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Abstract

The global financial crisis has led to even greater interest in credit default swap (CDS) markets. CDS markets are regarded as one of the underlying causes in the financial crisis, and given the circumstances that regulatory reviews have been progressed, rigorously examining price formation in CDS markets before and after the crisis would be important for considering the functions of the CDS market and how future regulation ought to be. Nevertheless, only a limited understanding of price formation in the Japanese CDS market has been accumulated so far. The aim of this paper is to empirically verify the determinants of CDS spreads whose reference entities are Japanese non-financial corporations. I regard as the possible determinants of CDS spreads both the structural variables and some state variables which capture overall market trends and macroeconomic development. Analyses in this paper succeed to find several characteristics of price formation in the CDS market, including some phenomena never reported before. First, structural variables satisfy the sign condition and are generally significant, but they cannot fully explain the fluctuation of CDS spreads. Even if market- and macro-related variables are included in addition to the structural variables as the independent variables, the explanatory power of the model is generally low. It is arguable that the so-called "credit spread puzzle" exists in the Japanese CDS market as well. Second, a phenomenon not reported in foreign countries is confirmed, namely, that the explanatory power of the regression model improves after the financial crisis. A possible reason for this is that, after the onset of the financial crisis, market fluctuations in foreign countries begin to have a considerable impact on the Japanese CDS market. Third, it seems that some unobservable systemic factors become main factors for CDS spreads variations after the financial crisis. These findings will help to understand the price formation mechanisms in the Japanese CDS market.

Keywords: Credit default swaps (CDSs), Structural model, Dynamic Heterogeneous Panel Model

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1. Introduction

The appraisal of credit default swaps (CDSs) changed considerably with the onset of the global financial crisis in 2007. Prior to the financial crisis, it seemed to be blindly believed that CDS markets lead to improvements in social welfare through improving the efficiency of resource allocation and lessening the financial restrictions on households and business. Since various transactions, including short selling, could be conducted with very small transaction costs in the CDS markets, investors with diverse trading motives, such as hedging or speculation, are supposed to participate in the markets, which could lead to more active information production and more efficient price discovery on the reference entities. Nevertheless, after the onset of the financial crisis, attention began to shift to negative views, including that CDS markets had amplified the systemic risk of the entire financial system and that they had lowered social welfare by provoking moral hazard and excessive risk taking in the banking sector. Furthermore, financial authorities show concern over unfair trading in CDS markets whereas several incidents of insider trading extending into CDS markets and stock markets occurred in some countries. Regulators in advanced countries began to examine measures for tightening the regulation against CDS markets, and some of them have already been implemented.[1]

Amid rising concern over CDS markets, empirical examinations on the functions and price formation in U.S. and European CDS markets have been advanced. The determinants of CDS spreads and the price discovery among CDS markets, bond markets, stock markets, and other related markets are designated as key research topics. In contrast, as for the Japanese CDS market, empirical investigations have been limited so far, so the characteristics of price formation are little understood. In particular, no empirical research has been reported on the CDS spreads of non-financial firms in Japan. Unlike CDSs in which a financial institution or the Japanese government is the reference entity, most CDS transactions of non-financial corporations are conducted domestically. Therefore, it is preferable that non-financial corporations are included in assessing price formation in the Japanese CDS market. In this paper, I will focus my attention on Japanese non-financial corporations, and will examine the determinants of their CDS spreads and the characteristics of price formation before and after the financial crisis.

The rest of this paper is structured as follows. In Chapter 2, I review previous studies and summarize the main aims of this paper. Chapter 3 explains the empirical method used in this paper. As the possible determinants of CDS spreads, I incorporate not only the structural variables but also a number of state variables, such as interest rates and others that indicate stock market trends. Chapter 4 shows the results of empirical analyses. I examine the validity of the structural model and discuss the significance of the

[1] Positive views about CDS markets can be found in Hellwig (1994), Allen and Gale (2006), Hakenes and Schnabel (2008), and Aschcraft and Santos (2009). Conversely, negative views have been detailed by Partnoy and Skeel (2007), Brunnermeier (2008), Hellwig (2008), and Hakenes and Schnabel (2009). For the regulations pertaining to CDS markets and details of recent changes, refer to BIS (2008) and IOSCO (2009).

state variables. I also turn my attention to the differences and characteristics before and after the recent financial crisis. In Chapter 5, I draw my conclusions.

2. Previous literature

One of the widely accepted theoretical models on the determinants of credit risk is known as the structural model or structural approach.[2] Structural models usually define a firm's value as a stochastic process, regard the situation where the firm value falls below a certain threshold (debt value) as default, and calculate the frequency (probability) of such a situation occurring based on option pricing theories. In a simplest structural model, the credit risk of a firm can be determined by three structural variables: leverage, volatility of firm values and the risk-free interest rate. Credit risk can be expressed as an increasing function of leverage and the volatility, and a decreasing function of risk-free interest rate.[3] A number of empirical studies have been carried out with regard to this theoretical conclusion: To what extent can the levels and fluctuations of credit spreads be explained by the three structural variables? If structural variables cannot fully explain the variation of credit spreads, what mechanisms are driving the credit spreads' fluctuation?

While a number of previous studies on bond spreads have confirmed that the structural variables satisfy the theoretical sign conditions, it has also been reported that the explanatory power of the structural models is generally low. This low explanatory power is often called the "credit spread puzzle." For example, Collin-Dufresne *et al*. (2001) investigate the determinants of bond spreads in the U.S. using a linear model in which structural variables are the explanatory variables, and report that the R^2 remains generally around 0.2 to 0.3. Faced with the credit spread puzzle, researchers have focused on other factors that might affect credit risk besides structural variables, such as taxes, liquidity risk and other systemic risks.[4] However, the mechanisms and variables by which fluctuations in credit risk can be explained with a sufficiently high degree of accuracy are yet to be discovered at the present point in time.

Recently, there has been another stream of studies examining the determinants of credit risk, that is, analyses of CDS markets. In evaluating credit risk, CDS spreads could be better indicators than bond spreads for a number of reasons.[5] Longstaff *et al*. (2005) report that the majority of CDS spreads can be

[2] Merton (1974), Black and Cox (1976), Longstaff and Schwarz (1995), Collin-Dufresne and Goldstein (2001), etc. Ammann (2001) describes various structural models.

[3] Depending on the assumptions of the model, it is possible that a positive relationship can occur between the risk-free interest rate and the credit risk (see, Longstaff and Schwartz (1995) for example). However, our discussion will consider that the structural model "assumes a negative relationship between the risk-free interest rate and the credit risk" for simplicity of explanation,.

[4] See, Elton *et al*. (2001) and Driessen (2005), for example.

[5] Two main reasons have been suggested. First is that CDS spreads are less arbitrary than bond spreads: the level of bond spreads changes depending on what is used for the benchmark (risk-free interest rate) while CDS spreads are calculated as the premium for a notional principal amount and no benchmark-related problems occur. Second, short selling on bond markets is quite difficult in reality, whereas in the CDS markets short sales can be conducted relatively easily. For this

explained using firm-specific bankruptcy risks. Ericsson *et al*. (2009) focus on structural models, and investigate the determinants of the changes of CDS spreads. They report that: (i) the estimated parameters of the structural variables are consistent with theory; (ii) the lower the credit-rating, the greater the absolute value of the parameters; (iii) while the R^2 is about 0.6 in the case of levels regression, it is around 0.2 in the case of difference regression. Blanco *et al*. (2005) also measure the effects of structural variables on CDS spreads while their focus is on comparing price discovery in the U.S. bond market and CDS market. They indicate that the explanatory power of the model measured by R^2 is low, at about 0.25, while signs of coefficients are in accordance with the theory. Di Cesare and Guazzarotti (2010) study the CDSs of U.S. non-financial firms before and after the global financial crisis. They direct their attention not only to structural variables but also to various market variables, such as stock price returns, difference between long-term and short-term interest rates, corporate bond spreads, the U.S. VIX index, and the theoretical value of CDS spreads. They report: (i) about half of all fluctuations in CDS spreads can be explained using their explanatory variables, and the explanatory power is higher than existing research; (ii) significant difference in the explanatory power of the model before and after the financial crisis cannot be detected; (iii) CDS spreads of many issuers increased simultaneously during the crisis situation, which implies that some common factors have influence on the CDS market.

Studies on the determinants of credit risk for Japanese firms include Ito and Harada (2004), Baba and Inada (2009), Ooyama and Sugimoto (2007), Shirasu and Yonezawa (2007), Inaba (2007), Nakashima and Saito (2009), and Ooyama and Hongo (2010). Of these, Ooyama and Sugimoto (2007), Shirasu and Yonezawa (2007), and Nakashima and Saito (2009) are few who analyze non-financial corporations. Ooyama and Sugimoto (2007) use OLS estimation to examine the determinants of bond spread changes, and report that: (i) although a negative relationship is often observed between the risk-free interest rate and bond spread, positive relationships also occur for some issuers; (ii) an increase in swaption volatility, which is supposed to represent the uncertainty of interest rates in the future, coincides with the increase in the bond spread; (iii) bond spreads seem to have no clear relationship with the stock price index return and the volatility thereof; (iv) R^2 is at a low level, which implies that some other factors not incorporated into the estimation model might cause changes in the bond spread. Shirasu and Yonezawa (2007) take the effects of the economic environment and liquidity factor into account as possible determinants of bond spread in addition to the intrinsic attributes of individual issues. Although the focus of their analysis is on investigating the presence of the “flight to quality” and “flight to liquidity” phenomena, we can confirm the following from the analyses described in the paper: (i) the signs of coefficients on the structural variables are different to those expected in the structural model for some firms; (ii) overall stock market trends and bond spreads are inversely correlated; (iii) contrary to theoretical inference, the difference of the risk-free interest rate has a positive effect on bond spreads. Nakashima and Saito (2009) propose to examine the determinants of bond spreads based on an

reason, it is expected that the evaluations of credit risk by market participants will be reflected more accurately in CDS markets.

estimation model in which time dummies and other factors are added to the structural model. They report that (i) estimates of the structural variables are consistent with the structural model, (ii) overall trends in financial markets affect bond spreads as stock price returns and change of bond spreads have a significant negative relationship. By comparing these existing studies on bond spreads, we can confirm that there are differences in the sign and significance of the parameter estimates for structural variables and other state variables.

There are many studies on the Japanese CDS market, but most of those are about CDSs whose reference entity is a major financial institution. Ito and Harada (2004) suggest that CDS spreads are an effective indicator capturing the credit risk of major banks. Inaba (2007) employs a structural model to examine the determinants of CDS spreads for three major banks. He adopts structural variables, swaption volatility and other variables as determinants of CDS spreads, and reports that the CDS spreads of major banks are determined consistently with the structural model and the spreads are also affected by the macro economy, such as by business trends. Baba and Inada (2009) explore the determinants of subordinated debt spreads and CDS spreads of four major banks, and further investigate the price discovery between the two spreads. They report that CDS spreads negatively react to stock price returns, and are positively related to the Japanese sovereign CDS spreads and the historical volatility of CDS spreads.

As shown above, previous studies on the credit risk of Japanese firms have been accumulated primarily around bonds and CDSs of financial institutions. As far as I know, no empirical research that investigates CDSs of non-financial firms has been reported so far. As mentioned earlier, in view of the limitations inherent in bond spreads, we should be wary about relying on the results of bond market analyses alone for examining the determinants of credit risk. Therefore, I will focus on the CDS transactions of non-financial corporations and examine their determinants. Specifically, I will clarify the extent to which actual fluctuations of CDS spreads can be accounted for by structural variables, and then will look at the mechanisms that can explain the part which cannot be captured by structural variables. Furthermore, I will compare the price formations of before and after the recent financial crisis.

