Sovereign Credit Default Swaps vs. Credit Ratings: Evidence from Error Correction Model

Chung-Hua Shen *
Department of Finance, National Taiwan University

Alex YiHou Huang +
Department of Finance, Yuan Ze University

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Abstract

This study presents the first application of time series regression to investigate the interdependence between credit ratings and CDS spreads for sovereigns. The credit ratings are transformed into a count variable with corresponding scores and examined in the framework of error correction model. The empirical outcomes find that, first, the credit ratings and CDS spreads are interdependent with each other in the long-run. Second, the two series converge in the short-run with error correcting dynamics significantly observed. Third, the first-differences of both CDS spreads and credit ratings are serial correlated, and for the entire sample, a two-way causality between the two series in the short-run is documented. For sub-samples, on the other hand, the existence and direction of causality vary across sovereigns in different regions and stages of developments.

Keywords: Credit default swap; Credit ratings; Sovereign; Error correction model

JEL classifications: G24; G32; C25; D81

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* Corresponding author. Address: No. 1, Sec. 4, Roosevelt Road, Taipei City 106, Taiwan (R.O.C.); Phone: +886-2-33661087; Fax: +886-2-83695817; Email: chshen01@ntu.edu.tw.
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1. Introduction

Credit Ratings have become increasingly more important in debt contracts because they are viewed as efficient credit quality benchmarks (Frost, 2006). Since the Credit Risk Agencies' provide opinions on the creditworthiness of entities and their financial obligation, their ratings are often used by the capital market to evaluate the credit risks. However, credit rating agencies are also often blamed by slowly provide the useful ratings. For example, credit ratings agencies downgrade the ratings of the Enron, Worldcom, and more companies after their bankruptcies around 2001 and 2002. Furthermore, during the financial crisis of 2008-2009, credit ratings have been accused as an inaccurate, coarse, and delayed indicator. In May 2010, after the downgrades of Greece, Spain, and Portugal's sovereign ratings, European leaders including President of the European Commission José Manuel Barroso, France's President Nicolas Sarkozy, and German's Chancellor Angela Merkel complained that the Standard & Poor's, Moody's, and Fitch Ratings were too slow to alert investors to the likely demise of Lehman Brothers in 2008. The European leaders called for a review of how these agencies work during the financial chaos and discussed possible establishment of a new European or international rating agency for sovereigns.

Recently, the other credit risk evaluator, Credit Default Swap (CDS) has attracted a lot of attention because it efficiently provides the market evaluation of the obligor's credit quality. A CDS is an instrument that provides insurance against a particular reference entity defaulting on its debt and is widely traded in OTC market. Contrast to credit ratings, the CDS spreads (a.k.a. the premium) are determined by the supply and demand of market participants and are continually updated with latest credit related information available.[1] Thus, whether CDS can become an important credit risk reference becomes an interesting issue.

[1] The CDS spreads data provided by brokers consists of bid and offer quotes from the OTC dealers. Once a quote has been agreed, the dealer is committed to trade the swap at a minimum principal, usually $10 million, at the quoted premium. Daily CDS spreads data are now widely available via many electronic financial platforms.

While quality of credit ratings is challenged and CRAs turns less trustworthy and CDS gradually receive more attention, market participants, regulators and academics still often use credit rating to decide the investment decision. Also, regulators typically outsource the supervision to the ratings agency in terms of requesting the minimum rating for the new businesses. Thus, it is interesting to know whether the two series can be the complement with each other or not.

The aim of this paper is to investigate the lead-lag interdependence between credit rating and CDS. Also, we examine whether the two credit risk evaluators converges or not. If they converge, they interpret the information in the same way though with different adjustment speed; thus, they could be the complements. If they do not converge, they interpret the information in a different way, indicating that one is correct and the other is not; they are substitutes. In our view, because both credit risk evaluators reflect the credit risk of the assets, they should converge in the long run, though not in the short run. We apply Engle and Granger's (1987) error correction model (ECM) to examine the dynamic relation between the two variables. The dynamic relationship between the two variables, i.e. credit ratings and CDS, has not yet been systematically documented, and this study intends to fill this gap by examining their interactive relation with the framework of error correction model.

