Dynamics and Determinants of Credit Risk Discovery: Evidence from CDS and Stock Markets

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Abstract

This paper investigates the dynamics and drivers of credit risk discovery between stock and CDS markets in the US. Our research is distinguished from the existing literature in three aspects: 1) We employ an improved method to measure the information share; 2) we discover new drivers of credit risk discovery; and 3) we assess the impact of central clearing counterparty (CCP) on the CDS market. By using the generalized information share (GIS) by Lien and Shrestha (2014), we address the issue that the CDS and stock prices do not have one-to-one cointegration relation. The empirical results support the use of GIS instead of more conventional measures. We also find that eliminating transitory price components increases the information share of the CDS market in the earlier period of the sample. The economic condition and funding cost turn out to affect the information share of the CDS market negatively. Another interesting finding is that the CDS of investment grade firms possess higher information shares compared to speculative grade firms. Finally, CCP seems to reduce the information share of CDS, which suggests that the CDS market is driven largely by insider trading.

Keywords: credit risk discovery, determinants, generalized information share

JEL Classification: G12, G14, G28

1. Introduction

Much attention has been given to credit risk especially after the financial crisis in the late 2000s. Witnessing unlikely failures of many big firms, whether credit risk is priced in a timely manner became an important question to academics and practitioners alike. As noted by Norden and Weber (2009), distinct market structures and different investors may cause the prices of different assets to respond to credit news non-synchronously. Accordingly, it is of interest to identify which market reflects credit risk information first and what factors can explain its informational dominance.

With respect to credit risk, three most important markets are stock, bond, and credit default swap (CDS) markets. While it is generally agreed that bonds lag behind stocks and CDS in incorporating credit risk information (e.g., Longstaff, Mithal and Neis, 2005; Forte and Peña, 2009), credit risk discovery leadership between stocks and CDS is still inconclusive. Norden and Weber (2009) argue that stocks lead CDS in most cases. This is supported by Forte and Peña (2009), Hilscher, Pollet and Wilson (2015), and Narayan, Sharma and Thuraisamy (2014). On the other hand, Acharya and Johnson (2007) document that CDS market tends to incorporate credit risk information first due to its severer insider trading. This is consistent with the findings of Xiang, Chng, and Fang (2013). Longstaff, Mithal and Neis (2005) claim that both markets have similar speeds to incorporate credit risk news, which is partially supported by Marsh and Wagner (2015) who observe that identical information processing speed emerges when negative firm specific news arrives. Meanwhile, Forte and Lovreta (2015) investigate time-varying relationship between CDS and stock markets in Europe during 2002-2008 and find that stocks dominate credit risk discovery during financial crisis while CDS impound credit risk news more quickly during tranquil times.

Identifying the factors that drive credit risk discovery is another important topic of credit risk discovery. Overall economic status does appear to affect informational dominance among markets. However, there is no consensus with regard to the direction of the impacts. Xiang, Chng, and Fang (2013) observe that the dominant role of CDS was enhanced during the sub-prime crisis. On the contrary, Forte and Lovreta (2015) find that information share of stocks increased during the dot-com bubble and the sub-prime crisis. They argue that this does not necessarily contradict insider trading hypothesis because credit condition is probably an important factor but not the major factor determining insider trading activities in the CDS market. Narayan, Sharma and Thuraisamy (2014) claim that financial crisis can induce a lagged market to be a credit risk discovery leader. Unlike overall credit risk level, it is commonly found that an adverse credit news such as credit rating downgrade is likely to be reflected in the CDS market first (e.g., Forte and Lovreta, 2015; Wang and Bhar, 2014). This finding is in line with firm-specific information hypothesis and insider trading hypothesis.[1] Forte and Lovreta (2015) also find that when the liquidity of a market increases, its information share rises as well. This is consistent with the liquidity hypothesis which suggests that informed trading is more likely to be operated in a more liquid market because traders can exploit their informational advantages without causing large price movements (Garbade and Silber, 1983).

As described above, previous findings on the credit risk discovery are mixed without any concrete evidence to draw a conclusion and research on the governing factors has emerged only recently. Also, we find that there are rooms to improve the methodologies employed in the existing studies. In this regard, we believe it is worth giving another look at the credit risk discovery mechanism between markets. Hence, the aim of this paper is to

[1] The firm-specific information hypothesis argues that, whilst some security prices may be more sensitive to market-wide information, many others adjust more rapidly to firm-specific information, especially negative corporate-specific news.

provide more concrete evidence on credit risk discovery between CDS and stock markets with improved methodologies. By doing so, we make contributions to the field in three aspects. First, we improve the method to measure credit risk discovery. We observe that stock and CDS prices do not satisfy one-to-one cointegration relation which is an essential assumption of the widely used Hasbrouck (1995) information share (IS) and Gonzalo and Granger (1995) component share (GG). Thus, we employ Generalized Information Share (GIS) recently developed by Lien and Shrestha (2014). GIS does not require one-to-one cointegration between the pair and therefore is more suitable for our analysis. We also eliminate transitory components from the price in order to extract the permanent price component only. Credit risk is related to the permanent price component and eliminating transitory effects is expected to give a clearer view on credit risk discovery. We provide a comprehensive analysis by comparing the advanced method with the conventional methods. Secondly, we discover new factors that drive credit risk discovery. While existing studies focus mostly on individual firm characteristics, we identify macroeconomic factors such as financial condition index and overall funding cost that affect relative informational dominance between markets. Finally, we assess the impact of the introduction of central clearing counterparty (CCP) on the informational efficiency of CDS. We divide CDS contracts into two groups, i.e., centrally cleared CDS and the rest, and compare their information shares. Contrary to the conventional wisdom that the CCP will enhance the CDS market efficiency, centrally cleared CDS turn out to have lower information shares.

The rest of the paper is organized as follows. In Section 2, an improved method to measure credit risk discovery is introduced. This includes elimination of the transitory components from the price, calculation of the credit spread implied by the stock price, and calculation of the generalized information share. In Section 3, we discuss the determinants of credit risk discovery and propose three new factors that are potentially relevant to the credit risk discovery between stock and CDS markets. Section 4 is devoted to empirical analyses using individual firm data from the US. Section 5 concludes.

2. Credit risk discovery

In this section, we briefly outline an improved procedure to calculate each market's contribution to credit risk discovery. The procedure consists of three steps: 1) extracting permanent price components from the stock and CDS prices; 2) calculating implied credit spreads from the stock prices; 3) calculating credit risk discovery contribution of each market.

2.1 Permanent price component

The price we observe is driven by many factors such as permanent change in firm value and transitory change in liquidity. As our focus is on the credit risk component of the price which is based on the long-term firm value, using price as it is could obscure the pure credit risk component and the credit risk discovery obtained from it could be misleading. Eliminating any transitory effects from the price should give a more clear view on credit risk discovery. In fact, this was also discussed by Forte and Lovreta (2015), who eliminate transitory liquidity components in their robustness test. They find that removing the transitory component does not significantly affect the credit risk informational dominance between stock and CDS markets. We bring this forward and conduct all empirical analyses using two sets of data, i.e., original price time series and permanent price component time series.

Similar to Forte and Lovreta (2015), we employ Gonzalo and Granger (1995) permanent-transitory decomposition method to eliminate transitory components from stock and CDS prices. We summarize the method only briefly. Interested readers are referred to Forte and Lovreta (2015) and Gonzalo and Granger (1995). First, specify a bivariate vector error-correction model (VECM) of bid and ask prices for each market.

$$\Delta B_t = c_1 + \alpha_1 EC_t + \sum_{i=1}^{k} b_{1i} \Delta B_{t-i} + \sum_{i=1}^{k} d_{1i} \Delta A_{t-i} + \epsilon_{1t} \quad (1)$$

$$\Delta A_t = c_2 + \alpha_2 EC_t + \sum_{i=1}^{k} b_{2i} \Delta B_{t-i} + \sum_{i=1}^{k} d_{2i} \Delta A_{t-i} + \epsilon_{2t} \quad (2)$$

where B_t and A_t are respectively bid and ask prices at time t and $EC_t = B_{t-1} + \lambda_0 - \lambda_1 A_{t-1}$ is the error correction process. Lag k is determined based on Schwarz Information Criterion (SBC). Then, the permanent price component (LP) is given by

$$LP_t = \frac{\alpha_2}{\alpha_2 - \alpha_1} B_t + \frac{\alpha_1}{\alpha_1 - \alpha_2} A_t \quad (3)$$

This is repeated for both stock and CDS prices.

2.2 Implied credit spread

Forte and Peña (2009) argue that stock prices are not consistent with CDS spreads as credit spreads are determined by not only stock prices but also other variables such as firm asset value and asset volatility. Hence, they advocate to use the credit spread implied in the stock price instead of stock price itself. The use of implied credit spread was also supported by Forte and Peña (2009) and Xiang, Chng, and Fang (2013) among others. In this paper, we follow Xiang, Chng, and Fang (2013) and adopt Finger, Finkelstein, Lardy, Pan, Ta, and Tierney (2002) CreditGrades model to derive implied credit spread (ICS). Unlike other structural models, the CreditGrades model does not suffer from the underpricing problem and thus has been widely used in the literature in extracting implied credit risk information (e.g., Bystrom, 2006; Yu, 2006). However, apart from the stock price, stock return volatility, debt per share, and risk-free rate, many other key parameters in CreditGrades model such as the recovery rate and the mean and standard deviation of the global recovery rate are not directly observable. Following Ou, Chlu, and Metz (2011) we use the Moody's average historical recovery rate on senior unsecured debt as a proxy for recovery rate and set the recovery rate R = 0.374. Given the absence of industry guidelines for setting the mean ($\bar{L}$) and standard deviation (λ) of the global recovery rate, we calibrate both $\bar{L}$ and λ to minimize the sum of squared difference between CDS and ICS using the first 20 daily observations and then apply the calibrated parameters for the rest of the sample.

$$[\bar{L}_i^*, \lambda_i^*] = argmin \sum_{j=1}^{20} \left(ICS_{i,t-j}(\bar{L}_i, \lambda_i) - CDS_{i,t-j} \right)^2 \quad (4)$$

Further details of CreditGrades and the calculation of ICS are provided in Appendix A.