3. Methodology

3.1. Selection of variables

Table 1 shows the list of variables in this study. Although no commonly acknowledged definition of the credit risk variable has been established in existing research, four different definitions — level value of credit risk spreads, level difference, logarithmic level value, and logarithmic difference — are often used.[6] Therefore, this paper will discuss the results of empirical analyses using these four definitions —

[6] The studies by Ericsson *et al*. (2009), Ooyama and Hongo (2010), Nakashima and Saito (2009), Duffee (1998), Collin-Dufresne *et al*. (2001), Di Cesare and Guazzarotti (2010), Greatrex (2008), Ooyama and Sugimoto (2007), Alexopoulou *et al*. (2009), and Gai *et al*. (2009) utilize level values and the differences thereof. In contrast, Edwards (1984), Das *et al*. (2009), and Forte (2009) suggest that logarithmic level values are theoretically better. Inaba (2007) uses logarithmic level

defined as $CDSS$, $ln(CDSS)$, $\Delta CDSS$, and $\Delta ln(CDSS)$ respectively — in so far as the explanation does not become complicated.

Explanatory variables are comprised of structural variables and other state variables. The structural variables are leverage ($LEVERAGE$), firm value volatility ($VOLATILITY$) and the risk-free interest rate (RF). In calculating $LEVERAGE$, periodic financial data are transformed to daily data using linear interpolation.[7] Firm value and its volatility cannot be observed directly in market places. Existing studies often use one of three proxy variables: volatility derived from option pricing theory, historical volatility, and GARCH-type volatility. In this paper, an option-based volatility measure that is calculated in accordance with the procedure outlined in the Appendix is selected.[8] Furthermore it is not necessarily evident which interest rate should be used for the risk-free interest rate. Most existing papers use either the yields on long-term government bonds or long-term swap rates. Similar to Ericsson *et al.* (2009) and others, I will use the ten-year government bonds yield as risk-free interest rate (RF).[9] As the treatment in many of previous papers, I add the square of the risk-free interest rate, ($SQR(RF)$), as an explanatory variable. Readers should note that "structural variables" do not include the square of the risk-free interest rate in the explanation below.

Since the credit spread puzzle was acknowledged, variables expressing the macro environment and market trends have been adopted as the possible determinants of credit risk. These variables could be construed as state variables for grasping the term structure of interest rates, the stochastic variation of firm values, the time-varying recovery rate and so forth. However, because the rigorous mathematical relation between these variables and credit risk has not been explicitly derived in most theoretical models, the questions of which indicators to be incorporated into the estimation model and how to incorporate them have to be left to the discretion of researchers.[10] I select the following variables that have been used frequently in existing studies as independent variables that capture the macro

values in order to stabilize the variance of the dependent variable. Forte and Peña (2009) and Ferrucci (2003) utilize logarithmic differences.

[7] In empirical analyses of credit risk, it is normal to use linearly interpolated financial data. For example, Collin-Dufresne *et al*. (2001), Greatrex (2008), Ericsson *et al*. (2009), Nakashima and Saito (2009), and Ooyama and Hongo (2010) utilize linear interpolation technique.

[8] Analyses are also conducted using the GARCH volatility (based on GARCH (1,1) model) and the historical volatility (90-day) of stock price returns as the proxy variable for firm value volatility. The outcomes are virtually the same as the findings in this paper. Thus, the claims made in this paper would also hold true for other proxy indexes for firm value volatility.

[9] Forte and Lovreta (2009) remark that it would be inappropriate to use the swap interest rate as a proxy variable for the risk-free interest rate during the recent financial crisis situation.

[10] For example, with regard to the positioning of state variables in structural models, the leading study examining the determinants of CDS spreads, Collin-Dufresne *et al*. (2001), only goes as far as presenting the relational expression $CS(t) = CS(V_t, r_t, [\boldsymbol{X}_t])$, where CS is credit spread, V is firm value, r is the swap rate, $\boldsymbol{X}$ is a variety of state variables, and t is time. But recently, using variables that grasp macroeconomic trends and overall market trends in credit risk evaluation models in an ad hoc fashion has become fairly widespread. At the same time, statistically evaluating the effects of these variables on credit risk has also been advanced. For example, Sommar and Shahnazarian (2009) take a statistical approach in examining the effects of industrial production, commodity prices and short-term interest rates on credit risk; and Simons and Rolwes (2009) take a similar approach in examining the effects of GDP, interest rates, foreign exchange, equity returns and the fluctuations thereof, as well as crude oil prices on credit risk. Chau-Lau (2006) presents a summary of statistical attempts that incorporate macro factors in a credit risk model.

environment and market trends: $SQR(RF)$, the difference between long-term and short-term interest rates (TS), return on the domestic stock market ($TOPIX$), the logarithmic market capitalization ($ln(MV)$), swaption volatility ($SWAPTION$), and U.S. VIX index (VIX).[11]

Additional explanations are necessary for some variables. As discussed in detail by Di Cesare and Guazzarotti (2010), the difference between long-term and short-term interest rates could have either a positive or negative effect on credit risk spread. Considering this ambiguity, I regard TS as a control variable in this paper. There is also uncertainty surrounding the interpretation of stock market returns. Blanco *et al*. (2005) is among the scholars who view a stock market return as a proxy variable for default recovery rates; but it could also be thought of as a state variable grasping macro environment trends. Although the return on individual stocks could possibly be added as an explanatory variable, I have not adopted it in this paper because it could have a high correlation with leverage and market capitalization. Logarithmic market capitalization is generally used as an indicator for firm size. If firm size correlates with trading volume in the CDS market, we could also regard $ln(MV)$ as a proxy of liquidity. Meanwhile, gathering necessary data to evaluate the overall liquidity of the Japanese CDS market and the liquidity of individual CDS issues is difficult, so I have positioned $ln(MV)$ as a control variable for liquidity concurrently with firm size. Swaption volatility could be regarded as an indicator capturing fluctuations of the risk-free interest rate and the uncertainty over future prospects of the interest rate environment. U.S. VIX index has been construed in previous studies as a proxy that reflects the uncertainty of the overall U.S. stock market as well as global event risk. No matter which interpretation is adopted, VIX can be regarded as an instability factor in overseas markets from the perspective of the Japanese CDS market or Japanese investors.

3.2. Estimation model

Many previous studies use the linear model of equation (1).

$$Spread_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} x_{i,k,t} + \varepsilon_{i,t} \qquad \cdots\cdots(1)$$

$Spread_{i,t}$ is the variable representing the credit risk of firm *i* at time *t*, and $CDSS, ln(CDSS), \Delta CDSS, \Delta ln(CDSS)$ are used separately as this variable. $x_{i,k,t}$ is the k^{th} explanatory variable of firm *i* at time *t*, and the explanatory variables (*k*=1,2,…,K) are comprised of structural variables and other state variables as mentioned in the previous section. $\varepsilon_{i,t}$ is the error term of firm *i* at time *t*. Previous research can be divided broadly depending on whether equation (1) is perceived as a time series model of each individual firm or it is treated as panel data. Collin-Dufresne *et al*. (2001), Ericsson *et al*. (2009) and Ooyama and Sugimoto (2007) are among those who use the OLS method to estimate equation (1) for each firm. Inaba (2007) also makes estimates for each individual firm, but uses the maximum likelihood method in which a moving average (MA) process is assumed in ε_t. In contrast, Di Cesare and

[11] When selecting non-structural variables, I referred to Collin-Dufresne *et al*. (2001), Blanco *et al*. (2005), Pan and Singleton (2006), Inaba (2007), Ooyama and Sugimoto (2007), Greatrex (2008), Ericsson *et al*. (2009), Nakashima and Saito (2009), and Di Cesare and Guazzarotti (2010).

Guazzarotti (2010), Baum and Wan (2010) use pooled OLS, fixed-effect models and random-effect models. In addition, Nakashima and Saito (2009) use an instrumental variable fixed-effect model which takes into account the endogeneity of credit risk spread and leverage, whereas Ötker-Robe and Podpiera (2010) use a dynamic panel model. Most studies that use panel analysis impose a constraint that the parameters excluding constant terms are homogenous for all *i*. If the true parameters are homogenous, estimating time series models for each firm will lead to loss in efficiency. On the other hand, it is known that imposing homogeneity in parameters in the panel model will result in biased estimators in cases where the parameters are heterogeneous in the true model.[12]

Using the dynamic heterogeneous panel (DHP) model is one possible solution to these problems. The DHP model is a model that allows parameters to differ in cross-section. Ferrucci (2003), Alexopoulou *et al*. (2009), and Gai *et al*. (2009) use the DHP model in their empirical analysis of credit risk. Following these previous attempts, this paper estimates a DHP model whose exact formulation is derived as follows. First, I suppose that credit spread (*Spread*) follows the autoregressive distributed lag model (ARDL (p, q1, …, qk)) as shown in equation (2).

$$Spread_{it} = \sum_{j=1}^{p} \lambda_{ij} Spread_{i,t-j} + \sum_{j=0}^{q} \delta_{ij}^{'} X_{i,t-j} + \mu_i + \varepsilon_{it} \qquad \cdots\cdots(2)$$

X_{it} is a K×1 vector composed of the explanatory variables while δ_{ij} is the K×1 vector of the parameters and λ_{ij} is a constant parameter. μ_i is the fixed effect specific to *i*, and ε_{it} is the error term. The explanatory variables include structural variables and other state variables. Reparameterization of equation (2) will produce the following error-correction representation:

$$\Delta Spread_{it} = \phi_i \left(Spread_{i,t-1} - \theta_i^{'} X_{it} \right) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta Spread_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}^{*} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \qquad \cdots\cdots(3)$$

where

$$\phi_i = -\left(1 - \sum_{j=1}^{p} \lambda_{ij}\right), \quad \theta_i = \sum_{j=0}^{q} \delta_{ij} \Big/ \left(1 - \sum_{k=1}^{K} \lambda_{ik}\right), \quad \lambda_{ij}^{*} = -\sum_{m=j+1}^{p} \lambda_{im} \quad (j = 1,2,\ldots,p-1),$$

$$\delta_{ij}^{*} = -\sum_{m=j+1}^{q} \delta_{im} \quad (j = 1,2,\ldots,q-1)$$

Inside the brackets of equation (3) is an expression that represents the long-run equilibrium. θ_i is called the long-run parameter. ϕ_i is a parameter that captures how fast the divergence is adjusted if the credit risk spread diverges from the long-run equilibrium level. In this paper, ϕ_i is called the adjustment parameter. If the adjustment parameter is negative and significant, the divergence converges toward the long-run equilibrium even if it occurs in the short run. The second and third terms on the right-hand side are the parts which reflect the short-term movements of the dependent variable. Throughout this paper, this is called the short-run adjustment equation. Pesaran *et al*. (1999) propose a pooled mean group (PMG) model, in which θ_i in equation (3) is common to all *i*, but which permits other parameters to be heterogeneous, and they derive the maximum likelihood estimator. Pesaran and Smith (1995) and

[12] See Pesaran and Smith (1995), Pesaran and Shin (1998), Pesaran *et al*. (1999), etc.

