Adjusted Spreads	Normal	89%
	Crisis	75%

Table 4. Price discovery

This table reports estimates of the Hasbrouck (S) and Gonzalo-Granger (G) information share measures for the individual CDS and bond pairs over the normal and crisis periods. The normal period is from January 2005 to June 2007 and the crisis period is from July 2007 to December 2009. For the Hasbrouck information share measure, we report the upper and lower bounds and the average.

Panel A: Observed CDS and bond spreads

		Hasbrouck (S)						Gonzalo-Granger (G)	
		CDS			Bond			CDS	Bond
		Up	Low	Average	Up	Low	Average		
Normal period	Mean	0.946	0.920	0.933	0.080	0.054	0.067	0.973	0.027
	Median	0.994	0.986	0.990	0.014	0.006	0.010	0.999	0.001
Crisis period	Mean	0.731	0.670	0.700	0.330	0.269	0.300	0.862	0.138
	Median	0.855	0.758	0.804	0.242	0.145	0.196	0.956	0.044

Panel B: Adjusted CDS and bond spreads

		Hasbrouck (S)						Gonzalo-Granger (G)	
		CDS			Bond			CDS	Bond
		Up	Low	Average	Up	Low	Average		
Normal period	Mean	0.944	0.915	0.930	0.085	0.056	0.070	0.980	0.020
	Median	0.995	0.987	0.990	0.013	0.005	0.010	0.999	0.001
Crisis period	Mean	0.859	0.825	0.842	0.175	0.141	0.158	0.885	0.115
	Median	0.970	0.938	0.956	0.062	0.030	0.044	0.992	0.008

Table 5. Pricing Discrepancies

This table reports co-movements of CDS and corporate bond spreads as a proportion of total observations. Results are reported for the whole sample (All), and for investment-grade (IG) and speculative-grade categories, respectively over non-overlapping time intervals of 5, 10, 25 and 50 days. Additionally, results are reported for the whole sample period and two subperiods: the normal and crisis periods. The normal period is from January 2005 to June 2007 and the crisis period is from July 2007 to December 2009. Co-movements are pricing discrepancies that represent arbitrage opportunities if $\Delta CDS*\Delta BYS>0$.

		The whole sample period			**The normal period**			**The crisis period**		
	Interval (Days)	**Fraction (%) $\Delta CDS*\Delta BYS<0$**	**Fraction (%) $\Delta CDS*\Delta BYS>0$**	**Fraction (%) $\Delta CDS*\Delta BYS=0$**	**Fraction (%) $\Delta CDS*\Delta BYS<0$**	**Fraction (%) $\Delta CDS*\Delta BYS>0$**	**Fraction (%) $\Delta CDS*\Delta BYS=0$**	**Fraction (%) $\Delta CDS*\Delta BYS<0$**	**Fraction (%) $\Delta CDS*\Delta BYS>0$**	**Fraction (%) $\Delta CDS*\Delta BYS=0$**
All	5	38.91	50.41	10.68	41.53	47.81	10.66	36.53	50.46	13.01
	10	38.98	54.02	7.00	42.16	50.75	7.09	36.71	54.09	9.21
	25	39.53	57.29	3.18	45.36	51.76	2.87	38.31	57.10	4.59
	50	41.62	57.18	1.21	52.05	46.92	1.03	42.77	55.64	1.59
IG	5	41.12	49.02	9.86	43.63	45.81	10.57	38.20	49.19	12.61
	10	41.27	51.82	6.91	44.60	47.72	7.68	38.48	52.25	9.26
	25	41.33	55.37	3.30	47.88	48.33	3.79	39.12	56.37	4.51
	50	42.36	56.38	1.26	53.31	45.16	1.54	42.26	56.22	1.52
SG	5	33.81	52.53	13.66	37.09	50.43	12.49	30.90	53.09	16.01
	10	33.87	57.64	8.49	37.18	55.15	7.67	31.01	58.30	10.69
	25	35.26	60.83	3.90	40.36	57.22	2.42	34.24	60.00	5.76
	50	39.71	58.69	1.60	48.97	50.44	0.58	42.18	55.33	2.50

Table 6. Firm Characteristics and Spread Cointegration

This table reports the mean difference tests on the characteristics of firms that reject or accept the cointegration test. We first calculate the mean of each impediment variable for the firms that reject or accept the cointegration test and then perform the mean difference test for the two groups of firms. Volatility is the firm's stock return volatility in the month; Amihud is the Amihud daily individual bond liquidity measure; EDF is the expected default rate calculated by the KMV model; Leverage is the ratio of the book value of debt to the sum of book value of debt and market value of equity; and Askbid is the CDS bid-ask spread. We report results for the whole sample period, and the normal and crisis periods. The normal period is from January 2005 to June 2007 and the crisis period is from July 2007 to December 2009. *, **, and *** indicate the 10%, 5%, and 1% levels of significance, respectively.