2.3 Generalized information share

Once the time series of CDS and ICS are obtained, the contribution of each market to credit risk discovery can be calculated. The most commonly used methods are Hasbrouck (1995) information share (IS) and Gonzalo and Granger (1995) component share (GG). Both IS and GG are established under the assumption that the common factor shared by interrelated markets have the same long-run equilibrium price, i.e., one-to-one cointegration. However, this assumption is realistic only for almost identical assets such as cross-listed stocks. In fact, as shown in Section 4, CDS and ICS do not satisfy one-to-one cointegration relationship. Also, IS suffers from variable ordering issue so that it cannot provide a unique price discovery contribution measure. This motivates us to employ the alternative measure that has been recently developed by Lien and Shrestha (2014), which is unique and does not require one-to-one cointegration. It only requires that all the $I(1)$ time series share one and only one common trend. We employ this generalized information share (GIS) measure as our main toolkit for credit risk discovery analysis and compare it with IS and GG measures throughout. The rest of this section briefly describes calculation of IS, GG, and GIS measures.

First, specify the VECM of CDS and ICS as follow:

$$\Delta CDS_t = c_1 + \alpha_1 EC_t + \sum_{i=1}^{k} b_{1i} \Delta CDS_{t-i} + \sum_{i=1}^{k} d_{1i} \Delta ICS_{t-i} + \epsilon_{1t} \quad (5)$$

$$\Delta ICS_t = c_2 + \alpha_2 EC_t + \sum_{i=1}^{k} b_{2i} \Delta CDS_{t-i} + \sum_{i=1}^{k} d_{2i} \Delta ICS_{t-i} + \epsilon_{2t} \quad (6)$$

where $EC_t = CDS_{t-1} + \lambda_0 - \lambda_1 ICS_{t-1}$. $\lambda = [1, -\lambda_1]'$ implies the long-run equilibrium relationship between CDS and ICS. Let $\alpha = [\alpha_1, \alpha_2]'$, with α_1 and α_2 denote the short-run adjustment speeds. Let $\epsilon_t = [\epsilon_{1t}, \epsilon_{2t}]'$ and $E[\epsilon_t \epsilon_t'] = \Omega$. Equation (5) and (6) can be rewritten in the vector moving average form

$$CDS_t = CDS_0 + \psi_1(1) \sum_{i=1}^{t} \epsilon_{1i} + \psi_1^*(L)\epsilon_{1t} \quad (7)$$

$$ICS_t = ICS_0 + \psi_2(1) \sum_{i=1}^{t} \epsilon_{2i} + \psi_2^*(L)\epsilon_{2t} \quad (8)$$

where $\psi_{\mathrm{i}}(1), \mathrm{i} = 1,2$, are the sum of the moving average coefficients. Let $\Psi(1) = [\psi_1(1),\ \psi_2(1)]'$. The Engle-Granger representation theorem implies that $\lambda'\Psi(1) = 0$ and $\Psi(1)\alpha = 0$. Under the assumption that $\lambda = [1, -1]'$, $\Psi(1)$ has identical rows. Let ψ be the identical row of $\Psi(1)$. Hasbrouck (1995) information share (IS) and Gonzalo and Granger (1995) component share (GG) are defined as:

$$IS_j = \frac{[\psi F]_j^2}{\psi \Omega \psi'},\ GG_j = \left[\frac{\alpha_2}{\alpha_2 - \alpha_1}, \frac{\alpha_1}{\alpha_1 - \alpha_2}\right]' \quad (9)$$

where F is the Cholesky factorisation of Ω. We adopt Baillie, Booth, Tse, and Zabotina (2002) approach and approximate a unique IS as the midpoint of the upper and lower bounds. Following Forte and Lovreta (2015), we replace the GG values that exceed the range [0, 1] with the boundary values.

For GIS, the factor structure of ϵ_t focuses on the diagonalization of the correlation matrix rather than the covariance matrix Ω. Denote Φ as the correlation matrix of the residuals and Λ as a diagonal matrix which consists of the eigenvalues of Φ on the diagonal. The corresponding eigenvectors construct a matrix G. Let W be a diagonal matrix having the standard deviations of the residuals on the diagonal. The cointegrating vector is unrestricted so that $\lambda = [1, -\lambda_1]'$ for an arbitrary λ_1. Let ψ_j^{λ} be the j-th row of $\Psi(1)$. According to the

Engle-Granger representation theorem, $\psi_1^\lambda = \lambda_{j-1}\psi_j^\lambda, j = 1,2,$ with $\lambda_0 = 1$. Then, GIS can be computed as:

$$GIS_j = \frac{\left(\psi_j^G\right)^2}{\psi_1^\lambda \Omega (\psi_1^\lambda)'} \qquad (10)$$

where $\psi^G = \psi_1^\lambda F^M$, $F^M = [G\Lambda^{-0.5}G'W^{-1}]^{-1}$, $\epsilon_t = F^M z_t$, $E[z_t] = 0$ and $E[z_t z_t'] = I_2$.

IS, GG, and GIS generally range from 0 to 1. The higher values of these measures indicate the higher contributions of the related asset prices to price discovery. To highlight the differences among these measures, we borrow Figucrola-Ferrctti, Gilbert, and Yan (2014)'s illustration: IS offers the greatest weight to the market incorporating the newest information, but the market with greatest IS cannot necessarily provide the best benchmark for the implicit efficient price. GG measures the extent to which the different market prices reflect the long-run equilibrium price. Hence, the dominant market identified by GG would offer the best price for the fundamental price. GIS imposes a different factor structure on the residuals and its factor decomposition is similar to principal component analysis. The price of market with the greatest GIS can be interpreted as a weighted average of all market prices, approximating the efficient price.

3. Determinants of credit risk discovery

Previous studies have found that neither the stock market nor the CDS market consistently dominates the other in credit risk discovery (e.g., Forte and Lovreta, 2015; Xiang, Chng, and Fang, 2013). Rather, as the participants of each market react differently to information flow, credit risk discovery mechanism seems to be largely affected by the overall economic status as well as individual firm characteristics. Most existing studies are devoted to identify firm specific events such as credit rating downgrade that affect the dynamics of credit risk discovery. When examining the effect of macroeconomic status on credit risk discovery, they rely on the use of dummy variable or sub-period analysis to indicate financial crises. However, these methods are unreliable due to arbitrary dating issue. Our aim is to identify continuous macroeconomic indicators that have potential impacts on the dynamics of credit risk discovery. With the evidences from previous studies, it seems obvious that the dynamics of credit risk discovery depends on the overall economic condition. In particular, when the economy is under stress, increased insolvency rate will increase demand for CDS, and the high and volatile CDS spreads may attract arbitragers and speculators with inside information. Consequently, more information will flow into the CDS market and it is expected to become the primary market of credit risk discovery. Based on this conjecture, we consider a financial condition index as a potential driver of credit risk discovery. Among the existing financial condition indexes, we choose Bloomberg Financial Condition Index (BFCIUS) and Goldman Sachs Financial Conditions Index (GSFCI). A lower BFCIUS or a higher GSFCI indicate a higher level of stress in the US financial markets.

Another factor that is likely to affect the dynamics of credit risk discovery is funding cost. CDS transaction requires a relatively high margin. For example, according to the margin requirements for credit default swaps set by Financial Industry Regulatory Authority (FINRA), shorting a 5-year single-name CDS contract requires a margin of 4% to 25% of the CDS spread. Margin requirement for speculative-grade CDS can be three to six times higher than those for investment-grade CDS. Thus, when the funding cost is high and volatile, traders would prefer the stock market to the CDS market. Consequently, it is anticipated that a rise in funding cost will result in an increased contribution of the stock market to credit risk discovery. Following Acharya, Schaefer, and Zhang (2015), the spread between 3-month financial commercial paper interest rate and 3-month T-bill rate is chosen as a proxy for funding cost (FC).

In December 2009, ICE Clear Credit, the first CDS clearing house launched by the Intercontinental Exchange (ICE), started single-name CDS central clearing service for the US market.[2] In general, central clearing counterparty (CCP) is expected to enhance CDS market transparency and accelerate CDS transaction settlement. However, distinct views exist about whether CCPs can effectively promote CDS market efficiency. On the one hand, Duffie and Zhu (2011) argue that introducing CCPs in CDS market only and constructing multiple CCPs instead of a unique CCP will reduce bilateral netting benefits and raise counterparty risk, unless CDS market becomes large enough. They also point out that most contract information still remains confidential and CCPs may not supply needed transparency to the CDS traders. On the other hand, Acharya and Bisin (2014) theoretically show that by disclosing trade positions of counterparties, CCPs can lower counterparty risk. Loon and Zhong (2014) empirically confirm that introducing CCPs reduces counterparty risk, decreases systemic risk, and improves CDS post-trade transparency. Using a dummy variable for CCP cleared CDS (which takes value of 1 from the first clearing date for the clearable CDS and 0 otherwise) we investigate whether CCPs can facilitate CDS market in detecting credit risk news.