Pesaran *et al*. (1999) propose another estimator, called the mean group (MG) estimator. In this model, θ_i is also thought to differ for each *i*, and so equation (2) is estimated for each *i*, and then the mean value of those estimates is calculated. Selection between the PMG model and MG model can be made by the Hausman test. In this paper, following Alexopoulou *et al*. (2009) and Gai *et al*. (2009), I will focus on an ARDL(1,1,…,1) model with an imposed lag of one period.[13]

The DHP model is useful in the analysis of financial asset prices which generally follow the I(1) process, and could be a suitable method when investigating an equilibrium mechanism. There are four reasons for this. First, the DHP model will produce a consistent and asymptotic normal estimator even if stationary variables and the I(1) process are mixed together in the model.[14] Second is the fact that the DHP model explicitly analyzes long-run equilibrium relationships. This means that, if a divergence from the long-run equilibrium relationship occurs, we can examine whether there is a force working to restore the equilibrium. Thirdly, using the DHP model, we can also analyze how the dependent variable responds to changes in explanatory variables in the short term. Moreover, the DHP model allows different short-term responses for each individual. Fourth, the DHP model can also be applied to data sets with small N but large T sample.

In view of the above discussion, both a time series model using OLS and a DHP model will be analyzed in this paper. I will report the results of OLS using the four variables as the dependent variable — $CDSS$, $\Delta CDSS$, $ln(CDSS)$, and $\Delta ln(CDSS)$ — in order to directly compare the results with the previous studies. With regard to the DHP model, I will estimate models in which $\Delta CDSS$ and $\Delta ln(CDSS)$ are used as the dependent variable.

4. Empirical results

4.1. Descriptive statistics

The sample in this paper covers the CDS transactions where the reference entities are 45 non-financial firms whose daily data are continuously available for the period from 1 April 2004 to 30 September 2009 (Table 2). Table 2 also shows the list of the reference entities and credit-rating class of the companies. The sample consists of several sectors; the manufacturing industry accounts for about half of the sample, with the remainder being such industry sectors as trading companies, real estate, utilities, and consumer finance. Viewed by the credit-rating, the sample data are distributed across each class of rating, with main focus on investment-grades.

Table 3 shows several basis statistics. Looking at the correlation between the CDS level variables and the explanatory variables, we can confirm some characteristics that are consistent with the

[13] To be precise, in this paper, I will use an ARDL (1,…,1) model and a model in which parameter constraints are imposed on the short-run adjustment equation and long-run equilibrium equation in the ARDL (1,…,1) model. A DHP model in which parameter constraints are imposed on an ARDL model can be seen in Martinez-Zarzoso and Bengochea-Morancho (2004), Alexopoulou *et al*. (2009), and Gai *et al*. (2009).
[14] However, certain conditions need to be satisfied, such as T being adequately long. For further details, see the references listed in footnote 12.

theoretical conclusions of the structural model and with existing empirical results. Furthermore, the maximum absolute value of correlation coefficients is about 0.6, so a multicollinearity is unlikely to be a serious concern. Table 3-(3) shows the results of the DF-GLS and PP tests of unit roots. $CDSS$, $ln(CDSS)$, $VOLATILITY$, $LEVERAGE$, and $ln(MV)$ can be confirmed to be the I(1) process for almost all firms. The results of the unit root tests show that regression analyses using the level variables may lead to the problem of spurious regression.

4.2. Time series model

Table 4 and Table 5 show the OLS results using the level variable and the difference variable respectively. [15] The “coef” and “s.e.” in the Tables are the cross-section mean values of the parameter estimates and standard errors respectively. In contrast, the “t-value” and “p-value” are the t-value and p-value pertaining to the constant term from the OLS estimation, in which the dependent variable consist of the parameter estimates derived from OLS regressions for each firm while the explanatory variable is a constant term.[16]

In cases where only structural variables are used as explanatory variables (hereafter “base model”), in almost all formulations, the results are in line with the structural model, regardless of whether the variables are level variables or difference variables. In other words, estimated coefficients of $LEVERAGE$ and $VOLATILITY$ are positive and significant,[17] and the coefficient of RF is negative and significant, except for one case. In terms of the validity of models, adj-R^2 is less than 0.04 for the model using the difference variables whereas it is relatively high at more than 0.6 for the model using the level variables.

In addition to structural variables, I select other explanatory variables that are indicative of market trends. Analyses are separated into two types; one including VIX and the other without it. The model without VIX is a formulation that considers domestic factors only. In contrast, the model including VIX can be regarded as the one which takes overseas factors into account. To begin with, looking at the estimation results of the level variables, we can confirm the following characteristics. First, similar to the results of the base model mentioned above, the signs of coefficients for structural variables are consistent with the structural model. However, coefficients of $LEVERAGE$ and RF are insignificant in a number of specifications. Second, the coefficients of TS take an opposite sign depending on whether the left-hand side variable is logarithmic form or not. As mentioned earlier, although parameters for TS

[15] Following Inaba (2007), I re-estimated the model reported below using the maximum likelihood method, assuming ARMA (1,1) for the error term. Since mostly similar results are obtained, only the results of the OLS estimation are reported below.
[16] To be precise, the t-value (p-value) is the t-value (p-value) for the null hypothesis that the parameter of the constant term is zero. This approach of using OLS estimates is a simplified method for understanding whether the each explanatory variable is significant across cross-section. Same method is used in cases where there are a large number of cross-sectional samples. Collin-Dufresne *et al*. (2001) and Blanco *et al*. (2005), for instance, adopt this method for their empirical analyses of credit risk spreads. Similar methods will be used when reporting the results of the PMG model.
[17] In this paper, the significance of hypothesis testing is basically assessed at the 1% level. Therefore, such expressions as “is significant (is not significant)” refer to assessments at the 1% level, unless otherwise noted.

could theoretically be either positive or negative, the fact that the sign changes depending on the form of the dependent variable is difficult to understand economically. It is expected that this results might be due to non-stationarity of the variables. Third, the estimated parameters for $TOPIX$ are positive and significant in all cases. If we regard $TOPIX$ as a proxy variable for recovery rate, this result would mean that an increase in recovery rate leads to an increase in credit risk. The finding that overall stock market trends have a positive effect on the credit risk spreads of individual firms can also be found in Ooyama and Sugimoto (2007) and Pynnönen *et al*. (2004), but the reasoning given in these previous studies has not necessarily been well defined. Fourth, in the model where $CDSS$ is used as the dependent variable, the coefficients for $SWAPTION$ become negative. This result is different from Ooyama and Sugimoto (2007) and Inaba (2007). Fifth, the coefficients for VIX are positive, indicating the possibility that the impact of any uncertainty in the U.S. stock market could reach to the Japanese CDS market. Finally, adj-R^2 are relatively high, at about 0.7 to 0.9.

In contrast, looking at the estimation results for the difference variable being used as a dependent variable, the following points are noted. First, although the coefficients' sign of the structural variables are no different to the results of the level variables, statistical significance of some variables changes; most of the coefficients of $LEVERAGE$ turn to be significant whereas the coefficients of ΔRF lose significance in the formulation on which $\Delta CDSS$ is used as the dependent variable. In the same formulations, none of the parameters of $\Delta SQR(RF)$, TS, or $\Delta SWAPTION$ are significant, suggesting that interest rate movements do not have any effect on $\Delta CDSS$. This finding differs from Nakashima and Saito (2009) who report a statistically significant relationship between credit risk spreads and interest rates. The second feature is that intuitively easy-to-understand results are obtained; the coefficients of $TOPIX$ and $\Delta SWAPTION$ are negative and positive respectively in all cases. Third, the coefficients of ΔVIX are positive and significant, which is similar to the results for the level variables. Fourth, the adj-R^2 rise no higher than 0.03 to 0.07, which is lower than those reported in previous studies on the U.S. market. The adj-R^2 calculated by Blanco *et al*. (2005) and Ericsson *et al*. (2009) using weekly data are about 0.15 to 0.25. Studies that use monthly data, such as Di Cesare and Guazzarotti (2010), Collin-Dufresne *et al*. (2001), and Greatrex (2008), report adj-R^2 from 0.3 to 0.5. After re-estimating the model in Table 5 using monthly data (monthly mean values), the adj-R^2 are calculated at around 0.3 to 0.4. Although the differences in explanatory variables and specifications of the models render it impossible to make simple comparisons, the above results seem to show that the explanatory power of the models in this paper is, at best, at a similar level as the empirical results of other countries.

4.3. Dynamic heterogeneous panel (DHP) model

The findings in section 4.2 indicate that regression analyses using level variables as the dependent variable could lead to the problem of spurious regression, and the estimations based on difference variables lead to the issue of the poor explanatory power. In contrast, as mentioned earlier, one of the features of the DHP model is that it does not require variables to be stationary. The DHP model can incorporate the information reflected in both level and differenced variables through the long-run equilibrium equation and the short-run adjustment equation. Accordingly, we could overcome the above problems if we use the DHP model.

To begin with I estimate models in which structural variables are the only independent variables, and then will move to models including other state variables as additional explanatory variables. The actual estimation model is equation (3) which is a variation of the ARDL model. Because VIX is an indicator that captures trends in overseas markets, it would not be regarded as a variable that determines the long-run equilibrium value of CDS spreads for Japanese corporations. Therefore, I regard it as an exogenous variable and only consider its effects via the short-run adjustment equation. Table 6 shows the estimation results. Irrespective of the form of dependent variable, the PMG model is selected as a result of the Hausman test (1% level). Consequently, I will report only the results of the PMG models.

Before expanding on the features of the estimation results, an explanation needs to be given as to the figures in the Tables. The figures for the long-run equilibrium equation in the PMG model report the parameters that are common to all i. In other words, the "coef", "s.e.", "z-value", and "p-value" in the Tables can be interpreted in the same way as ordinal regression analyses. In contrast, with respect to each of the variables in the short-run adjustment equation, the parameters are permitted to be different between individual reference entities. The "coef" in the Tables relating to these heterogeneous parameters is the cross-sectional average of the estimated coefficients. The reported "s.e.", "z-value", and "p-value" of these variables are the standard error, z-values, and p-values relating to the constant term in the OLS estimation, in which the parameter estimates of each issue are the dependent variables while a constant term is the only explanatory variable. "χ(p-value)" are test statistics and associated p-value of the null hypothesis that the parameters are common to each issue. The adj-R^2 in the lower part of the Tables is the cross-sectional average of adj-R^2.