The issues have not been explored in the past studies, which mainly examined whether the credit ratings can help to explain the movement of the CDS spreads. Daniels and Jensen (2005) found that credit rating is an important determinant of CDS spreads, especially for non-investment-grade issues. Zhang et al. (2009) showed that stock return volatility risk and jump risk respectively explained 48% and 19% of the variation of CDS spreads, and when controlling credit ratings along with other key information, 73% of the variation became determined. Ericsson et al. (2009) found that the explanatory power of CDS determinants differs across cases with different credit ratings. In particular, leverage and stock volatility generate higher impacts on CDS spreads for lower rated firms, and CDS spreads of higher rated firms are less sensitive to interest rate. Greatrex (2009) uses CDS index to explain CDS spreads and concludes that such rating-based index is the most important determent of CDS premium. However, they do not examine whether the two series will converge in the long run or not. The next section reviews literatures and section 3 discusses the econometric methodology of this study. Section 4 presents the empirical findings, and the final section concludes this research.

2. Literature Review

Credit rating is important because it has become an anchor for investment decisions by almost all participants in the capital market. It is also used by the regulators as a minimum criterion for financial institutions to issue the new financial products or other financial activities in the market. It is important because it is supposed to provide the correct credit ratings objectively in a timely manner.

While studies of credit ratings are abundant, we focus on its impacts on the capital market. West (1973) and Ederington et al. (1987) find that credit ratings are significant predictors of yield to maturity in addition to the other information available to public investors in predicting credit spreads. Hand et al. (1992) document statistically significant negative excess bond and stock returns upon the announcement of credit rating downgrades. Ederington and Goh (1998) demonstrate that credit rating downgrades lead to downward revision of earnings forecasts by analysts, and the revision is a result of the downgrade itself rather than earlier negative information of the firms. Graham and Harvey (2001) show that level of credit ratings is a key factor for CEOs in constructing their capital structure. The authors document that more than 50% of CEOs agree that credit ratings as important concern when they determine the amount of debt for their firms. Kisgen (2006) finds that firms near a credit rating upgrade or downgrade issue less debt proportional to equity than other firms.

Such relation between ratings and capital structure decision is due to the discrete benefits or costs associated with different rating levels, where many institutional investors such as banks or pension funds are regulated to participate bond or equity investments according to level of credit ratings.

Recent financial crisis have spurred the argument that credit ratings often failed to promptly reflect credit risk characteristics of new financial underlying assets. Bolton et al. (2009) and Mathis et al. (2009) provide evidences of rating inflation prior to financial crisis where the ratings greatly understated the risks of structured debt securities. The studies argue that such rating inflation may have resulted from collusion between credit rating agencies (CRAs) and issuers at the expense of investors. Partnoy (2006) shows that CRAs face the most serious conflicts of interest than other financial gatekeepers do. Griffin and Tang (2009) find that ratings reported by CRAs were inflated relative to those predicted by their models. Mason and Rosner (2007) show that Moody's only began to collect key measures of credit risk such as loan to value ratio, FICO score, and debt-to-income level in late 2007, and such neglect of information made the existing rating process and results less reliable. Pagano and Volpin (2010) show a significant failure of credit ratings by CRAs due to rating inflation and coarse information disclosure. Bar-Isaac and Shapiro (2010) demonstrate a significant relation between rating quality and business cycle, where the CRAs tend to issue less accurate ratings in boom than during recession periods. Longstaff et al. (2005) use CDS spreads as direct measure of the default components in corporate yield spreads.

In addition, prior empirical evidences have documented that CDS data react to the changes of credit quality faster than ratings changes, particular for cases of credit deterioration. By event study approach, Norden and Weber (2004) find that CDS market anticipates both credit rating downgrades and the CRAs' reviews of those downgrades. The authors also show that the magnitudes of impacts on CDS from rating downgrades are stronger for firms with lower old rating. Hull et al. (2004) also document the anticipation of

CDS data on credit rating downgrades. Their results showed that both the level and change of CDS spreads can be used in predicting negative rating changes.

Figure 1 presents the series of credit rating and CDS spreads for the Republic of Iceland between 2008 and mid-2009, where the letter credit ratings from Standard & Poor's (S&P) are converted into a numerical values according to Reinhart (2002). In the figure, the series of CDS spreads clearly jumped around one month prior to the national address by the Prime Minister of Iceland, Geir H. Haarde on October 6, 2008.[2] In the address, the Prime minister admitted the financial deterioration of the nation. On the same date, the S&P downgraded its sovereign ratings by two notches from A- to BBB. Thus, the CDS market and credit move toward the same direction although CDS reacts to the event at least one month ahead. After the address, Iceland conducted a series of economic reform to the banking system, including raising interest rate to 18% on October 28, 2008 in fulfilling the loan requirement by IMF. Since then, the Iceland CDS spreads moved downward trendily, indicating that the market provides the positive responses for the reform. However, S&P further downgraded the sovereign rating to BBB- on November 24, 2008, making CDS and the ratings move toward different direction. Thus, while both CDS and ratings reflect the credit risk of the underylying assket, they may not move toward the same direction always. It is interesting to know whether they will converge in the long run.