We construct a panel regression equation using the three factors proposed above, i.e., financial condition index (FCI), funding cost (FC), and CCP dummy (CCP). We also include four factors found significant in Forte and Lovreta (2015) as control variables. The four control variables are relative market liquidity between CDS and stock markets (RML), credit condition of reference entity (CCON), relative frequency of adverse shocks (ADS3), and credit rating downgrades events (CRDOWN). We compute the bid-ask spreads relative to the

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[2] There are two approved CCPs in the US, the ICE Clear Credit (previously called the ICE Trust) and the CME Group. The clearable instruments of the ICE Clear Credit include both single-name corporate CDS contracts and CDS indices (ICE, 2015), whereas the CME Group only involve in clearing CDS indices (CME, 2015). Since we focus only on single-name corporate CDS contracts, all the clearable CDS contracts in our sample are cleared by the ICE Clear Credit.

mid-quote price for the stock market and the CDS market, respectively, and average them over the past 120 days. RML is defined as the ratio of the average stock bid-ask spread to the average CDS bid-ask spread. CCON is defined as the time-varying mean of the CDS spreads, calculated from the 120-day rolling window. ADS3 is defined by the equation

$$\mathrm{ADS3} = \frac{\mathrm{No.\ of}\ ((\mathrm{x_t} - \bar{\mathrm{x}}) > 3 * \sigma)}{120} \tag{11}$$

where $\mathrm{x_t}$ is CDS spread at time t, and $\bar{\mathrm{x}}$ and σ are sample mean and standard deviation of the CDS spread obtained from the sample $[\mathrm{x_{t-120}}, \ldots, \mathrm{x_{t-1}}]$. CRDOWN takes value of 1 if a credit rating downgrade occurs during the past 120 days and 0 otherwise. The final panel regression equation has the form:

$$y_{it} = \beta_0 + \beta_1 RML_{it} + \beta_2 CCON_{it} + \beta_3 ADS3_{it} + \beta_4 CRDOWN_{it} + \beta_5 FCI_t + \beta_6 FC_t + \beta_7 CCP_{it} + e_{it} \tag{12}$$

where y_{it} is a measure for the information share (GIS, IS, or GG) of CDS of firm i at time t.

4. Empirical analysis

4.1 The data

The sample consists of liquid US dollar-denominated 5-year CDS contracts written on senior unsecured debts from January 1st 2006 to December 31st 2013. As our focus is on corporate level, CDS contracts on sovereigns are excluded. CDS contracts on financial firms are also excluded due to their distinguished capital structures. Given the changes in contract and convention since the 2009 CDS 'Big Bang', ex-restructuring clauses are preferred. Finally, we consider only active CDS contracts by excluding the firms whose CDS data are consecutively unavailable for more than 90 business days within one year. After filtering, our sample is comprised of 113 non-financial firms from 9 industry sectors. Daily CDS quote data are collected from two data sources: CMA DataStream (before September 30th 2010) and Markit TickHistory (from September 30th 2010).[3] In addition, financial data of stock market, such as stock prices, market capitalizations, and liabilities, are obtained from Bloomberg.

All the data required for the empirical analysis and their sources are summarized in Table 1. Figure 1 displays the distributions of the firms in the sample across credit ratings and industry classifications. Credit ratings are based on the S&P Domestic Long Term Issuer Credit Ratings as of 31/12/2013. Among 113 firms, 94 firms (83%) are investment-grade firms (BBB or higher) and 19 firms (17%) are speculative-grade firms (BB or lower). The firms are spread across industries with no highly concentrated industry. The largest sector is Consumer Discretionary with 28 firms (25%).

The remainder of the section presents the results of the empirical analysis. Throughout the paper, CDS refers to either CDS itself or CDS spread depending on the context, and ICS refers to the credit spread implied by the stock price. LCDS and LICS respectively refer to the CDS and the ICS obtained from the permanent price components after eliminating transitory components.

4.2 Credit risk discovery

4.2.1 CDS and ICD time series

Descriptive statistics of CDS and ICS are reported in Tables 2 and 3, and the cross-sectional means of CDS and ICS are plotted in Figure 2. As shown in the Figure, CDS and

[3] Due to a contract issue, CMA CDS data are available in DataStream only until September 30th 2010. In TickHistory, the majority of Markit CDS data are available after November 1st 2010. Mayordomo, Peña, and Schwartz (2013) compare five CDS databases, GFI, Fenics, Reuters EOD, CMA, and Markit, and find that CMA and Markit are more consistent with each other. Loon and Zhong (2014) also show that between 2009 and 2011, differences between CDS spreads provided by CMA and Markit are negligible for the US single-name CDS market. Hence, we expect that the merge of two databases should not influence our results significantly.

ICS share similar development patterns except for the financial crisis period in 2009-2010: while CDS returns to its previous level quickly, ICS remains high for an extended period. This results in ICS about 40bp higher than CDS: 176.6 (LCIS) vs 137.3 (LCDS) and 173.7 (CIS) vs 136.0 (CDS). Although short-term discrepancies exist between each pair of credit spreads during some periods, the generally comparable dynamics imply the existence of cointegration in most pairs. Comparing the two graphs in Figure 2, it appears that eliminating transitory components from the prices does not make substantial differences. From Table 2, the overall credit spreads increase slightly after eliminating transitory components; 1.26 bp for CDS and 2.87 bp for ICS. Nevertheless, the difference is more distinguishable at individual firm level (not reported here). In general, when the credit spread level is high, its standard deviation is high as well. This is also true across credit ratings as shown in Table 3. Except for the reversal between B and CCC, a higher grade is associated with a lower credit spread and a lower credit spread variation.

4.2.2 Unit-root and cointegration test

We first test whether CDS and ICS follow $I(1)$ processes using Augmented Dickey-Fuller (ADF) unit root test. We also test one-to-one cointegration between CDS and ICS by testing stationarity of their difference: if CDS and ICS are one-to-one cointegrated, the difference should be stationary. The results are summarized in Table 4.[4] The test statistics show that CDS and ICS are $I(1)$ processes and they do not satisfy one-to-one cointegration assumption in most cases. This justifies our choice of GIS over IS or GG measures.

After testing unit-root, we proceed to detect the long-run cointegration relations using Johansen cointegration test. The number of lags is determined by SBC. As shown in Table 5, cointegration is detected in 60% of the firms for LCDS-LICS pairs and 71% of the firms for

[4] The full test results are available upon request.

CDS-ICS pairs. However, failure to detect cointegration using statistical tests does not necessarily imply the non-existence of a long-run equilibrium relationship. The power of cointegration tests depend on sample periods. The shorter sample period, the less cointegration pairs (Forte and Lovreta, 2015). Thus, to avoid omitting any possible cointegration relations, we opt to keep all the firms in our sample regardless of the test results. Nevertheless, in section 4.4, we examine the sensitivity of our results by repeating the estimations for a sub-sample of firms for which cointegration relation does exist.

4.2.3 Contribution to credit risk discovery

The contribution of each market to credit risk discovery is measured by three measures, i.e., GIS, IS, and GG. These measures are updated daily using a 120-day rolling window. The cross-sectional averages of GIS, IS, and GG of CDS are plotted in Figure 3. More detailed views of these measures are also reported in Tables 6 and 7. Table 6 is for the results from LCDS and LICS and Table 7 is for the results from CDS and ICS. As the two sets of results are similar, we base our analysis on the results of LCDS and LICS.

First, when we compare the measures, it appears that all three measures offer qualitatively similar patterns. This is consistent with the findings of Lien and Shrestha (2014) and Xiang, Chng, and Fang (2013). However, it is noteworthy that the level of GIS is generally higher than that of the other two measures. For instance, the average GIS over the whole sample period is 0.45 whereas the average IS is 0.37 and the average GG is 0.33. These values by themselves do not tell us which measure should be favoured over others. Nevertheless, if we consider the fact that current markets are fairly efficient, GIS measure which is closer to 0.5 seems more reasonable. During the entire sample period, the firms for which the average information share of CDS is larger than 0.5 is 31% based on GIS. This value is only 8% based on IS and 7% based on GG, which is unrealistic. Also, GIS has a lower volatility over time and less extreme values. All these observations, at least partially, support using GIS for credit risk discovery analysis.

Based on GIS results, the contribution of the CDS market to credit risk discovery is generally smaller than the stock market save for the sub-prime crisis period. During the crisis (2008.2 - 2010.1), the contribution of the CDS market rises and it often dominates the stock market. This finding is robust for both types of credit spreads. Xiang et al. (2013) also find a positive relationship between the contribution of the swap market and economic instability.

A close look at Table 6 reveals an interesting point. While the variation of the number of firms for which CDS is the credit discovery leader (GIS of CDS > 0.5) is large over time, GIS is relatively stable over time. This is same for other measures. This implies that even when the credit risk discovery leadership is handed over from one market to the other, the relative informational dominance does not change much.

On average, eliminating transitory price components does not alter the results substantially. However, if we look at the change at individual firm level, the impact is rather striking. Figure 4 highlights the change of credit risk discovery leadership after eliminating transitory components. Overall, there are more firms for which the credit risk discovery leadership is handed over from stock to CDS. This is more apparent in the earlier period of the sample, especially before the sub-prime crisis. This suggests that the role of CDS market in credit risk discovery was more important than normally believed when it was loosely regulated.