Panel A and Panel B in Table 6 report the results of the PMG models where $\Delta CDSS$ and $\Delta ln(CDSS)$ are used as a dependent variable respectively. The signs of coefficients in the long-run equilibrium equation are, on the whole, consistent with the structural model and previous studies. Meanwhile, three variables among the explanatory variables in the short-run adjustment equation — ΔTS, $\Delta TOPIX$, and $\Delta ln(MV)$ — have not been used much as explanatory variables in existing literature. In addition, it would be hard to think of any economic significance these variables would have on CDS spreads. Thereupon, I decide to re-estimate the DHP model with zero restrictions imposed on the parameters of these three variables, and examine the results in detail below.[18]

The estimation results of the restricted model are shown in Table 7. I estimate two models just as with Table 6; one including VIX and the other without VIX. The PMG models are selected as a result of the Hausman test in all cases, and so only the results of the PMG models are reported. The following features of the estimation results are worthy of attention. First, the coefficients of the structural variables

[18] As we could not observe any great difference between the estimation results in Table 6 and Table 7, whether restrictions are imposed upon ΔTS, $\Delta TOPIX$, $\Delta ln(MV)$ has no great bearing on the sign or significance of the parameters of the other explanatory variables. For this reason, the basic assertions below hold true regardless of whether there are restrictions or not.

both in the long-run equilibrium equation and in the short-run adjustment equation have the same signs as those suggested by the structural model, and moreover, most of the coefficients are significant. Consequently, the price formation mechanism suggested by the structural model is considered to be at work. Second, the coefficients of TS, $TOPIX$, and $SWAPTION$ in the long-run equilibrium equation are significant in all cases. Furthermore, considering the fact that the adjustment parameter is significantly negative, there is a strong possibility that an equilibrium relationship has formed between $CDSS$ ($ln(CDSS)$) and the variables contained in the long-run equilibrium equation. This result also suggests limitations of the structural model, in the sense that the structural variables alone are not enough to explain the equilibrium levels of CDS spreads. In addition, the speed of adjustment towards a long-run equilibrium is supposed to be different for each CDS since the null hypothesis that the adjustment parameters are the same for all issues can be rejected. Third is the finding that the parameters of ΔVIX are significantly positive. Also, the adj-R^2 increase considerably by adding ΔVIX to the explanatory variables. In the estimation of the time series model, VIX and ΔVIX are significant, but it is not confirmed that adding these variables to the independent variables would cause a considerable increase in the adj-R^2. These results of the PMG model show that the U.S. market trends and perhaps global event risks have a strong effect over the Japanese CDS market in the short term. However, the level of the adj-R^2 per se could hardly be called high compared to previous studies, and in this sense I would have to say that the credit spread puzzle exists in Japan too.

As described in footnote 8, the results thus far generally hold true even if we change the definition of firm value volatility. I will now, however, confirm the robustness of the results from a different perspective. Specifically, I will use the distance-to-default indicator (DD) as an explanatory variable in place of three structural variables. As evident from the process for deriving this indicator outlined in the Appendix, this measure can be thought of as a variable that aggregates the information contained in three structural variables.[19] If this measure reflects credit risk accurately and investors are acting rationally, the parameters of DD should be negative and significant. Looking at the estimation results in Table 8, in all but one case, the signs of coefficients pertaining to DD are negative, and in most cases, they are significant. However, positive and significant results can also be seen in the formulation in which $\Delta CDSS$ is used as the dependent variable. The fact that the negative and significant result could not be obtained consistently throughout might suggest that either the structural model providing the theoretical basis for DD does not indicate true credit risk, or that investors are not acting rationally in accordance with the structural model.[20] Although we need to be mindful of this point, the estimation results using DD confirm the adjustment parameter to be negative and significant, and so there seems to be a strong possibility that a long-run equilibrium relationship exists between CDS spreads and

[19] See Vassalou and Xing (2004), Byström (2006), Das *et al*. (2009), Bharath and Shumway (2008), and Du and Suo (2007).
[20] This is a composite hypothesis that commonly occurs when examining market efficiency. It is difficult to clarify which of the two hypotheses is rejected.

explanatory variables. Moreover, we could reconfirm such phenomena as an improved adj-R^2 by adding VIX variable in the model.

4.4. Before and after the financial crisis

4.4.1. DHP model

The recent global financial crisis has resulted in attention being switched to more negative perceptions of CDS markets than positive views. Some authors, such as Di Cesare and Guazzarotti (2010) and the IMF (2009), note that price formation in CDS markets has changed after the financial crisis. In the rest of this section, I examine whether the financial crisis prompted a change in the price formation in CDS spreads in Japan. Dividing the sample into before and after the financial crisis, I will examine the differences in estimated coefficients. Following the discussion of Di Cesare and Guazzarotti (2010), I regard the financial crisis happened July 2007. I designate the period from April 1, 2004 through to June 29, 2007 as the pre-crisis period; and the period from July 1, 2007 through to September 30, 2009 as the crisis period.[21] Different formulations in section 4.3 are also conducted, but since no major differences are found, only the results on the model that includes ΔVIX will be discussed for the rest of this section.

Table 9 shows the estimation results. Regardless of whether $\Delta CDSS$ or $\Delta ln(CDSS)$ is used as a dependent variable, some common features can be identified. First, the significance of individual variables is more apparent and the overall fitness of the model is better in the second half. Although some variables in the long-run equilibrium equation and in the short-run adjustment equation are not significant in the first half, almost all variables are significant in the second half. Furthermore the adj-R^2 in the second half is clearly higher than that in the first half. Second, the possibility of stronger interconnection between CDS markets and bond markets/stock markets can be observed in the second half. For example, coefficients on interest rate related variables in the second half clearly differ from those in the first half. In the first half, coefficients of RF and $SQR(RF)$ in the long-run equilibrium equation as well as the difference series of these variables in the short-run adjustment equation are not significant; but in the second half, almost all of these coefficients become significant. In addition, the coefficient of $TOPIX$ also becomes negative and significant in the second half. Furthermore, the estimated parameter of TS is positive in the first half, but switches to negative in the second half. The first-half results signify that increases in term spreads lead to an expansion of credit risk spreads. This phenomenon has also been confirmed in Blanco *et al*. (2005), but there is no consensus as to the underlying mechanism. In any case, we could say that these results suggest the possibility that, following the onset of the financial crisis, CDS markets have become more easily susceptible to trends in other financial markets and in the overall financial market. Third, whereas the adjustment parameter

[21] June 2007 is the period when the failure by a hedge fund under the control of Bear Stearns in subprime loan investments was viewed with apprehension in the marketplace, and when subprime-related securitized papers began to be downgraded.

is -0.003 to -0.005 in the first half, it declines as far as -0.012 to -0.016 in the second half.[22] The fact that the negative range of the adjustment parameter becomes broader suggests that CDS spreads are moving toward convergence at the long-run equilibrium level at a greater speed.[23]

4.4.2. Principal component analysis

In the analyses thus far, it is found that the explanatory power is limited no matter how we formulate the model, except for the time series model using level variables as the dependent variable, for which there is another concern of spurious regression. Previous studies on the U.S. and European credit markets report somewhat paradoxical outcomes; the majority of variation in credit spreads that cannot be captured through regression analysis ends up being explained using some systemic factors.[24] I will examine whether such a phenomenon can also be observed in the Japanese CDS market. Specifically, I will use principal component analysis to investigate how much of the CDS spread's fluctuations can be explained by unobservable common factors.

Table 10 shows the results of the principal component analysis conducted on the four variables; $\Delta CDSS$, $\Delta ln(CDSS)$, and two residual series from the full models with $\Delta CDSS$ or $\Delta ln(CDSS)$ as a dependent variable. Principal component analysis has been separately conducted on samples before and after the financial crisis. Looking at Table 10, we can confirm that the contribution ratio of the first principal component of the original series ($\Delta CDSS$, $\Delta ln(CDSS)$) increases in the second half. This suggests that, some factors common to the sample firms become the main determinants of credit risk during the second half. A similar trend can also be observed for the first principal component of the residual series of $\Delta ln(CDSS)$. In other words, it would seem that systemic factors that cannot be fully understood using explanatory variables in the full model become the main variation factors in $\Delta ln(CDSS)$, especially during the second half. Figure 1 is a scatter diagram, with the eigenvector of the first principal component calculated from the original series of $\Delta ln(CDSS)$ on the horizontal axis, and the eigenvector of the first principal component calculated from the residuals of the full model on the vertical axis. As the figure clearly shows, there is a strong positive correlation between them. This suggests the possibility that systemic factors included in the original series remain in the residuals without being fully captured even by regression analysis. In light of these results, it is expected that some systemic factors other than the explanatory variables adopted in the estimation model are causing fluctuation of CDS spreads.

4.4.3. Discussion

The abovementioned analyses suggest that the price formation in the CDS markets changed around the time of the financial crisis. Results of the DHP model confirm that the significance of each

[22] Even if the estimation periods are changed in various ways, for the most part, these patterns can be confirmed.
[23] This does not necessarily mean that CDS spreads are being determined close to the long-run equilibrium level. In other words, despite the adjustment speed accelerating, it is feasible that the gap between the CDS spreads and the long-run equilibrium during the second half period will be broader than that in the first half.
[24] See Collin-Dufresne *et al*. (2001), Ericsson *et al*. (2009) and Di Cesare and Guazzarotti (2010).

explanatory variable and the overall fitness of the model improved after the financial crisis. These finding are arguably contrary to the previous studies on the U.S. and European markets.[25] What are the reasons for the explanatory power of the model to improve amid the crisis? The first thing that comes to mind is the possibility that the Japanese CDS market has begun to be strongly influenced by market trends in foreign countries, in particular in the U.S. stock market. This is confirmed by the coefficients of VIX. Pan and Singleton (2006), for instance, also confirm that the U.S. VIX index has a significantly positive effect on the CDS spreads whose reference entity is the Japanese government or major Japanese banks. In contrast, to the best of the author's knowledge, no empirical finding has been reported on the U.S. and European markets, which shows that adding the VIX index as an independent variable improves the explanatory power of a model after the onset of the financial crisis. Second, CDS spreads seem to have been determined with a fair degree of "independence" from the bond and stock markets prior to the financial crisis. One of the notable features of the analyses before the financial crisis is that almost all the variables that are related to the other financial market — such as RF, TS and $TOPIX$ — are not significant while the coefficients of $LEVERAGE$ and $VOLATILITY$ are significant. This suggests that the interconnection between CDS market and bond/stock market did not manifest before the financial crisis. In other words, the onset of the crisis has led to various transactions extending across these markets, and as a result, the information efficiency of market prices has improved. The changes in the adjustment parameter seen in Table 9 indirectly support this hypothesis.

On the other hand, the results of the principal component analysis suggest that systemic factors common to all firms triggered fluctuations of CDS spreads during the financial crisis. The question of what these systemic factors are is an issue for the future research. However, given that it is getting clear that liquidity is having a notable impact on price formation in the U.S. CDS markets, and that variables related to the overall liquidity of CDS markets and to the liquidity of individual CDSs have not been considered in this paper, liquidity might be related to the systemic factors. As of the time of writing this paper, there are no public data on both overall liquidity of the Japanese CDS market and liquidity of individual CDSs. When relevant data become accessible, we will need to confirm the effect of the liquidity on price formation in the Japanese CDS market.

5. Conclusion

In this paper, I examined the pricing of the Japanese CDSs in which non-financial corporations are the reference entity. I relied on a simple time series model and DHP model, focusing on structural variables and other state variables that capture financial market and macroeconomic trends. The results confirm that price formation mechanisms suggested by the structural model are at work, but that price fluctuations in the CDS market cannot be fully explained even using structural variables and other

[25] For a comparison before and after the financial crisis and the effects of VIX, see Di Cesare and Guazzarotti (2010), Ferrucci (2003), and Greatrex (2008). For the effects of liquidity, see Driessen (2005), Tang and Yan (2008), Acharya *et al*. (2008), Bongaerts *et al*. (2008, 2011), and Nashikkar *et al*. (2009).

market variables. I also point out that, price formation in CDS markets changed when the financial crisis hit, and some kind of systemic factors have been influencing CDS spreads particularly since the onset of the financial crisis.