Period	Variable	Non-cointegrated	Cointegrated	Difference	t-statistic
Whole sample period	Volatility	0.022	0.019	0.003*	1.95
	Amihud	-0.996	-0.795	-0.202**	-2.44
	EDF	0.258	0.156	0.102**	2.11
	Leverage	0.611	0.558	0.053*	1.72
	Askbid	14.016	10.037	3.979*	1.86
Normal period	Volatility	0.012	0.012	0.000	0.02
	Amihud	-0.519	-0.468	-0.051	-1.14
	EDF	0.219	0.157	0.062	1.12
	Leverage	0.621	0.558	0.063**	2.05
	Askbid	5.687	5.130	0.556	1.33
Crisis period	Volatility	0.030	0.024	0.006***	2.80
	Amihud	-1.198	-1.006	-0.192*	-1.79
	EDF	0.312	0.177	0.135***	3.74
	Leverage	0.640	0.568	0.072**	2.33
	Askbid	16.278	10.327	5.952***	4.13

Table 7. Regressions for Kendall Ratios

This table reports coefficient estimates of the simple regression of Kendall κ over different horizons τ against each explanatory variable for the whole sample period, and the normal and crisis periods. The normal period is from January 2005 to June 2007 and the crisis period is from July 2007 to December 2009. Volatility is the firm's stock return volatility calculated based on the daily stock return of the month; Amihud is the daily Amihud individual bond liquidity measure; EDF is the expected default rate calculated by the KMV model; Leverage is the ratio of the book value of debt to the sum of book value of debt and market value of equity; and Askbid is the CDS bid-ask spread. For the Amihud measure, we multiply the original illiquidity measure by -1 to convert it into the liquidity measure. *, **, and *** indicate the 10%, 5%, and 1% levels of significance, respectively.

Period	Horizons	Volatility	Amihud	EDF	Leverage	Askbid
Whole	τ =5	1.23***	-3.54***	1.43	0.23*	0.27***
		(2.66)	(-3.58)	(1.56)	(1.72)	(5.77)
	τ =10	2.40***	-5.01***	0.40***	0.14	0.37***
		(5.06)	(-4.75)	(4.09)	(0.93)	(8.19)
	τ =25	2.97***	-6.16***	0.63***	0.88***	0.46***
		(5.49)	(-5.10)	(5.94)	(5.31)	(8.37)
	τ =50	2.75***	-7.15***	0.55***	1.13***	0.40***
		(7.47)	(-4.50)	(3.84)	(5.23)	(5.26)
Normal	τ =5	1.83	-3.14**	0.05	0.37**	0.34**
		(1.31)	(-1.97)	(0.49)	(2.13)	(2.23)
	τ =10	3.42**	-4.57***	0.07	0.31	0.48***
		(2.21)	(-2.57)	(0.66)	(0.79)	(3.05)
	τ =25	6.06***	-8.07***	0.29**	0.49**	0.64***
		(3.29)	(-3.74)	(2.18)	(2.03)	(3.38)
	τ =50	2.62*	-5.28	0.48***	0.96***	0.61**
		(1.83)	(-1.59)	(2.49)	(2.90)	(2.18)
Crisis	τ =5	1.79***	-3.28***	0.96***	0.24*	0.33***
		(3.34)	(-2.73)	(5.21)	(1.84)	(6.42)
	τ =10	2.92***	-4.90***	1.39***	0.51***	0.43***
		(5.11)	(-3.65)	(7.49)	(2.76)	(8.40)
	τ =25	3.31***	-5.18***	1.36***	1.38***	0.48***
		(4.94)	(-3.32)	(6.14)	(6.48)	(6.87)
	τ =50	4.04***	-10.43***	0.85***	1.76***	0.46***
		(7.96)	(-4.64)	(2.86)	(5.53)	(4.04)

Table 8. Impulse Response Analysis

This table reports the speed and dynamic responses to a unit shock in the CDS and bond market during the normal and crisis periods corresponding to Figure 2. For a unit shock in the CDS market, this table shows the highest orthogonal impulse response function (IRF), and the steps it takes to go down to 0.75, 0.5, and 0.25 of the highest response value, which are labeled as 3Q, 2Q, 1Q, respectively. For the bond market, we ignore the initial jump in reporting the highest IRF, which better reflects the manner in which the IRF tapers off to 0.