To investigate whether credit rating has an effect on credit risk information share, we divide the firms into two groups, investment grade firms and speculative grade firms, and compute GIS for each group. The results are summarized in Table 8 and the cross-sectional average of GIS for each group is plotted in Figure 5. It can be clearly seen that the information share of CDS is higher for the investment grade firms. As shown in the figure, it is also less volatile during the sample period. This might result from higher liquidity of the CDS contracts of these firms. However, given the relatively small number of firms with a speculative grade, more evidence is needed to draw a conclusion.

We also compare the firms whose CDS are centrally cleared with the rest of the firms. This should provide some information about the impact of the CCP on the CDS market efficiency. The results are summarized in Table 9. Since the first CCP was introduced in late 2009, the sample period starts from 2010. Although the difference between two groups is often large in each period, no discernible pattern is observed. In fact, the overall information share of the CCP-cleared CDS is smaller than that of non-cleared CDS. This result contradicts the positive effects of CCPs found by Loon and Zhong (2014) and casts a doubt on the function of CCPs.

4.3 Determinants of credit risk discovery

We first examine the correlations between regressors and find all the pairs have a correlation coefficient within (-0.5, 0.5), which implies no multicollinearity problem. Based on Hausman test, the panel equation is estimated by using fixed-effects model.[5] The regression results for LCDS are reported in Table 10.[6]

It turns out that the coefficients of all the independent variables are significant and mostly have the expected signs. BFCIUS, a financial condition index which is positively correlated with the financial condition, has a negative sign. This suggests that the information share of CDS increases when the financial markets are under significant stress. This is

[5] Given that the macro variables, e.g., BFCIUS and FC, do not vary across different firms, we do not include time fixed effects in the regression estimations and only consider firm fixed effects.

[6] We repeated the same regression using CDS data but the results were similar except CRDOWN became insignificant for GIS. The results are available upon request.

consistent with our previous results in which we observed increased information share of CDS during the sub-prime crisis. Xiang, Chng, and Fang (2013) also draw a similar conclusion whereas Forte and Lovreta (2015) find the opposite in the European markets. The funding cost is significant and has a negative relationship with the information share of CDS. This result was anticipated as higher funding cost would prevent investors from entering the CDS market resulting in slow information flow into the market.

The CCP dummy is significant and has a negative coefficient. This is against the general belief that CCP will enhance the efficiency and transparency of the CDS market. This result was already anticipated in the previous section where CCP-cleared CDS were found to have lower information shares. A possible explanation for this is given by Acharya and Johnson (2007) who argue that higher level of information asymmetry motives insiders to trade CDS rather than stock, whereas more transparent CDS market may reduce their profits. Other researchers also express doubts about the efficiency of CCP, see Duffie and Zhu (2011) and Marsh and Wagner (2015), for example. Overall, the result supports the hypothesis that the CDS market is driven largely by insider trading.

As to the four control variables, the results of CRDOWN and CCON are consistent with the findings of Forte and Lovreta (2015). Also, when the liquidity of the CDS market becomes relatively higher (high RML), GIS, GG and IS of the CDS market increase significantly. However, the results of ADS3 contradict the results found in Forte and Lovreta (2015). Although both CRDOWN and ADS3 measure negative credit events, our findings imply that the credit risk measured by ADS3 is less severe than credit downgrades, and the information is still impounded in the stock market first.

4.4 Robustness check

To check the robustness of our results against the conjecture that cointegration relation generally exists for all the firms in our sample, we conduct a sub-sample analysis by excluding the firms for which cointegration relation does not exist statistically. Figure 6 compares the average GIS of all firms with the average GIS of the firms with cointegration. It confirms that the calculation of the generalized information share (GIS) measure is not sensitive to the existence of significant cointegration relationship. The panel regression results presented in Table 11 also support our initial conclusions drawn from the full sample.

5. Concluding remarks

In this paper, we investigate the dynamics and drivers of credit risk discovery between stock and CDS markets in the US from 2006 to 2013. Our research is distinguished from the existing literature in several aspects: 1) We employ an improved method to measure the information share; 2) we discover new drivers of credit risk discovery; and 3) we assess the impact of CCP on the CDS market.

CDS spreads and the implied credit spreads from the stock prices do not satisfy one-to-one cointegration which is an essential assumption of Hasbrouck (1995) information share (IS) and Gonzalo and Granger (1995) component share (GG). We address this issue by employing the generalized information share (GIS) proposed by Lien and Shrestha (2014), which is free from one-to-one cointegration assumption. The empirical results suggest that GIS is a more suitable measure for the credit risk discovery analysis between stock and CDS markets. When GIS is used, the relative informational dominance becomes much less extreme than when IS or GG is used. We also eliminate transitory components from the prices to obtain pure credit risk components. This exercise has a substantial impact on the results in the earlier period, possibly because the CDS market was less efficient back then.

We propose financial condition index and funding cost as potential drivers of credit risk discovery and they both turn out to be significant. The empirical results suggest that the information share of the stock market is generally higher but the role of the CDS market becomes bigger when the economy is suffering. Higher funding cost adversely affects the information share of the CDS market. We also find that the CDS of investment grade firms possess higher information shares compared to speculative grade firms. Finally, we do not find an evidence that CCP enhances the efficiency and transparency of the CDS market. Rather, we find that CCP reduces the information share of CDS which supports insider trading hypothesis.

Appendix A: CreditGrades Model and Implied Credit Spread (ICS)

According to Finger, Finkelstein, Lardy, Pan, Ta, and Tierney (2002), CreditGrades model introduces randomness to default barrier although the distribution of default barrier is time-invariant. Also, in comparison with other structural credit risk models, CreditGrades model is more practical and easier for implementation as it links most of the model parameters, e.g., asset value and asset volatility, to market observables (Xiang, Chng, and Fang, 2013). In order to extract implied credit spreads from equity market, survival probability is calculated and then survival probability is converted to stock implied credit spreads. The first step is to obtain survival probability. Assume asset value V follows a Geometric Brownian Motion:

$$\frac{dV_t}{V_t} = \sigma dW_t + \mu_D dt \tag{A.1}$$

where W_t is a standard Brownian motion and has the distribution $W_t \sim N(0, t)$. σ is the asset volatility and μ_D is the asset expected mean. Default barrier is defined as the amount of the firm's assets remaining when default occurs, which is equal to the recovery value that the debt holders receive, $L \cdot D$, where L follow a time-independent lognormal distribution with mean $\bar{L}$ and percentage standard deviation λ.

$$\bar{L} = EL, \lambda^2 = var(log\,L), LD = \bar{L}De^{\lambda Z - \lambda^2/2} \tag{A.2}$$

where Z$\sim N(0,1)$ and Z is independent of the Brownian motion W_t. Z is unknown until the time of default. For an initial asset value V_0, default occurs once

$$V_0 e^{\sigma W_t - \sigma^2 t/2} < \bar{L}De^{\lambda Z - \lambda^2/2} \tag{A.3}$$

The survival probability of the company at time t is given by the probability that the asset value does not touch the default barrier before time t. Denote a process as X_t,

$$X_t = \sigma W_t - \frac{\sigma^2 t}{2} - \lambda Z - \frac{\lambda^2}{2}, and\ X_t > log\left(\frac{LD}{V_0}\right) - \lambda^2, \text{when } t \geq 0, X_t \sim N\left(-\frac{\sigma^2 t}{2} - \frac{\lambda^2}{2}, \sigma^2 t + \sigma^2 \lambda^2\right)$$

(A.4)

The survival probability up to time t is given by

$$P(t) = \Phi\left(-\frac{A_t}{2} + \frac{log(d)}{A_t}\right) - d \cdot \Phi\left(-\frac{A_t}{2} - \frac{\log(d)}{A_t}\right), \quad \text{(A.5)}$$

where $\Phi(\cdot)$ is the cumulative distribution function, $d = \frac{V_0}{\overline{L}D} e^{\lambda^2}$ and $A_t^2 = \sigma^2 t + \lambda^2$. Denoting the density function of default $f(t) = -\frac{dP(t)}{dt}$, the cumulative default probability up to time t is given by $1 - P(0) + \int_0^t \mathrm{d}s f(s)$, and the present value of the loss compensation by a CDS with maturity t is given by $(1-R)\left[1 - P(0) + \int_0^t f(s) \cdot e^{-rs}\, ds\right]$, where r is the risk-free rate and R is the recovery rate of the underlying debt.

The CDS stops paying its spread when the underlying debt defaults and therefore the present value of the spread payments is given by

$$ICS \int_0^t P(s) \cdot e^{-rs} ds, \quad \text{(A.6)}$$

where ICS is the spread of the CDS. The price of the CDS is the difference between the discounted spreads and loss compensation:

$$CDS = (1-R)\left[1 - P(0) + \int_0^t f(s) \cdot e^{-rs}\, ds\right] - ICS \int_0^t P(s) \cdot e^{-rs} ds. \quad \text{(A.7)}$$

For the value of the CDS to be zero at time t = 0, the following should hold:

$$(1-R)\big(1-P(0)\big) - \left(\frac{ICS}{r}\right)\left(P(0) - P(t)e^{-rt}\right) = -\left(1 - R + \frac{ICS}{r}\right) e^{r\xi}[G(t+\xi) - G(\xi)]$$

(A.8)

with $\xi = \frac{\lambda^2}{\sigma^2}$, $G(t) = d^{z+\frac{1}{2}} \Phi\left(-\frac{log(d)}{\sigma\sqrt{\mathrm{t}}} - z\sigma\sqrt{t}\right) + d^{-z+\frac{1}{2}} \Phi\left(-\frac{log(d)}{\sigma\sqrt{t}} + z\sigma\sqrt{t}\right)$, and $z = \sqrt{\frac{1}{4} + \frac{2r}{\sigma^2}}$. Solving for ICS, we obtain:

$$ICS = r(1-R)\left[\frac{1 - P(0) + H(t)}{P(0) - P(t)e^{-rt} - H(t)}\right], \ with\, H(t) = e^{r\xi}(G(t+\xi) - G(\xi)). \quad \text{(A.9)}$$

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Table 1

Data sources

This table summarizes the data required for empirical analysis and their sources. CDS quotes are collected from two data sources as none of them covers the whole sample period. BFCIUS, GSFCI, and CCP respectively refer to the Bloomberg Financial Condition Index, Goldman Sachs Financial Condition Index, and the central clearing counterparty.