In conclusion, I will summarize the implications derived from these results, separated into suggestions for research and significance for public policy and financial business. With respect to the suggestions for future research, first, it can be pointed out that using a model like the DHP model, which allows heterogeneous parameters and long-run equilibrium relationships, is preferable when estimating CDS spreads. While time series models and panel analyses with homogeneous parameter restrictions have been widely used in existing studies, the results in this paper show the possible superiority of the DHP model over the existing quantitative models. It should be noted that in addition to structural variables, a range of variables that capture market trends need to be incorporated as determinants of CDS spreads. In particular, given that U.S. VIX has high explanatory power in analyses in this paper, effects from overseas need to be taken into full account when estimating the determinants of credit risk in domestic markets. Second, the CDS market seems not to have been linked to the bond and stock markets for the pre-crisis period. If this low-level interconnection has been caused by the lack of an arbitrage function extending across these markets, then we should be cautious about the possibility that the efficient allocation of resources and the risk sharing function through the CDS market have not been fully manifested. In addition to a more detailed investigation into the interconnection between CDS markets and other financial markets, the effects of CDS markets on economic welfare will also need to be examined. On the other hand, the fact that CDS spread fluctuations have not been fully elucidated — the credit spread puzzle — has important implications for financial businesses. That is, this uncertainty in pricing will need to be fully considered when conducting CDS trading and associated risk management. It is also expected that this puzzle will make it difficult for regulatory authorities to assess the validity of CDS spreads. As a consequence, it may be becoming more difficult to identify unfair trading related to CDS markets.

Appendix: Derivation of Firm Value Volatility and the Distance-to-Default Indicator

In this appendix, I describe the method for deriving firm value volatility ($VOLATILITY$) and the distance-to-default measure (DD). The concept underlying the calculation of $VOLATILITY$ and DD is the nature of equity as a call option (Black and Scholes 1972, 1973., etc.). In other words, an equity can be viewed as the right of claim against residual assets in case where the firm value exceeds the debt value at some point in the future (maturity). The method of derivation below follows Gropp *et al*. (2002). A detailed description of the derivation and the characteristics of the DD can be found in the paper, and so will be omitted here.

In preparation for the explanation, I shall define a number of variables as follows:

- V_E: market value of equity (market capitalization)
- V_A: firm value
- D: debt value
- r: risk-free interest rate
- σ_A: volatility of a firm's asset value
- σ_E: equity volatility
- T: time until the maturity of the debt liabilities
- ε: standard normal distribution
- $N()$:cumulative standard normal distribution function
- dz: standard Wiener process

To begin with, if we assume the premises of the basic option pricing theory by Black and Scholes (1972), the following relationship between firm value and stock value applies.

$$\begin{cases} V_E = V_A N(d1) - De^{-rT} N(d2) \\ d1 = \dfrac{\ln\left(V_A / D\right) + \left(r + \sigma_A^2 / 2\right)T}{\sigma_A \sqrt{T}} \\ d2 = d1 - \sigma_A \sqrt{T} \end{cases} \quad \cdots\cdots(i)$$

Here, the following equation holds true between firm value volatility and stock volatility:

$$\sigma_E = \left(\frac{V_A}{V_E}\right) N(d1) \sigma_A \quad \cdots\cdots(ii)$$

Thus, if V_E, σ_E, D, r, and T are once determined, we can calculate V_A and σ_A from equations (i) and (ii) using convergence calculation. In this paper, V_A and σ_A are calculated assuming V_E is market capitalization, σ_E is the (60-day) historical volatility of the stock price series, D is the book value of the total debt liabilities, r is the yield on government bonds, and T is 1 (year). The σ_A calculated by following this procedure is the firm value volatility ($VOLATILITY$) set forth in this paper.

If we consider that firm value follows the geometric Brownian motion, we get the following formula for firm value at time *t*.

$$\ln V_A^t = \ln V_A + \left(r - \frac{\sigma_A^2}{2} \right) t + \sigma_A \sqrt{t} \varepsilon \qquad \cdots\cdots (iii)$$

Here, we regard a default to be the state that firm value is less than its debt value until the maturity of the debt. In this setting, the default probability can be defined by equation (iv), and we can define the distance to default measure (DD) as in equation (v).

$$P_t = N \left[- \frac{\ln \frac{V_A}{D} + \left(r - \frac{\sigma_A^2}{2} \right) t}{\sigma_A \sqrt{t}} \right] \qquad \cdots\cdots (iv)$$

$$DD_t = \frac{\ln \frac{V_A}{D} + \left(r - \frac{\sigma_A^2}{2} \right) t}{\sigma_A \sqrt{t}} \qquad \cdots\cdots (v)$$

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Table 1: Definition of Variables

Name of variable	Definition	Source
CDSS	Level value of CDS spread	J-CDS database published by Tokyo Financial Exchange Inc.
ln(CDSS)	Natural logarithm of *CDSS*	〃
⊿*CDSS*	*CDSS* at time t minus *CDSS* at time t-1	〃
⊿*ln(CDSS)*	*ln(CDSS)* at time t minus *ln(CDSS)* at time t-1	〃
LEVERAGE	{Debt Total ÷(Debt Total＋Market Value of Equity)} is transfomed to monthly data using linear interpolation method. Financial data are semiannual.	Collected by Astra Manager database (QUICK)
VOLATILITY	Calculated based on the procedure in Appendix.	〃
RF	Interest rate on 10 year government bond in the secondary market	〃
TS	Interest rate on 10 year government bond - interest rate on 1 year government bond	〃
TOPIX	Differece of natural logarithm of TOPIX Index at time t compared to previous day	〃
ln(MV)	Natural logarithm of Market Value of Equity	〃
SWAPTION	Implied volatility of Swaption (5 years, 1 month maturity)	Bloomberg
VIX	Implied volatitily of S&P500 index	〃

Table 2: List of Sample

(1) Name of reference entity

Security ID	Name of firm	Security ID	Name of firm
4005	Sumitomo Chemical Company, Limited	8031	Mitsui & Co., Ltd.
4183	Mitsui Chemicals, Inc.	8053	Sumitomo Corporation
5001	Nippon Oil Corporation	8058	Mitsubishi Corporation
5401	Nippon Steel Corporation	8515	Aiful Corporation
5802	Sumitomo Electric Industries, Ltd	8564	Takefuji Corporation
6501	Hitachi, Ltd.	8572	Acom Co., Ltd.
6502	Toshiba Corporation	8574	Promise Co., Ltd.
6503	Mitsubishi Electric Corporation	8591	ORIX Corporation
6701	NEC Corporation	8801	Mitsui Fudosan Co., Ltd.
6702	Fujitsu Limited	8802	Mitsubishi Estate Co., Ltd.
6752	Panasonic Corporation	9005	Tokyu Corporation
6753	Sharp Corporation	9041	Kintetsu Corporation
6758	Sony Corporation	9042	Hankyu Hanshin Holdings, Inc.
6764	SANYO Electric Co., Ltd.	9202	All Nippon Airways Co., Ltd.
6952	Casio Computer Co., Ltd.	9205	Japan Airlines Corporation
7011	Mitsubishi Heavy Industries, Ltd.	9433	KDDI Corporation
7012	Kawasaki Heavy Industries, Ltd.	9437	NTT DOCOMO, INC.
7201	Nissan Motor Co.,Ltd.	9501	The Tokyo Electric Power Company,
7203	Toyota Motor Corporation	9502	Chubu Electric Power Co.,Inc.
7267	Honda Motor Co., Ltd.	9503	The Kansai Electric Power Company,
7269	SuzukiI Motor Corporation	9531	Tokyo Gas Co., Ltd.
7731	Nikon Corporation	9532	Osaka Gas Co., Ltd.
7752	Ricoh Company, Ltd.		

(2) By rating class

Rating	2004/4/1		2007/6/29		2009/9/30	
	# of firms	share	# of firms	share	# of firms	share
AAA	1	2.2%	1	2.2%	1	2.2%
AA+	7	15.6%	7	15.6%	7	15.6%
AA	4	8.9%	4	8.9%	3	6.7%
AA-	6	13.3%	7	15.6%	8	17.8%
A+	6	13.3%	8	17.8%	7	15.6%
A	8	17.8%	8	17.8%	8	17.8%
A-	5	11.1%	3	6.7%	4	8.9%
BBB+	4	8.9%	2	4.4%	1	2.2%
BBB	3	6.7%	4	8.9%	3	6.7%
BB+	1	2.2%	1	2.2%	1	2.2%
BB-	0	0.0%	0	0.0%	1	2.2%
CCC+	0	0.0%	0	0.0%	1	2.2%
Total	45	100.0%	45	100.0%	45	100.0%

Rating is the R&I's long-term domestic-currency credit rating.

Table3: Summary Statistics

(1) Basic Statistics

Name of variable	Obs	Mean	S.D.	Min	Max
CDSS	60,750	89.256	334.047	2.500	7654.960
ln(CDSS)	60,750	3.356	1.204	0.916	8.943
LEVERAGE	60,750	0.157	0.094	0.018	0.904
VOLATILITY	60,750	0.289	0.144	0.057	1.357
RF	60,750	0.015	0.002	0.012	0.020
SWAPTION	60,615	46.835	10.404	25.300	84.000
TS	60,750	0.012	0.002	0.007	0.019
TOPIX	60,750	0.000	0.016	-0.100	0.129
ln(MV)	60,750	27.996	0.942	23.306	31.036
VIX	58,770	20.474	12.024	9.890	80.860

(2) Correlation

	CDSS	*ln(CDSS)*	*Leverage*	*σA*	*rf*	*Swaption*	*TS*	*⊿ln(TOPIX)*	*Ln(MV)*	*VIX*
CDSS	1									
ln(CDSS)	0.5914*	1								
LEVERAGE	0.5606*	0.6170*	1							
VOLATILITY	0.1881*	0.4829*	0.1039*	1						
RF	-0.1661*	-0.3275*	-0.2311*	-0.1136*	1					
SWAPTION	0.0193*	0.1206*	0.1344*	-0.0092*	-0.3888*	1				
TS	-0.1329*	-0.3194*	-0.0951*	-0.3995*	0.2970*	0.3429*	1			
TOPIX	0.001	-0.0138*	-0.0184*	-0.0182*	0.0219*	-0.005	0.0774*	1		
ln(MV)	-0.3861*	-0.5299*	-0.4837*	-0.1422*	0.1793*	-0.1343*	0.0220*	0.0107*	1	
VIX	0.2933*	0.5918*	0.2971*	0.6419*	-0.3397*	0.1747*	-0.5276*	-0.0979*	-0.1856*	1

* refers to the statistical significance at the 5% level.

Table3 (continued)

(3) Unit Root Test

(3) -1. Firm specific variables

	DF-GLS test					
	Level			First difference		
	1%	5%	10%	1%	5%	10%
CDSS	6	3	0	45	0	0
ln(CDSS)	0	0	0	43	2	0
VOLATILITY	7	3	0	45	0	0
LEVERAGE	0	0	0	37	3	0
ln(MV)	1	1	0	38	4	0

	PP test					
	Level			First difference		
	1%	5%	10%	1%	5%	10%
CDSS	1	0	0	45	0	0
ln(CDSS)	0	0	0	45	0	0
VOLATILITY	4	1	0	45	0	0
LEVERAGE	1	1	0	45	0	0
ln(MV)	1	1	0	45	0	0

The number in the table is the number of firms for which the null hypotesis is rejected. Total number of samples is 45.