Bonds	Steps	CDS		BYS	
		Normal Period	Crisis Period	Normal Period	Crisis Period
Investment grade	Highest IRF	0.013	0.111	0.017	0.095
	3Q	7	14	6	13
	2Q	12	31	10	28
	1Q	19	65	17	61
Speculative grade	Highest IRF	0.111	0.727	0.061	0.397
	3Q	8	9	5	8
	2Q	15	22	8	21
	1Q	25	45	12	44

Table 9. Persistence analysis

We report the persistence estimate as measured by the long memory parameter (*d*) based on the rescaled range R/S statistic for different bond groups and periods. Estimation is conducted using the daily data and its time aggregates from 2 to 10 days. Detail estimation method is described in Appendix C. Persistence analysis is performed on the basis, the absolute basis, and absolute basis changes as a proxy for volatility.

Panel A: Long memory *d* estimates and two-sample *t*-tests by bond grade

We test of the null of the same persistence for speculative- and investment-grade (IG) bonds, against a one-sided alternative hypothesis that the former is more persistent. Estimation is conducted over the whole sample period. The persistence measure and significance test results (p-values) are reported.

	Basis	|Basis|	Volatility = |ΔBasis|
Speculative grade	0.398	0.393	0.235
Investment grade	0.373	0.357	0.183
Difference	0.025	0.036	0.052
p-value	0.035	0.006	0.000

Panel B: Long memory *d* estimates and two-sample *t*-tests by subperiod

We test the null of the same persistence during crisis and normal periods, against a one-sided alternative hypothesis that it is more persistent during crisis. Estimation is conducted over the normal and crisis periods. The persistence measure and significance test results (p-values) are reported.

	Basis	|Basis|	Volatility = |ΔBasis|
Crisis period	0.390	0.381	0.210
Normal period	0.347	0.336	0.164
Difference	0.043	0.045	0.046
p-value	0.000	0.000	0.000

Panel C: Long memory *d* estimates and two-sample *t*-tests by bond grade and sample period

	Investment grade	Speculative grade	Difference	*p*-value
Basis				
Crisis period	0.385	0.400	0.015	0.153
Normal period	0.343	0.357	0.014	0.215
Difference	0.042	0.043		
p-value	0.000	0.000		
Absolute basis: |Basis|				
Crisis period	0.378	0.388	0.010	0.218
Normal period	0.323	0.363	0.040	0.021
Difference	0.055	0.025		
p-value	0.000	0.021		
Absolute basis changes: |ΔBasis|				
Crisis period	0.202	0.225	0.023	0.087
Normal period	0.143	0.205	0.061	0.000
Difference	0.058	0.020		
p-value	0.000	0.075		

Table 10. Persistence Analysis with Long Memory FIGARCH Model

This table reports the MA(1)-FIGARCH(1,1) estimation result for $\Delta Basis$ of investment-grade (IG) bonds and speculative-grade (SG) bonds over the normal and crisis periods. The normal period is from January 2005 to June 2007 and the crisis period is from July 2007 to December 2009. *P*-value is given in parentheses. The model is: $\Delta basis_t = c + e_t - \theta_1 e_{t-1}$ where $(1-(\alpha_1+\beta_1)B)(1-B)^d e_t^2 = \alpha_0 + (1-\beta_1 B)v_t$ with $v_t = e_t^2 - \sigma_t^2$.

Bonds	Period	c	θ_1	α_0	β_1	α_1	d
Investment grade	Normal	0.000	-0.762	0.000	0.774	0.694	0.121
		(0.493)	(0.000)	(0.123)	(0.000)	(0.000)	(0.087)
	Crisis	0.001	-0.529	0.000	0.830	0.396	0.740
		(0.236)	(0.000)	(0.036)	(0.000)	(0.000)	(0.000)
Speculative grade	Normal	0.000	-0.725	0.004	0.474	0.369	0.131
		(0.399)	(0.000)	(0.188)	(0.106)	(0.150)	(0.099)
	Crisis	0.006	-0.617	0.007	0.784	-0.074	0.974
		(0.154)	(0.006)	(0.000)	(0.000)	(0.246)	(0.000)