Category	Data	Source
CDS market	CDS quotes (<30/09/2010)	Datastream
	CDS quotes (≥30/09/2010)	TickHistory
Stock market	Stock quotes	Bloomberg
	Market capitalization	
	Liabilities	
	Minority interests	
	Preferred shares	
Risk-free rate	5-year swap rate	Datastream
Firm characteristics	Credit rating	Compustat
	Industry classification	
Determinants	BFCIUS	Bloomberg
	GSFCI	Bloomberg
	3M CP and 3M T-bill	FRB reports
	CCP Clearing dates	ICE Clear Credit

Table 2

Descriptive statistics of CDS and ICS

This table reports descriptive statistics of CDS and ICS along the sample period. LCDS and LICS respectively refer to the CDS and the ICS obtained from the permanent price components after eliminating transitory components. All the credit spreads are expressed in basis points.

	LCDS				LICS			
	Mean	Std	Min	Max	Mean	Std	Min	Max
2006	50.04	83.97	0.20	976.41	112.23	154.54	0.32	1240.10
2007	59.56	111.60	1.70	1853.60	104.57	175.59	0.12	1176.29
2008	169.10	323.15	13.00	10210.71	187.64	273.37	0.27	2907.39
2009	191.04	474.20	14.14	14475.64	438.26	375.64	3.62	2665.26
2010	123.67	116.28	21.26	780.94	150.54	186.05	0.58	1176.62
2011	145.39	147.51	20.45	1128.45	120.80	161.16	0.30	1085.66
2012	162.03	223.63	15.20	2427.62	149.17	192.75	0.15	1372.41
2013	126.45	198.55	11.50	2279.32	100.35	161.76	0.06	1331.56
All	128.09	251.13	0.20	14475.64	172.23	248.09	0.06	2907.39
	CDS				ICS			
	Mean	Std	Min	Max	Mean	Std	Min	Max
2006	50.72	84.77	2.50	987.50	63.30	119.91	0.37	1232.66
2007	60.54	114.34	2.90	1958.60	72.12	150.77	0.09	1164.68
2008	171.40	338.09	15.50	11095.00	198.07	280.98	0.28	2946.19
2009	192.29	478.50	15.61	14624.75	460.33	385.46	3.56	2701.16
2010	123.77	116.95	20.50	793.07	158.55	188.68	0.59	1181.32
2011	141.74	145.57	19.50	1112.69	126.80	161.17	0.31	1085.01
2012	157.10	215.96	11.50	2259.00	155.51	193.68	1.10	1373.11
2013	122.37	191.64	9.36	2182.90	103.45	163.20	0.38	1332.48
All	127.24	253.28	2.50	14624.75	168.69	253.47	0.09	2946.19

Table 3

Descriptive statistics of CDS and ICS – credit ratings

This table reports descriptive statistics of CDS and ICS across credit ratings. LCDS and LICS respectively refer to the CDS and the ICS obtained from the permanent price components after eliminating transitory components. All the credit spreads are expressed in basis points.

	LCDS				LICS			
	Mean	Std	Min	Max	Mean	Std	Min	Max
AAA	26.17	18.03	0.20	117.39	17.80	27.32	0.32	152.88
AA	43.25	31.82	2.00	225.12	37.35	41.07	1.09	285.45
A	50.10	30.82	4.78	350.00	81.99	119.11	0.06	1006.36
BBB	129.84	294.61	4.97	14475.64	168.25	222.14	0.43	2907.39
BB	252.68	181.89	25.00	1697.53	310.11	320.53	0.29	1590.63
B	520.96	589.18	24.80	12033.19	691.81	334.93	39.48	2093.80
CCC	452.14	517.47	35.70	2427.62	313.29	219.43	37.98	899.65
	CDS				ICS			
	Mean	Std	Min	Max	Mean	Std	Min	Max
AAA	25.81	18.10	2.50	115.00	22.71	27.15	0.68	152.51
AA	39.18	26.24	3.00	180.00	38.73	43.64	1.42	299.38
A	49.46	30.71	5.50	360.00	80.05	122.15	0.09	1014.04
BBB	129.41	299.72	7.40	14624.75	161.75	230.11	0.47	2946.19
BB	252.91	183.79	26.50	1717.03	333.26	349.85	7.58	1958.61
B	517.54	576.74	26.50	11877.19	658.68	322.05	37.42	1373.11
CCC	434.96	492.23	34.20	2259.00	339.11	238.00	24.95	926.29

Table 4

Unit-root test

This table summarises the results of the ADF unit-root tests on CDS, ICS, and their difference, CDS-ICS. LCDS and LICS respectively refer to the CDS and the ICS obtained from the permanent price components after eliminating transitory components. Unit root test on CDS-ICS is to test one-to-one cointegration of the pair. If the difference is non-stationary, one-to-one cointegration relationship is rejected. The figures are the number of non-stationary time series with their percentage values in parenthesis. The significance level is 10%.

	LCDS	LICS	LCDS-LICS
Levels	100 (88%)	111 (98%)	107 (95%)
First Differences	0 (0%)	0 (0%)	0 (0%)
	CDS	ICS	CDS-ICS
Levels	103 (91%)	112 (99%)	106 (94%)
First Differences	0 (0%)	0 (0%)	0 (0%)

Table 5

Johansen cointegration test

This table summarises the results of the Johansen cointegration tests on LCDS-LICS pairs and CDS-ICS pairs. LCDS and LICS respectively refer to the CDS and the ICS obtained from the permanent price components after eliminating transitory components. The figures in the first row are the number of firms for which cointegration is detected with their percentage values in parenthesis. The significance level is 10%.

	LCDS-LICS	CDS-ICS
Cointegration	68 (60%)	80 (71%)
No cointegration	45 (40%)	33 (29%)

Table 6

Information share of CDS market (LCDS)

This table reports the credit risk discovery contribution of CDS market measured by generalized information share (GIS), information share (IS), and component share (GG). The first column represents semi-annual sub-periods. LCDS refers to the CDS obtained from the permanent price components after eliminating transitory components. For each measure, the first column is the average measure, the second column is the number of firms for which the measure exceeds 0.5, and the last column is the number of firms converted into percentage.

	GIS			IS			GG		
	GIS	>0.5	%	IS	>0.5	%	GG	>0.5	%
2006.2	0.53	63	56	0.50	61	54	0.50	59	52
2007.1	0.51	60	53	0.47	53	47	0.47	52	46
2007.2	0.48	53	47	0.38	36	32	0.36	29	26
2008.1	0.40	30	27	0.27	7	6	0.22	6	5
2008.2	0.39	28	25	0.37	19	17	0.33	17	15
2009.1	0.55	67	59	0.40	29	26	0.38	32	28
2009.2	0.49	48	42	0.42	35	31	0.40	34	30
2010.1	0.60	83	73	0.52	65	58	0.50	54	48
2010.2	0.50	60	53	0.40	37	33	0.30	19	17
2011.1	0.37	31	27	0.30	20	18	0.26	22	19
2011.2	0.42	40	35	0.36	23	20	0.28	16	14
2012.1	0.38	34	30	0.29	14	12	0.22	14	12
2012.2	0.38	29	26	0.31	22	19	0.25	19	17
2013.1	0.45	48	42	0.31	19	17	0.26	19	17
2013.2	0.34	24	21	0.25	8	7	0.16	7	6
All	0.45	35	31	0.37	9	8	0.33	8	7

Table 7

Information share of CDS market (CDS)

This table reports the credit risk discovery contribution of CDS market measured by generalized information share (GIS), information share (IS), and component share (GG). The first column represents semi-annual sub-periods. For each measure, the first column is the average measure, the second column is the number of firms for which the measure exceeds 0.5, and the last column is the number of firms converted into percentage.

	GIS			IS			GG		
	GIS	>0.5	%	IS	>0.5	%	GG	>0.5	%
2006.2	0.49	54	48	0.39	37	33	0.38	36	32
2007.1	0.45	51	45	0.33	24	21	0.30	25	22
2007.2	0.45	46	41	0.34	21	19	0.30	18	16
2008.1	0.39	29	26	0.27	5	4	0.22	4	4
2008.2	0.38	30	27	0.36	14	12	0.32	12	11
2009.1	0.54	68	60	0.42	32	28	0.40	39	35
2009.2	0.49	52	46	0.42	36	32	0.40	34	30
2010.1	0.61	84	74	0.53	67	59	0.51	65	58
2010.2	0.52	60	53	0.42	40	35	0.32	21	19
2011.1	0.36	25	22	0.31	16	14	0.27	21	19
2011.2	0.44	46	41	0.39	34	30	0.33	24	21
2012.1	0.40	36	32	0.32	20	18	0.24	14	12
2012.2	0.38	29	26	0.33	22	19	0.27	22	19
2013.1	0.47	51	45	0.33	22	19	0.27	19	17
2013.2	0.35	25	22	0.26	10	9	0.17	8	7
All	0.45	34	30	0.36	8	7	0.32	6	5

Table 8

Information shares of investment-grade CDS versus speculative-grade CDS

This table compares the generalized information share (GIS) measure of investment-grade CDS with that of speculative-grade CDS. The first column represents semi-annual sub-periods. For each measure, the first column is the average measure, the second column is the number of firms for which the measure exceeds 0.5, the third column is the number of firms converted into percentage, and the last column is the number of firms in each group. All calculations are based on the permanent price components.