(3) -2. variables common to firms

	DF-GLS test		PP test	
	Level	First difference	Level	First difference
RF	-2.47	-9.48 ***	-2.78	-38.83 ***
SWAPTION	-2.23	-0.41	-4.31 ***	-50.89 ***
TS	-2.77 *	-8.63 ***	-2.87	-39.02 ***
TOPIX	-36.92 ***	-0.52	-37.97 ***	-358.79 ***
VIX	-1.73	-27.85 ***	-2.77	-44.17 ***

***, **, and * refer to the statistical significance at 1%, 5%, and 10% respectively.

Table4: Time Series Regression (Level Variable)

adj-R^2, F-value, obs, coef, s.e. are cross-sectional average of estimation results for each firm. Figures in parentheses are cross-sectionla median for coef and s.e. Robust standard erros are used in OLS. t-value and p-value are the t-value and p-value pertaining to the constant term from the OLS estimation in which dependent variable consist of the parameter estimates derived from OLS regressions for each firm while explanatory variable is a constant term. The coef and s.e. for SQR(RF) are expressed devided by 10000.

	y=*CDSS*											
	coef	s.e.	t-value	p-value	coef	s.e.	t-value	p-value	coef	s.e.	t-value	p-value
LEVERAGE	859 <524>	59 <40>	3.410	0.001	1,159 <795>	232 <136>	1.250	0.217	1,104 <794>	226 <135>	1.900	0.065
VOLATILITY	218 <131>	22 <6.56>	3.020	0.004	174 <89>	20 <6.64>	3.580	0.001	62 <48>	23 <11>	2.570	0.014
RF	-8,982 <-2,479>	955 <364>	-2.730	0.009	-100,980 <-33,244>	11,475 <5,146>	-3.960	0.000	-92,353 <-38,552>	10,831 <5,113>	-4.160	0.000
SQR(RF)	—	—	—	—	279 <100>	36 <16>	4.010	0.000	249 <107>	33 <16>	4.300	0.000
TS	—	—	—	—	13,235 <935>	1,242 <489>	1.690	0.098	16,006 <2,422>	1,232 <522>	2.180	0.035
TOPIX	—	—	—	—	206 <116>	112 <56>	5.790	0.000	254 <133>	119 <58>	5.690	0.000
Ln(MV)	—	—	—	—	3.90 <-7.20>	35 <14>	0.030	0.980	27 <25>	33 <16>	0.290	0.772
SWAPTION	—	—	—	—	-0.502 <-0.053>	0.207 <0.092>	-0.860	0.396	-1.009 <-0.278>	0.214 <0.096>	-2.100	0.041
VIX	—	—	—	—	—	—	—	—	1.683 <0.491>	0.367 <0.181>	2.180	0.034
constant	24.27 <-23.19>	20.00 <7.82>	0.360	0.719	411 <107>	996 <371>	0.090	0.927	-306 <-331>	930 <483>	-0.120	0.908
adj-R^2	0.67				0.77				0.79			
F-value	545				356				343			
obs	1,350				1,347				1,303			

	y=*ln(CDSS)*											
	coef	s.e.	t-value	p-value	coef	s.e.	t-value	p-value	coef	s.e.	t-value	p-value
LEVERAGE	14 <9.188>	0.564 <0.441>	4.570	0.000	6.293 <1.204>	1.874 <1.563>	0.970	0.338	5.020 <5.608>	1.927 <1.572>	0.850	0.401
VOLATILITY	3.432 <3.364>	0.129 <0.119>	13.970	0.000	2.507 <2.251>	0.130 <0.124>	13.790	0.000	1.862 <1.757>	0.167 <0.152>	12.210	0.000
RISKFREE	-62 <-57>	6.671 <6.383>	-7.590	0.000	-613 <-584>	83.013 <77>	-11.000	0.000	-603 <-631>	80 <77>	-12.420	0.000
SQR(RF)	—	—	—	—	1.887 <1.740>	0.257 <0.242>	11.690	0.000	1.840 <1.836>	0.249 <0.239>	13.260	0.000
TS	—	—	—	—	-33 <-27>	7.842 <7.176>	-2.400	0.021	-16 <-5.017>	8.392 <8.006>	-1.280	0.207
TOPIX	—	—	—	—	1.330 <1.310>	0.708 <0.689>	11.550	0.000	1.611 <1.620>	0.758 <0.750>	13.110	0.000
ln(MV)	—	—	—	—	-0.961 <-1.499>	0.220 <0.183>	-1.320	0.193	-0.950 <-1.047>	0.219 <0.186>	-1.560	0.126
SWAPTION	—	—	—	—	0.006 <0.005>	0.001 <0.001>	4.500	0.000	0.004 <0.004>	0.002 <0.001>	3.570	0.001
VIX	—	—	—	—	—	—	—	—	0.009 <0.007>	0.002 <0.002>	3.480	0.001
constant	1.868 <1.424>	0.147 <0.135>	6.160	0.000	34 <51>	6.321 <5.202>	1.630	0.111	34 <32>	6.314 <5.342>	1.910	0.063
adj-R^2	0.74				0.83				0.85			
F-value	1,799				1,074				1,039			
obs	1,350				1,347				1,303			

Table 5: Time Series Regression (Differenced Variable)

adj-R^2, F-value, obs, coef, s.e. are cross-sectional average of estimation results for each firm. Figures in parentheses are cross-sectionla median for coef and s.e. Robust standard erros are used in OLS. t-value and p-value are the t-value and p-value pertaining to the constant term from the OLS estimation in which dependent variable consist of the parameter estimates derived from OLS regressions for each firm while explanatory variable is a constant term. The coef and s.e. for SQR(RF) are expressed as divided by 10000.

	y=⊿CDSS											
	coef	s.e.	t-value	p-value	coef	s.e.	t-value	p-value	coef	s.e.	t-value	p-value
⊿LEVERAGE	213 <127>	76 <39>	4.900	0.000	130 <38>	90 <53>	2.720	0.009	131 <25>	94 <46>	2.640	0.011
⊿VOLATILITY	28 <11>	27 <13>	2.750	0.009	24 <8.480>	27 <13>	2.420	0.020	26 <7.994>	30 <13>	2.470	0.017
⊿RF	-330 <-235>	447 <187>	-2.450	0.018	-8.333 <25>	469 <199>	-0.070	0.944	-80 <-5.953>	470 <186>	-0.790	0.435
⊿SQR(RF)	—	—	—	—	-9.627 <-2.826>	73 <32>	-0.430	0.666	-25 <-7.387>	75 <31>	-0.970	0.337
TS	—	—	—	—	-45 <-50>	100 <28>	-1.010	0.317	-29 <-39>	104 <28>	-0.580	0.567
TOPIX	—	—	—	—	-21 <-21>	21 <9.112>	-2.440	0.019	-5.915 <-13>	23 <9.636>	-0.540	0.592
ln(MV)	—	—	—	—	-1.322 <-0.287>	1.032 <0.281>	-2.670	0.011	-1.294 <-0.187>	1.058 <0.265>	-2.430	0.019
⊿SWAPTION	—	—	—	—	0.013 <0.003>	0.062 <0.022>	0.850	0.400	0.005 <0.001>	0.067 <0.023>	0.260	0.797
⊿VIX	—	—	—	—	—	—	—	—	0.212 <0.074>	0.133 <0.056>	3.650	0.001
constant	0.258 <0.021>	0.156 <0.068>	1.990	0.053	37 <8.455>	28 <8.360>	2.740	0.009	36 <5.962>	29 <7.905>	2.480	0.017
adj-R^2	0.03				0.06				0.06			
F-value	7.49				5.80				5.00			
obs	1,350				1,345				1,257			

	y=⊿ln(CDSS)											
	coef	s.e.	t-value	p-value	coef	s.e.	t-value	p-value	coef	s.e.	t-value	p-value
⊿LEVERAGE	1.876 <1.656>	0.451 <0.361>	8.220	0.000	0.716 <0.426>	0.520 <0.424>	3.500	0.001	0.672 <0.354>	0.518 <0.416>	3.740	0.001
⊿VOLATILITY	0.323 <0.305>	0.161 <0.156>	11.650	0.000	0.271 <0.260>	0.155 <0.149>	10.000	0.000	0.242 <0.229>	0.152 <0.144>	9.170	0.000
⊿RF	-6.755 <-7.354>	3.055 <2.896>	-12.720	0.000	-2.064 <-1.608>	3.018 <2.931>	-5.470	0.000	-2.703 <-2.523>	3.052 <2.994>	-7.370	0.000
⊿SQR(RF)	—	—	—	—	0.327 <0.374>	0.693 <0.656>	4.120	0.000	0.204 <0.209>	0.703 <0.672>	2.550	0.014
TS	—	—	—	—	-0.873 <-0.870>	0.388 <0.344>	-15.410	0.000	-0.764 <-0.739>	0.376 <0.341>	-14	0.000
TOPIX	—	—	—	—	-0.308 <-0.319>	0.092 <0.092>	-16.390	0.000	-0.173 <-0.185>	0.096 <0.093>	-9.420	0.000
ln(MV)	—	—	—	—	-0.002 <-0.002>	0.003 <0.003>	-2.620	0.012	-0.002 <-0.002>	0.003 <0.003>	-2.570	0.014
⊿SWAPTION	—	—	—	—	0.0003 <0.000>	0.000 <0.000>	8.560	0.000	0.0002 <0.000>	0.000 <0.000>	5.710	0.000
⊿VIX	—	—	—	—	—	—	—	—	0.001 <0.001>	0.001 <0.001>	24	0.000
constant	0.001 <0.001>	0.001 <0.001>	9.290	0.000	0.071 <0.062>	0.093 <0.083>	3.080	0.004	0.070 <0.055>	0.095 <0.085>	2.940	0.005
adj-R^2	0.04				0.06				0.07			
F-value	10.33				6.39				6.34			
obs	1,350				1,345				1,257			

Table6: PMG Model (without Restriction, Full Sample)

χ^2 is the test statistics for the null hypothesis that parameters are homogeneous, and figures in parentheses are associated p-value. The coef and s.e. for SQR(RF) and ⊿SQR(RF) are expressed as divided by 10000. Figures in long-run equilibrium equation are results about homogeneous parameters. coef of other explanatory variables are cross-sectional average of coefficients for each firms. s.e., z-value, and p-value of these variables are the standard error, z-values and p-values relating to the constant term in the OLS estimation in which the parameter estimates of each issue are the dependent variable while the constant term is explanatory variable. adj-R^2 is cross-sectional average. The results on constant terms are omitted.

Panel A: dependent variable＝⊿*CDSS*

		PMG					PMG					PMG				
		coef	s.e.	z-value	p-value	χ^2(p-value)(i)	coef	s.e.	z-value	p-value	χ^2(p-value)(i)	coef	s.e.	z-value	p-value	χ^2(p-value)(i)
long-term equation	*LEVERAGE*	491	33	14.750	0.000		920	105	8.720	0.000		629	57	11.040	0.000	
	VOLATILITY	289	10	27.950	0.000		205	16	12.970	0.000		177	8.745	20.200	0.000	
	RF	-2,703	616	-4.390	0.000		-196,053	15,709	-12.480	0.000		-106,400	8,133	-13.080	0.000	
	SQR(RF) (ii)	—	—	—	—		657	51	12.920	0.000		355	26	13.660	0.000	
	TS	—	—	—	—		-20,236	1,384	-14.620	0.000		-10,169	656	-15.500	0.000	
	TOPIX	—	—	—	—		-7,858	455	-17.270	0.000		-3,719	180	-20.630	0.000	
	ln(MV)	—	—	—	—		69	15	4.700	0.000		41	7.610	5.440	0.000	
	SWAPTION	—	—	—	—		5.394	0.367	14.700	0.000		2.999	0.172	17.410	0.000	
short-term equation	*adjustment paramerter* (ϕ_i)	-0.006	0.001	-7.450	0.000	487.55(0.0000)	-0.005	0.001	-8.130	0.000	474.91(0.0000)	-0.007	0.001	-8.570	0.000	805.80(0.0000)
	⊿*LEVERAGE*	205	43	4.720	0.000	646.95(0.0000)	252	91	2.780	0.005	282.28(0.0000)	238	97	2.440	0.015	279.85(0.0000)
	⊿*VOLATILITY*	24	10	2.390	0.017	157.05(0.0000)	20	11	1.830	0.067	164.99(0.0000)	22.391	12	1.870	0.062	174.04(0.0000)
	⊿*RF*	-325	136	-2.390	0.017	43.28(0.5023)	511	275	1.860	0.063	11.24(1.0000)	525	297	1.770	0.077	12.96(1.0000)
	⊿*SQR(RF)* (ii)	—	—	—	—	—	-42	18	-2.350	0.019	20.26(0.9992)	-59	18.697	-3.140	0.002	21.75(0.9980)
	⊿*TS*	—	—	—	—	—	-1,034	382	-2.710	0.007	13.06(1.0000)	-1,032	359	-2.880	0.004	12.28(1.0000)
	⊿*TOPIX*	—	—	—	—	—	23	3.110	7.280	0.000	388.35(0.0000)	23	3.961	5.820	0.000	377.60(0.0000)
	⊿*ln(MV)*	—	—	—	—	—	15	20.772	0.730	0.465	190.14(0.0000)	12	23.117	0.530	0.595	186.48(0.0000)
	⊿*SWAPTION*	—	—	—	—	—	0.011	0.017	0.670	0.502	41.05(0.5987)	0.003	0.016	0.180	0.856	43.27(0.5029)
	⊿*VIX*	—	—	—	—	—	—	—	—	—	—	0.194	0.056	3.450	0.001	187.03(0.0000)
	log likelihood	-146,988					-144,997					-132,144				
	adj-R^2	0.04					0.08					0.23				
	obs	60,749					60,524					56,564				

Table6 (continued)

Panel B: dependent variable＝⊿*ln(CDSS)*

		PMG					PMG					PMG				
		coef	s.e.	z-value	p-value	χ^2(p-value)[1]	coef	s.e.	z-value	p-value	χ^2(p-value)[1]	coef	s.e.	z-value	p-value	χ^2(p-value)[1]
long-term equation	*LEVERAGE*	8.604	0.658	13.080	0.000		6.716	1.023	6.570	0.000		7.784	1.013	7.680	0.000	
	VOLATILITY	5.988	0.245	24.420	0.000		2.750	0.186	14.820	0.000		2.970	0.184	16.130	0.000	
	RF	-88	14	-6.120	0.000		-2,897	182	-15.900	0.000		-2,569	175	-14.670	0.000	
	SQR(RF) [(ii)]	—	—	—	—		10	0.587	16.210	0.000		8.544	0.564	15.140	0.000	
	TS	—	—	—	—		-314	16	-19.930	0.000		-281	15	-18.950	0.000	
	TOPIX	—	—	—	—		-97	4.710	-20.550	0.000		-73.1	3.908	-18.710	0.000	
	ln(MV)	—	—	—	—		-0.037	0.161	-0.230	0.819		0.026	0.159	0.160	0.871	
	SWAPTION	—	—	—	—		0.054	0.003	16.290	0.000		0.054	0.003	16.400	0.000	
short-term equation	*adjustment paramerter* (ϕ_i)	-0.004	0.000	-12.810	0.000	138.92(0.0000)	-0.006	0.000	-29.400	0.000	125.74(0.0000)	-0.006	0.000	-24.350	0.000	125.99(0.0000)
	⊿*LEVERAGE*	1.832	0.227	8.070	0.000	368.14(0.0000)	0.875	0.328	2.670	0.008	138.29(0.0000)	1.187	0.360	3.300	0.001	140.09(0.0000)
	⊿*VOLATILITY*	0.293	0.027	10.770	0.000	212.90(0.0000)	0.185	0.024	7.750	0.000	141.78(0.0000)	0.157	0.023	6.770	0.000	117.65(0.0000)
	⊿*RF*	-6.555	0.527	-12.440	0.000	49.38(0.2668)	-7.214	0.902	-8.000	0.000	27.74(0.9736)	-7.880	1.004	-7.850	0.000	35.30(0.8225)
	⊿*SQR(RF)* [(ii)]	—	—	—	—	—	0.049	0.076	0.650	0.517	26.49(0.9830)	-0.108	0.075	-1.450	0.146	26.37(0.9838)
	⊿*TS*	—	—	—	—	—	4.353	0.775	5.620	0.000	21.35(0.9984)	4.453	0.866	5.140	0.000	26.20(0.9848)
	⊿*TOPIX*	—	—	—	—	—	0.256	0.009	27.170	0.000	93.27(0.0000)	0.234	0.009	25.560	0.000	92.24(0.0000)
	⊿*ln(MV)*	—	—	—	—	—	0.040	0.037	1.060	0.287	126.17(0.0000)	0.074	0.037	2.010	0.045	112.54(0.0000)
	⊿*SWAPTION*	—	—	—	—	—	0.0001	0.000	2.420	0.015	18.18(0.9998)	0.00004	0.000	0.950	0.343	22.20(0.9975)
	⊿*VIX*	—	—	—	—	—	—	—	—	—	—	0.001	0.000	17.100	0.000	48.38(0.3007)
	log likelihood	128,465					129,710					123,437				
	adj-R^2	0.00					-0.01					0.13				
	obs	60,749					60,524					56,564				

Table7: PMG Model (With Restriction, Full Sample)

χ^2 is the test statistics for the null hypothesis that parameters are homogeneous, and figures in parentheses are associated p-value. The coef and s.e. for SQR(RF) and ⊿SQR(RF) are expressed as divided by 10000. Figures in long-run equilibrium equation are results about homogeneous parameters. coef of other explanatory variables are cross-sectional average of coefficients for each firms. s.e., z-value, and p-value of these variables are the standard error, z-values and p-values relating to the constant term in the OLS estimation in which the parameter estimates of each issue are the dependent variable while the constant term is explanatory variable. adj-R2 is cross-sectional average. The results on constant terms are omitted.

Panel A: dependent variable＝⊿*CDSS*

		PMG					PMG				
		coef	s.e.	z-value	p-value	χ^2(p-value)(i)	coef	s.e.	z-value	p-value	χ^2(p-value)(i)
long-term equation	*LEVERAGE*	752	85	8.890	0.000		578	49	11.760	0.000	
	VOLATILITY	182	13	14.400	0.000		162	7.553	21.420	0.000	
	RF	-172,041	12,414	-13.860	0.000		-101,162	7,067	-14.320	0.000	
	SQR(RF) (ii)	575	40	14.330	0.000		336	23	14.900	0.000	
	TS	-18,166	1,105	-16.440	0.000		-9,981	577	-17.290	0.000	
	TOPIX	-3,578	205	-17.430	0.000		-1,479	94	-15.680	0.000	
	ln(MV)	47	12	4.040	0.000		30	6.402	4.750	0.000	
	SWAPTION	4.417	0.278	15.900	0.000		2.607	0.146	17.820	0.000	
short-term equation	*adjustment paramerter* (ϕ_i)	-0.005	0.001	-8.510	0.000	542.69(0.000)	-0.008	0.001	-8.660	0.000	830.37(0.000)
	⊿*LEVERAGE*	132.428	47.300	2.800	0.005	485.53(0.000)	126.537	46.220	2.740	0.006	426.66(0.000)
	⊿*VOLATILITY*	19.790	10.342	1.910	0.056	165.81(0.000)	22.228	11.254	1.980	0.048	171.7(0.000)
	⊿*RF*	-106.802	140.211	-0.760	0.446	33.39(0.8779)	-47.287	117.962	-0.400	0.689	22.75(0.9967)
	⊿*SQR(RF)* (ii)	-32.919	17.564	-1.870	0.061	19.32(0.9996)	-46.729	16.502	-2.830	0.005	19.94(0.9993)
	⊿*SWAPTION*	0.008	0.010	0.790	0.430	35.50(0.8157)	-0.003	0.010	-0.330	0.741	36.93(0.7660)
	⊿*VIX*	—	—	—	—	—	0.190	0.046	4.150	0.000	194.2(0.000)
	log likelihood	-145,627					-132,748				
	adj-R^2	0.07					0.21				
	obs	60,524					56,564				

Table7 (continued)

Panel B: dependent variable＝⊿*ln(CDSS)*

		PMG					PMG				
		coef	s.e.	z-value	p-value	χ^2(p-value)(i)	coef	s.e.	z-value	p-value	χ^2(p-value)(i)
long-term equation	*LEVERAGE*	6.581	0.973	6.760	0.000		7.731	0.98	7.910	0.000	
	VOLATILITY	2.748	0.174	16	0.000		2.948	0.17	16.870	0.000	
	RF	-2,821	167	-17	0.000		-2,614	165	-15.850	0.000	
	SQR(RF) (ii)	9.269	0.537	17	0.000		8.68	0.53	16.320	0.000	
	TS	-322	15	-22	0.000		-297.9	14.33	-20.780	0.000	
	TOPIX	-49	2.533	-19	0.000		-28.5	2.08	-13.660	0.000	
	ln(MV)	-0.160	0.151	-1.060	0.287		-0.082	0.15	-0.540	0.590	
	SWAPTION	0.052	0.003	17	0.000		0.053	0.00	17.140	0.000	
short-term equation	*adjustment paramerter* (ϕ_i)	-0.006	0.000	-26.150	0.000	117.87(0.0000)	-0.006	0.00	-23.290	0.000	110.22(0.0000)
	⊿*LEVERAGE*	0.657	0.175	3.750	0.000	324.59(0.0000)	0.594	0.15	4.070	0.000	284.51(0.0000)
	⊿*VOLATILITY*	0.213	0.025	8.570	0.000	157.64(0.0000)	0.178	0.02	7.400	0.000	129.39(0.0000)
	⊿*RF*	-2.488	0.447	-5.570	0.000	34.62(0.8436)	-2.994	0.44	-6.880	0.000	34.04(0.8602)
	⊿*SQR(RF)* (ii)	0.119	0.078	1.530	0.125	27.11(0.9787)	-0.05	0.08	-0.670	0.502	27.13(0.9786)
	⊿*SWAPTION*	0.000	0.000	4.350	0.000	20.74(0.9989)	0.000	0.00	2.230	0.026	23.44(0.9953)
	⊿*VIX*	—	—	—	—	—	0.001	0.00	21.390	0.000	50.04(0.2461)
	log likelihood	129,010					122,839				
	adj-R^2	-0.01					0.13				
	obs	60,524					56,564				

Table 8: PMG Model (DD, Full Sample)

χ^2 is the test statistics for the null hypothesis that parameters are homogeneous, and figures in parentheses are associated p-value. The coef and s.e. for SQR(RF) and ⊿SQR(RF) are expressed as divided by 10000. Figures in long-run equilibrium equation are results about homogeneous parameters. coef of other explanatory variables are cross-sectional average of coefficients for each firms. s.e., z-value, and p-value of these variables are the standard error, z-values and p-values relating to the constant term in the OLS estimation in which the parameter estimates of each issue are the dependent variable while the constant term is explanatory variable. adj-R2 is cross-sectional average. The results on constant terms are omitted.