	Investment Grade				Speculative Grade			
	GIS	>0.5	%	Firms	GIS	>0.5	%	Firms
2006.2	0.54	53	56	94	0.50	10	53	19
2007.1	0.52	53	56	94	0.42	7	37	19
2007.2	0.48	44	47	94	0.49	9	47	19
2008.1	0.39	23	24	94	0.44	7	37	19
2008.2	0.39	26	28	94	0.35	2	11	19
2009.1	0.55	55	59	94	0.53	12	63	19
2009.2	0.50	40	43	94	0.44	8	42	19
2010.1	0.62	71	76	94	0.54	12	63	19
2010.2	0.50	50	53	94	0.50	10	53	19
2011.1	0.38	28	30	94	0.29	3	16	19
2011.2	0.42	33	35	94	0.41	7	37	19
2012.1	0.40	32	34	94	0.26	2	11	19
2012.2	0.38	25	27	94	0.35	4	21	19
2013.1	0.47	43	46	94	0.39	5	26	19
2013.2	0.33	19	20	94	0.39	5	26	19
All	0.46	32	34	94	0.42	3	16	19

Table 9

Information shares of CCP-cleared CDS versus non-cleared CDS

This table compares the generalized information share (GIS) measure of CCP-cleared CDS with that of non-cleared CDS. The first column represents semi-annual sub-periods. For each measure, the first column is the average measure, the second column is the number of firms for which the measure exceeds 0.5, the third column is the number of firms converted into percentage, and the last column is the number of firms in each group. All calculations are based on the permanent price components.

	CCP Cleared				Non Cleared			
	GIS	>0.5	%	Firms	GIS	>0.5	%	Firms
2010.1	0.59	23	72	32	0.61	60	74	81
2010.2	0.49	19	49	39	0.51	41	55	74
2011.1	0.40	16	35	46	0.34	15	22	67
2011.2	0.46	24	52	46	0.40	16	24	67
2012.1	0.42	17	37	46	0.35	17	25	67
2012.2	0.36	9	17	52	0.39	20	33	61
2013.1	0.47	26	50	52	0.44	22	36	61
2013.2	0.31	9	16	56	0.37	15	26	57

Table 10

Determinants of credit risk discovery (LCDS)

This table reports the results of the panel regression (12). The dependent variable is either GIS, IS or GG of LCDS. The independent variables are relative market liquidity between stock and CDS markets (RML), credit condition of reference entity (CCON), relative frequency of adverse shocks (ADS3), credit rating downgrades events (CRDOWN), Bloomberg Financial Condition Index (BFCIUS), Goldman Sachs Financial Condition Index (GSFCI), funding cost (FC), and the central clearing counterparty dummy (CCP). ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

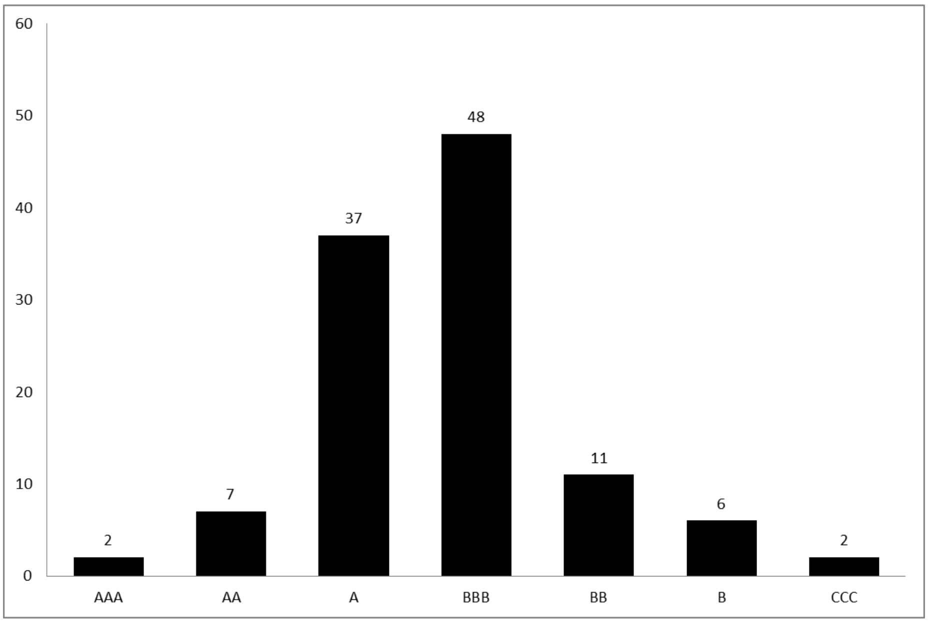
	GIS		IS		GG	
Constant	48.62***	49.14***	42.67***	43.05***	39.69***	40.25***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RML	3.84***	2.96***	7.82***	6.65***	10.58***	9.47***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CCON	0.00***	-0.01***	-0.01***	-0.02***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ADS3	-23.92***	-24.39***	-29.82***	-29.13***	-33.70***	-33.91***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CRDOWN	1.43***	1.02***	2.79***	2.37***	3.71***	3.22***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BFCIUS	-1.21***		-1.64***		-1.54***	
	(0.00)		(0.00)		(0.00)	
GSFCI		4.07***		4.27***		4.78***
		(0.00)		(0.00)		(0.00)
FC	-4.23***	-2.51***	-5.31***	-2.55**	-5.10***	-2.79**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CCP	-7.98***	-5.52***	-11.21***	-8.67***	-15.50***	-12.62***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed	No	No	No	No	No	No
R-squared	0.01	0.02	0.03	0.04	0.04	0.05

Table 11

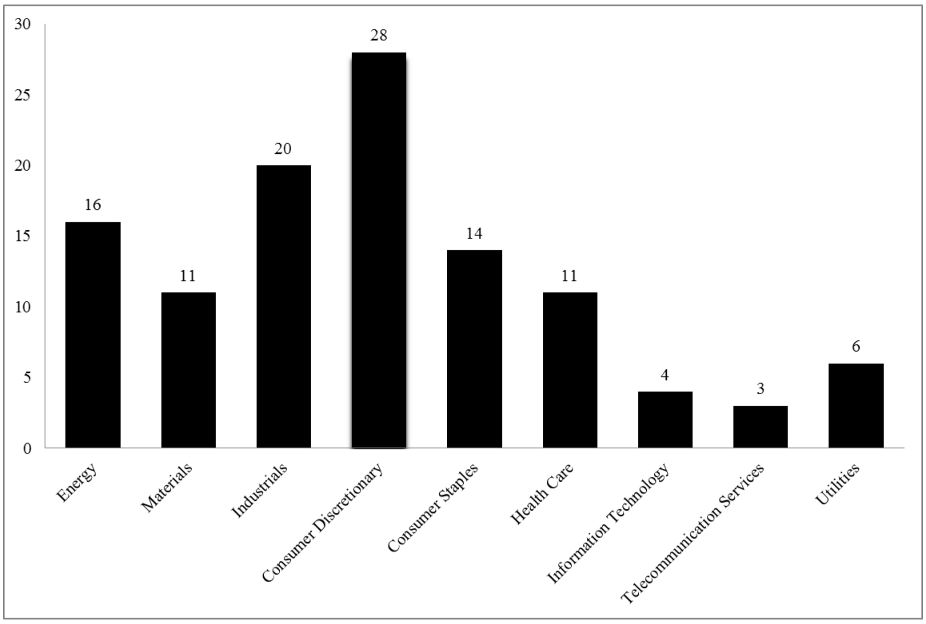
Robustness check

This table reports the results of the panel regression (12). The sample consists of only the firms for which CDS and ICS are statistically cointegrated. The dependent variable is either GIS, IS or GG of LCDS. The independent variables are relative market liquidity between stock and CDS markets (RML), credit condition of reference entity (CCON), relative frequency of adverse shocks (ADS3), credit rating downgrades events (CRDOWN), Bloomberg Financial Condition Index (BFCIUS), Goldman Sachs Financial Condition Index (GSFCI), funding cost (FC), and the central clearing counterparty dummy (CCP). ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	GIS		IS		GG	
Constant	47.13***	47.74***	37.07***	37.49***	31.01***	31.65***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RML	5.77***	4.58***	9.75***	8.72***	14.86***	13.94***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CCON	0.00***	0.00***	0.00***	-0.01***	0.00***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ADS3	-31.22***	-31.06***	-40.05***	-39.36***	-49.90***	-50.60***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CRDOWN	3.72***	2.75***	3.53***	2.80***	4.22***	3.30***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BFCIUS	-1.57***		-1.35***		-1.22***	
	(0.00)		(0.00)		(0.00)	
GSFCI		4.62***		3.56***		4.21***
		(0.00)		(0.00)		(0.00)
FC	-5.44***	-3.02***	-3.57***	-1.35***	-2.39***	-0.70***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CCP	-10.16***	-7.47***	-9.68***	-7.61***	-15.28***	-12.81***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed	No	No	No	No	No	No
R-squared	0.01	0.03	0.03	0.04	0.04	0.06



(a) Distribution of firms across credit ratings

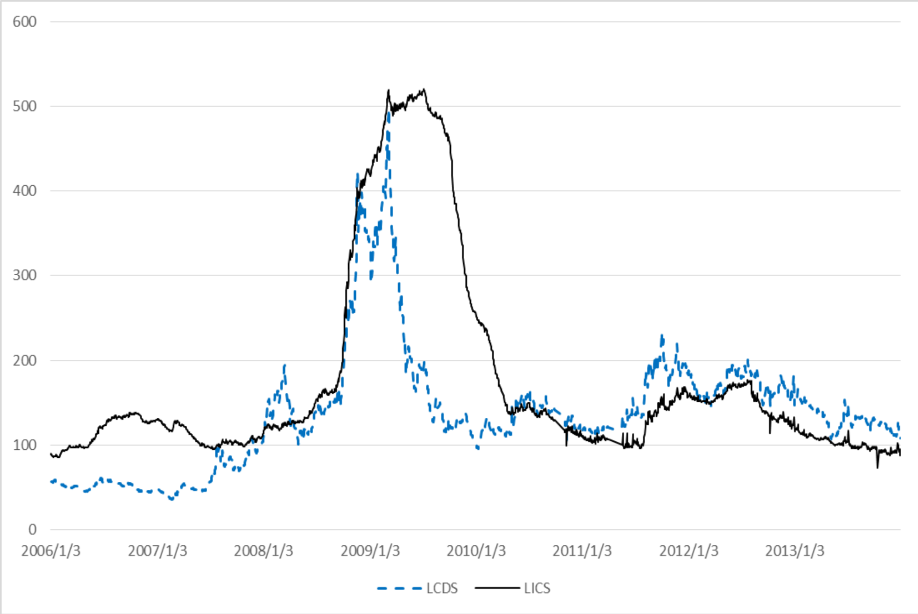


(b) Distribution of firms across industry sectors

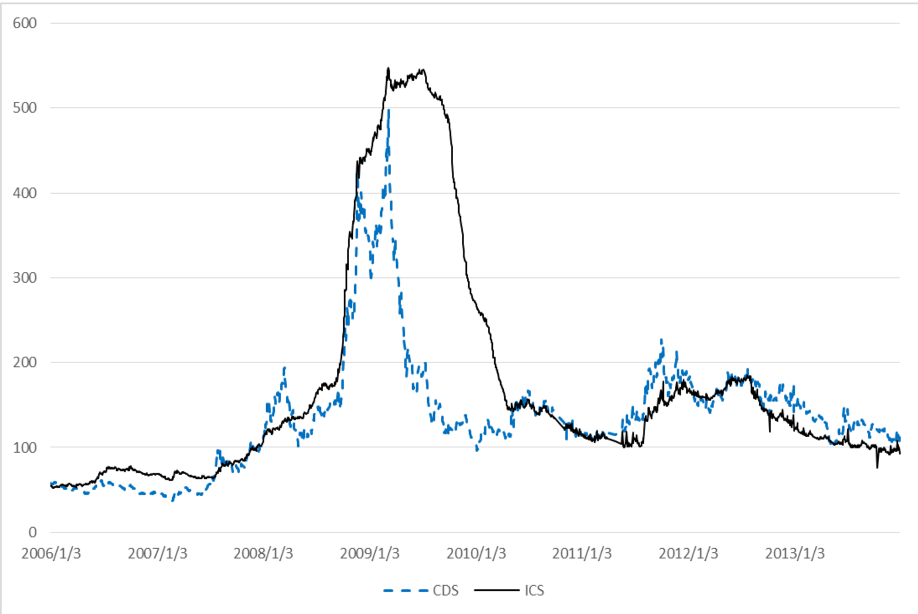
Figure 1

Distribution of the firms

This figure illustrates credit ratings and industry sectors of the 113 firms in the sample. Credit ratings are based on the S&P Domestic Long Term Issuer Credit Ratings as of 31/12/2013 and industry classifications are based on the Global Industry Classification Standard (GICS).



(a) Cross-Sectional Means of LCDS and LICS

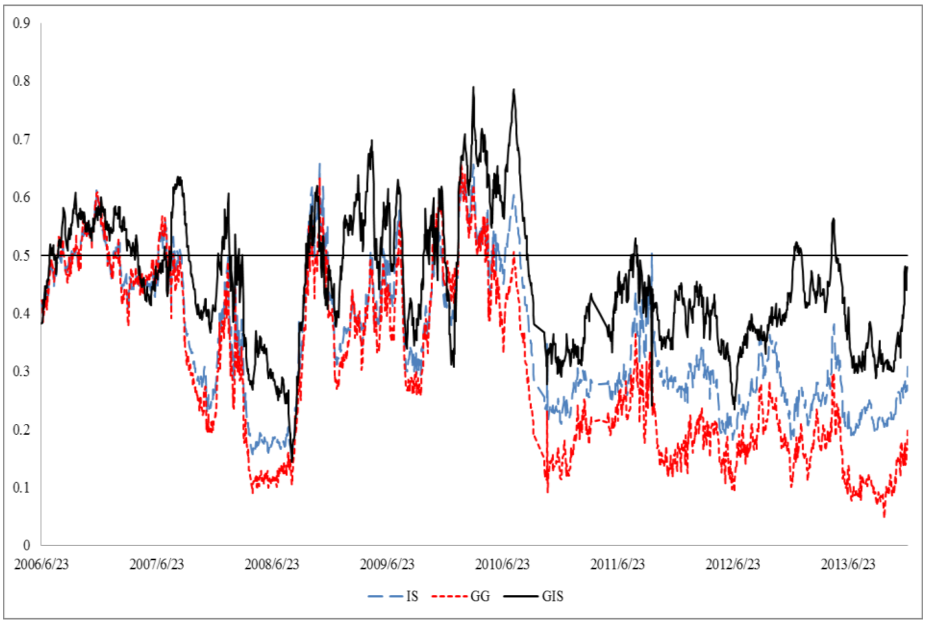


(b) Cross-Sectional Means of CDS and ICS

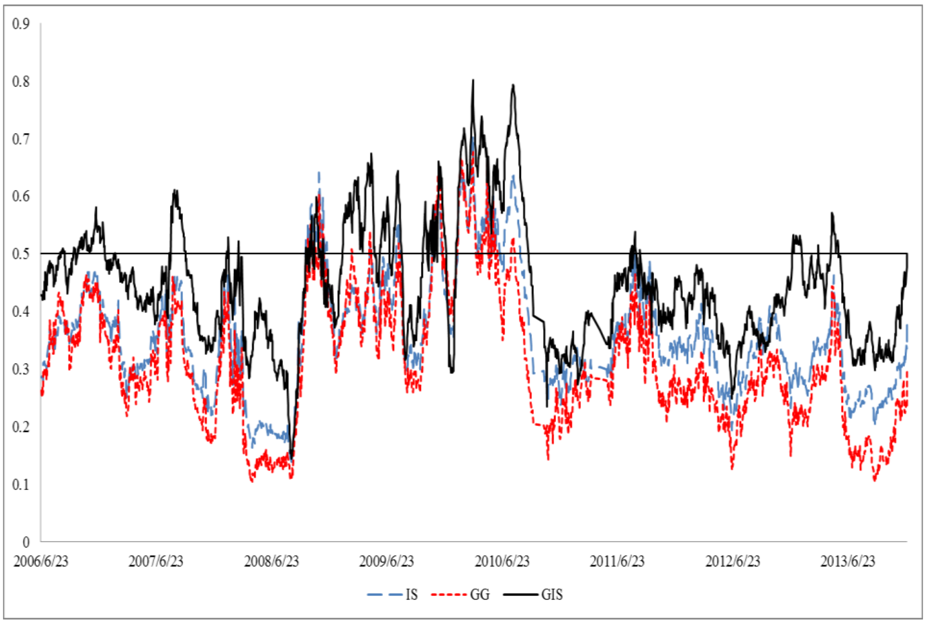
Figure 2

Cross-sectional means of CDS and ICDS

This figure plots the cross-sectional means of CDS and ICS over the sample period, January 2006 to December 2013. LCDS and LICS respectively refer to the CDS and the ICS obtained from the permanent price components after eliminating transitory components. All the credit spreads are expressed in basis points.