Panel A: dependent variable＝⊿*CDSS*

		PMG					PMG				
		coef	s.e.	z-value	p-value	χ^2(p-value)[(i)]	coef	s.e.	z-value	p-value	χ^2(p-value)[(i)]
long-term equation	*DD*	9.374	2.417	3.880	0.000		-0.220	0.582	-0.380	0.706	
	SQR(RF) [(ii)]	261	30	8.560	0.000		63	5.369	11.750	0.000	
	TS	-105,078	10,693	-9.830	0.000		-26,749	1,536	-17.410	0.000	
	TOPIX	-18,702	1,951	-9.590	0.000		-3,549	224	-15.850	0.000	
	ln(MV)	-224	29	-7.790	0.000		-75	7.094	-10.550	0.000	
	SWAPTION	22	2.386	9.080	0.000		5.501	0.366	15.020	0.000	
short-term equation	*adjustment paramerter* (ϕ_i)	-0.002	0.000	-5.02	0.00	156.61(0.0000)	-0.004	0.001	-7.80	0.00	460.02(0.0000)
	⊿*DD*	-0.352	0.214	-1.64	0.10	20.78(0.9989)	-0.650	0.445	-1.46	0.14	26.88(0.9804)
	⊿*SQR(RF)* [(ii)]	-59.229	22.378	-2.65	0.01	22.07(0.9977)	-59.386	20.879	-2.84	0.00	22.94(0.9963)
	⊿*SWAPTION*	0.026	0.027	0.97	0.33	38.88(0.6903)	0.015	0.018	0.84	0.40	45.07(0.4271)
	⊿*VIX*	—	—	—	—	—	0.257	0.066	3.89	0.00	217.19(0.0000)
	log likelihood	-146,143					-133,325				
	adj-R^2	0.05					0.20				
	obs	60,524					56,564				

Table 8 (continued)

Panel B: dependent variable = $\Delta ln(CDSS)$

		PMG					PMG				
		coef	s.e.	z-value	p-value	χ^2(p-value)[i]	coef	s.e.	z-value	p-value	χ^2(p-value)[i]
long-term equation	*DD*	-0.052	0.009	-5.74	0.00		-0.045	0.010	-4.43	0.00	
	SQR(RF) [ii]	0.720	0.077	9.35	0.00		0.898	0.087	10.30	0.00	
	TS	-471	25	-18.51	0.00		-474	27	-17.72	0.00	
	TOPIX	-79	4.547	-17.48	0.00		-54	3.619	-14.98	0.00	
	ln(MV)	-1.487	0.096	-15.53	0.00		-1.659	0.101	-16.45	0.00	
	SWAPTION	0.068	0.005	14.36	0.00		0.073	0.005	14.12	0.00	
short-term equation	*adjustment paramerter* (ϕ_i)	-0.005	0.000	-37.88	0.00	103.01(0.0000)	-0.004	0.000	-31.33	0.00	80.08(0.0007)
	Δ*DD*	-0.008	0.001	-6.96	0.00	121.99(0.0000)	-0.007	0.001	-6.10	0.00	108.29(0.0000)
	Δ*SQR(RF)* [ii]	-0.008	0.082	-0.10	0.92	28.75(0.9633)	-0.162	0.083	-1.94	0.05	29.72(0.9510)
	Δ*SWAPTION*	0.000	0.000	5.26	0.00	20.71(0.9989)	0.000	0.000	2.71	0.01	24.76(0.9915)
	Δ*VIX*	—	—	—	—	—	0.001	0.000	19.94	0.00	57.37(0.0851)
	log likelihood	128,580					122,442				
	adj-R^2	-0.01					0.14				
	obs	60,524					56,564				

Table 9: PMG Model (Before and After Crisis)

χ^2 is the test statistics for the null hypothesis that parameters are homogeneous, and figures in parentheses are associated p-value. The coef and s.e. for SQR(RF) and ⊿SQR(RF) are expressed as divided by 10000. Figures in long-run equilibrium equation are results about homogeneous parameters. coef of other explanatory variables are cross-sectional average of coefficients for each firms. s.e., z-value, and p-value of these variables are the standard error, z-values and p-values relating to the constant term in the OLS estimation in which the parameter estimates of each issue are the dependent variable while the constant term is explanatory variable. adj-R2 is cross-sectional average. The results on constant terms are omitted.

Panel A: dependent variable＝⊿*CDSS*

		Before the crisis (PMG)					After the crisis (PMG)				
		coef	s.e.	z-value	p-value	χ^2(p-value)[i]	coef	s.e.	z-value	p-value	χ^2(p-value)[i]
long-term equation	*LEVERAGE*	124	28	4.450	0.000		808	99	8.170	0.000	
	VOLATILITY	38	7.163	5.310	0.000		77	13	5.900	0.000	
	RF	-4,609	2,877	-1.600	0.109		-178,331	14,228	-12.530	0.000	
	SQR(RF) [ii]	4.424	9.349	0.470	0.636		593	46	12.880	0.000	
	TS	4,238	613	6.920	0.000		-19,825	1,544	-12.840	0.000	
	TOPIX	44	46	0.950	0.341		-1,486	128	-11.610	0.000	
	ln(MV)	-6.513	3.629	-1.790	0.073		-14	14	-1.050	0.293	
	SWAPTION	-0.909	0.134	-6.800	0.000		3.066	0.250	12.270	0.000	
short-term equation	*adjustment paramerter* (ϕ_i)	-0.005	0.001	-7.900	0.000	86.93 (0.0001)	-0.012	0.001	-9.700	0.000	449.70(0.0000)
	⊿*LEVERAGE*	35	19	1.870	0.061	136.64(0.0000)	150	73	2.050	0.040	211.08(0.0000)
	⊿*VOLATILITY*	3.370	1.325	2.540	0.011	164.61(0.0000)	44	29	1.500	0.133	161.75(0.0000)
	⊿*RF*	97	90	1.080	0.281	32.33(0.9035)	-336	242	-1.390	0.164	24.97(0.9907)
	⊿*SQR(RF)* [ii]	-8.202	8.797	-0.930	0.351	26.64(0.9820)	-104	31	-3.340	0.001	18.98(0.9996)
	⊿*SWAPTION*	0.007	0.002	3.210	0.001	23.39(0.9955)	-0.023	0.034	-0.660	0.506	51.09(0.2150)
	⊿*VIX*	0.006	0.014	0.450	0.656	31.86(0.9138)	0.182	0.049	3.730	0.000	83.55(0.0003)
	log likelihood			-18,502					-63,341		
	adj-R^2			0.07					0.24		
	obs			33,390					23,174		

Table 9 (continued)

Panel B: dependent variable = ⊿*ln(CDSS)*

		Before the crisis (PMG)					After the crisis (PMG)				
		coef	s.e.	z-value	p-value	χ^2(p-value)[i]	coef	s.e.	z-value	p-value	χ^2(p-value)[i]
long-term equation	*LEVERAGE*	2.817	2.591	1.090	0.277		2.251	0.832	2.710	0.007	
	VOLATILITY	0.282	0.485	0.580	0.561		0.439	0.140	3.130	0.002	
	RF	-353	257	-1.370	0.170		-2,902	161	-18	0.000	
	SQR(RF) [ii]	0.182	0.853	0.210	0.831		9.264	0.525	18	0.000	
	TS	467	75	6.190	0.000		-145	16	-8.890	0.000	
	TOPIX	3.359	4.129	0.810	0.416		-15	1.259	-12	0.000	
	ln(MV)	-1.052	0.348	-3.030	0.002		-0.955	0.152	-6	0.000	
	SWAPTION	-0.082	0.015	-5.380	0.000		0.052	0.002	22	0.000	
short-term equation	*adjustment paramerter* (ϕ_i)	-0.003	0.000	-16	0.000	22.35(0.9973)	-0.016	0.001	-23	0.000	147.17(0.0000)
	⊿*LEVERAGE*	0.834	0.146	5.700	0.000	184.61(0.0000)	0.265	0.149	1.780	0.076	100.86(0.0000)
	⊿*VOLATILITY*	0.247	0.032	7.600	0.000	185.60(0.0000)	0.120	0.033	3.600	0.000	95.94(0.0000)
	⊿*RF*	0.890	0.439	2.030	0.043	29.29(0.9567)	-8.794	0.839	-10	0.000	46.60(0.3661)
	⊿*SQR(RF)* [ii]	-0.001	0.096	-0.010	0.994	29.49(0.9542)	-0.421	0.124	-3.400	0.001	28.20(0.9692)
	⊿*SWAPTION*	0.000	0.000	7.000	0.000	21.55(0.9982)	0.000	0.000	-0.610	0.544	40.54(0.6208)
	⊿*VIX*	0.001	0.000	6.660	0.000	34.29(0.8533)	0.001	0.000	19	0.000	25.25(0.9896)
	log likelihood	83,846					45,268				
	adj-R^2	0.05					0.12				
	obs	33,390					23,174				

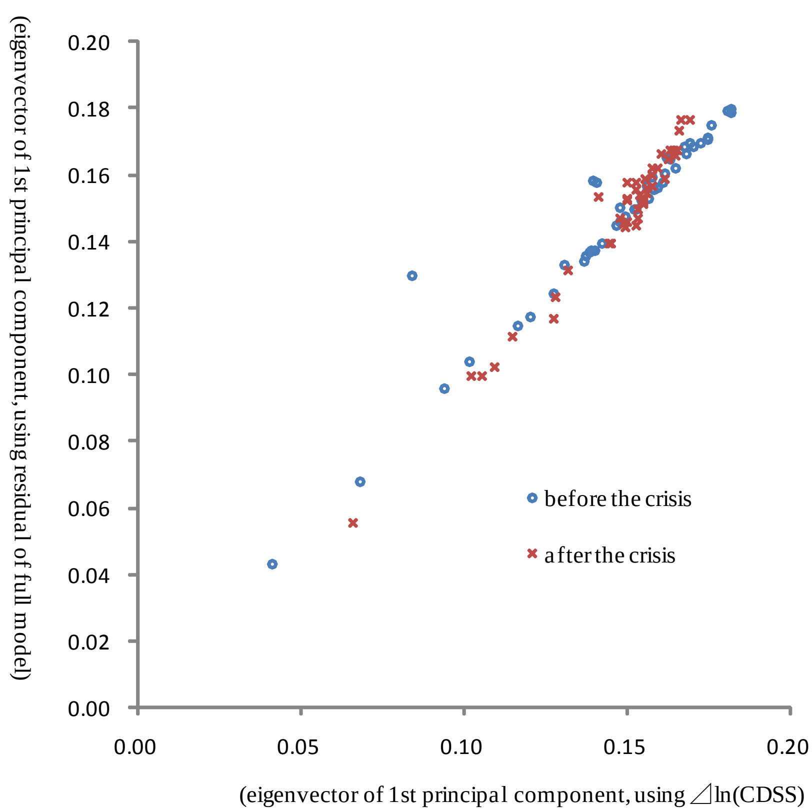
Table 10: Principal Component Analysis

Figures are the contributions of principal components.

	⊿CDSS			
	raw variable		residuals from full model	
	Before the Crisis	After the crisis	Before the Crisis	After the crisis
1st principa component	38.0%	45.8%	38.5%	38.9%
2nd principal component	6.3%	7.8%	6.2%	7.3%
3rd principal component	5.2%	5.4%	4.8%	6.4%
4th principal component	4.0%	3.9%	4.0%	4.7%
5th principal component	3.6%	3.3%	3.6%	3.6%

	⊿ln(CDSS)			
	raw variable		residuals from full model	
	Before the Crisis	After the crisis	Before the Crisis	After the crisis
1st principa component	35.5%	58.4%	36.0%	50.2%
2nd principal component	6.9%	5.0%	6.8%	5.5%
3rd principal component	5.1%	4.3%	4.7%	5.0%
4th principal component	4.0%	2.8%	4.0%	3.4%
5th principal component	3.4%	2.4%	3.4%	3.0%

Figure 1: Scatter Plot of Eigenvectors of 1st Principal Components



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