(a) Information share of LCDS

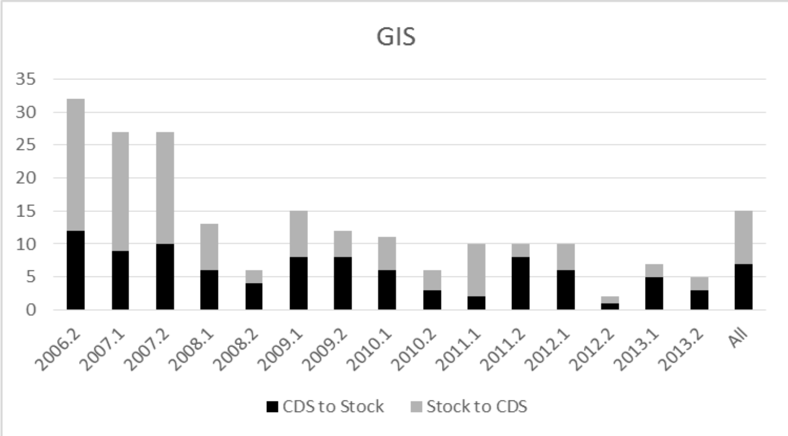


(b) Information share of CDS

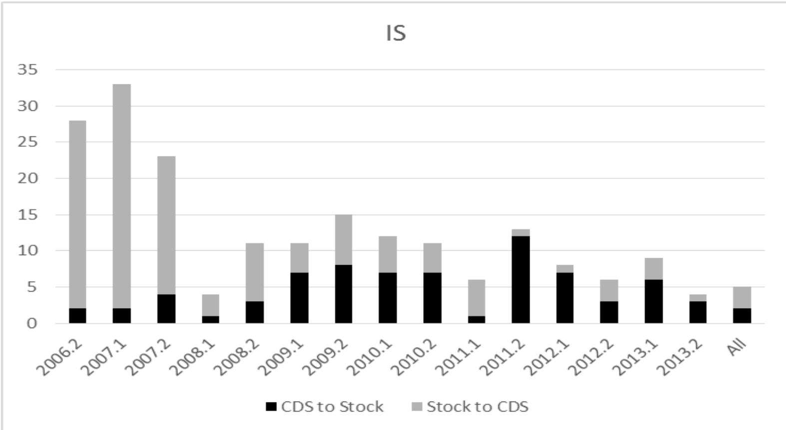
Figure 3

Information shares of the CDS market

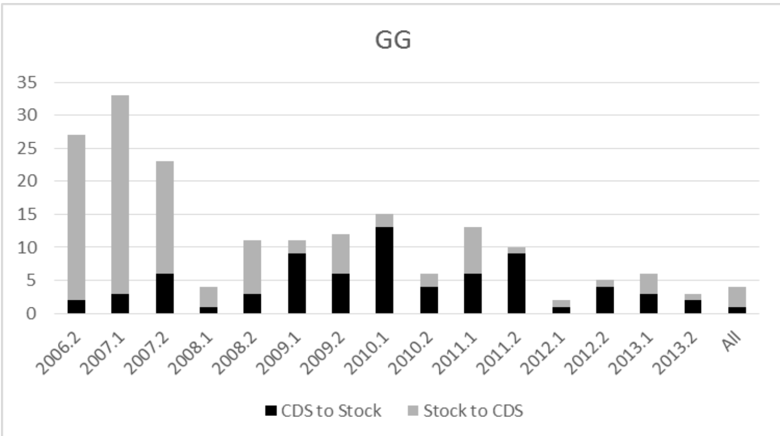
This figure plots the information share of CDS market measured by GIS, IS, and GG over the sample period. The upper graph is based on the permanent price components (LCDS and LICS) and the lower graph is based on the original prices (CDS and ICS). LCDS and LICS respectively refer to the CDS and the ICS obtained from the permanent price components after eliminating transitory components.



(a) Lien and Shrestha (2014) generalized information share (GIS)



(b) Hasbrouck (1995) information share (IS)



(c) Gonzalo and Granger (1995) component share (GG)

Figure 4

Impact of transitory components on credit risk discovery leadership

This chart shows the number of firms for which the credit risk discovery leadership is reversed after eliminating transitory components. ’CDS to Stock’ refers to the firms for which the leadership has moved from CDS to stock and ’Stock to CDS’ refers to the opposite case.

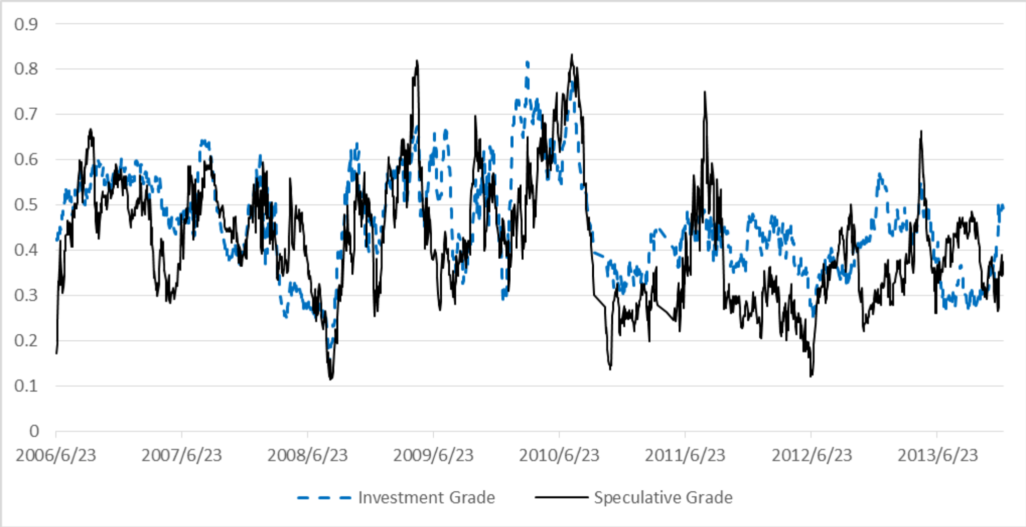
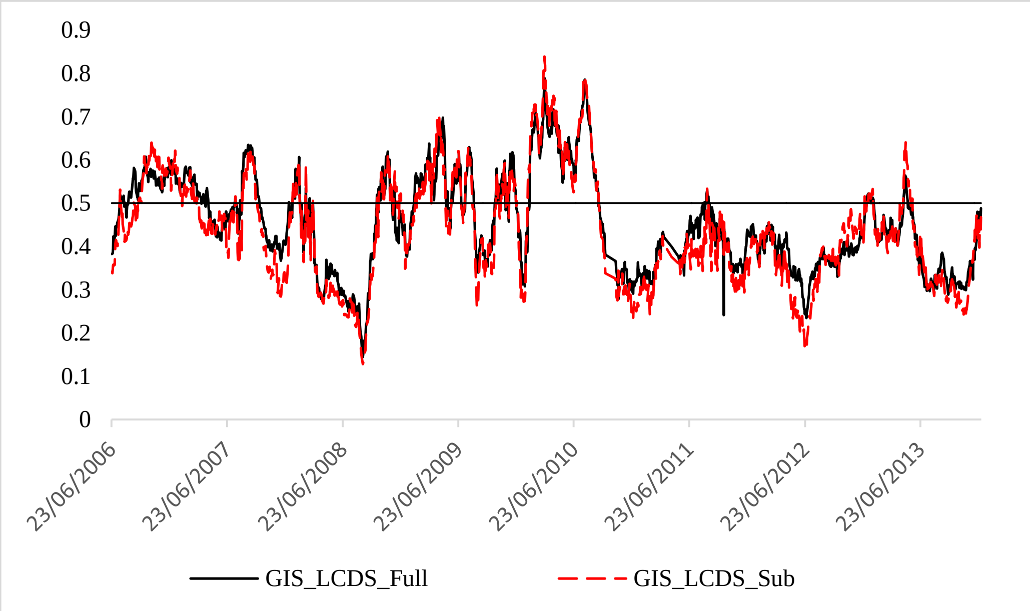


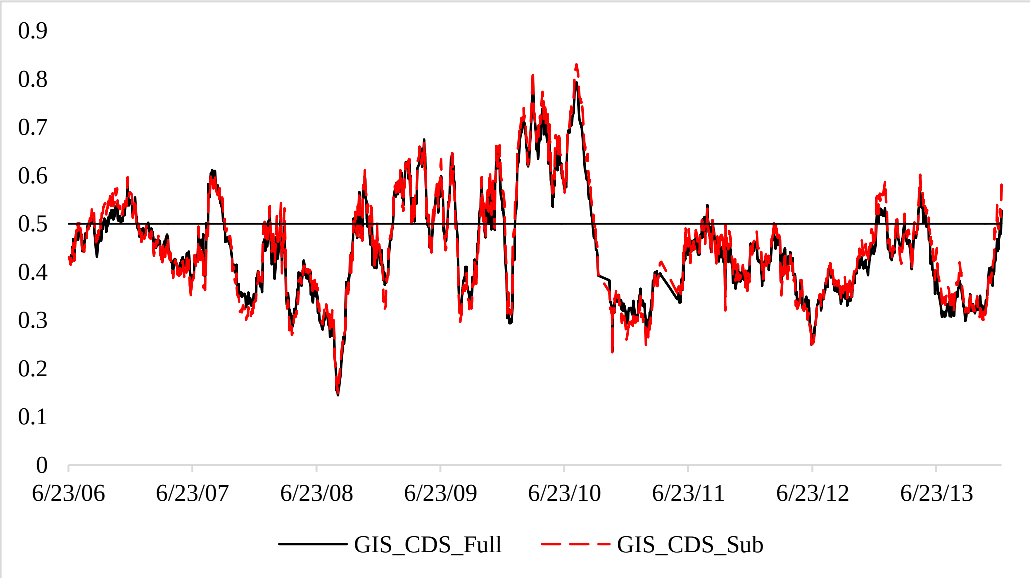
Figure 5

Information shares of investment-grade CDS versus speculative-grade CDS

This figure plots the cross-sectional means of generalized information share (GIS) for investment-grade CDS and speculative-grade CDS. All calculations are based on the permanent price components.



(a) Information share of LCDS



(b) Information share of CDS

Figure 6

Information shares of the CDS market (robustness)

This figure plots the generalized information share (GIS) of CDS market for both the full sample and a sub-sample of firms for which CDS and ICS are statistically cointegrated. The upper graph is based on the permanent price components (LCDS and LICS) and the lower graph is based on the original prices (CDS and ICS).