3. Econometric Model

In order to investigate the interactive relationship between the two variables, first, credit ratings are transformed into numerical scores according to Reinhart (2002), and Table 1 shows the corresponding ratings and scores. Second, the time series regression of error

[2] The CDS spreads of Iceland increased from 256.3 on September 1, 2008 to 728.3 on October 1, 2008 and reached to its historical highest of 1,473.3 on October 10, 2008.

correction model (ECM) is adopted for empirical applications. Engle and Granger (1987) propose the ECM representation to examine relationships between two variables, and for example, in this study, the ECM to explain dynamics of credit ratings can be shown as Following Engle and Granger's (1987) two-step estiamtion, we first regress rating against CDS, where the resulting residuals are saved. Then, we use the difference form to show

$$Rating_t = \alpha_1 + \alpha_{11} CDS_t + e_{1t}, \tag{1}$$

$$\Delta Rating_t = \beta_{10} + \lambda_1 \hat{e}_{1t-1} + \sum_{i=1}^{k} \beta_{11}^{i} \Delta CDS_{t-i} + \sum_{j=1}^{h} \beta_{12}^{j} \Delta Rating_{t-j} + \varepsilon_{2t}, \tag{2}$$

where the subscript t denotes the time $Rating_t$ and CDS_t are the ratings and CDS spreads series, respectively, and Δ stands for the first-differences of the variables. Equation (1) describes the "long-term" relation between $Rating_t$ and CDS_t.

It is noted that because higher the rating score denotes better the credit quality, the relationship between $Rating_t$ and CDS_t should be negatively correlated if they reflect the same credit fundamental; hence, we expect a negative α_1. The $\hat{e}_{1t-1}$ in equation (2) is the lagged residual from equation (1) representing the error correction term with λ_1 as the correcting coefficient.

Granger (1988) points out two sources of causality from the ECM specification. First, the lagged first-differences of $Rating_t$ and CDS_t explain $\Delta Rating_t$ in the short-term. Second, the error correction term incorporates the long-term relationship between the two series in order to explain the first-difference of target variable. Specifically, when the error correction term is negative, the lagged $Rating_t$ is smaller than lagged ($\hat{\alpha}_1 + \hat{\alpha}_{11} CDS_t$), i.e. the long-term equilibrium. When such negative error correction term enters equation (2), therefore, an increase of $Rating_t$ (i.e. positive $\Delta Rating_t$) should be corresponded, if there exhibits stationary relationship between $Rating_t$ and CDS_t. Consequently, a negative estimation of λ_1 should be observed. Since the variable of $\Delta Rating_t$ is highly persistent in natural, two lagged terms are included in equation (2).[3] With same spirits, The ECM to explain CDS dynamics can be shown as

$$CDS_t = \alpha_2 + \alpha_{12} Rating_t + e_{2t}, \tag{3}$$

$$\Delta CDS_t = \beta_{20} + \lambda_2 \hat{e}_{2t-1} + \sum_{i=1}^{k} \beta_{21}^{i} \Delta CDS_{t-i} + \sum_{j=1}^{h} \beta_{22}^{j} \Delta Rating_{t-j} + \varepsilon_{2t} \,. \tag{4}$$

Both ECMs are estimated in a two-step application, where the pooled OLS is used to estimate the level relationships between ratings and CDS spreads and produce the residuals for each individual sovereign. Following Arellano and Bond (1991), the generalized method of moment (GMM) is then applied to estimate the first-difference regressions (i.e. equations 2 and 4) in the content of dynamic panel data. Based on Arellano and Bond (1991), the GMM approach is able to produce consistent estimates in the present of serial correlations among residuals and individual fixed effects of each sovereign. The ratings series is a non-zero count variable with integrals, therefore, optimal criteria check in autoregression and stationarity test are omitted. The empirical results from the entire sample, as well as for sub-samples by levels of development and regions, are presented and discussed in next section.

4. Data, Summary Statistics and Empirical Results

4.1. Data and summary statistics

Monthly data of country CDS spreads and sovereign credit ratings of S&P between January 2000 and February 2010 are collected from the original daily data that are extracted from Bloomberg.[4] S&P's sovereign credit ratings are used. Following prior studies, the data of 5 year contracts of CDS are employed obtained,[5] and the sample lengths vary across

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[3] In the empirical applications of this study, both models with one lagged term and two lagged terms of $\Delta Rating_t$ are separately estimated for comparison purpose.

[4] The foreign currency rating LT of S&P's is used as the credit ratings. Grande and Parsley (2005) show that the S&P's ratings provide broadest coverage and precede ratings by other CRAs. Monthly closes of daily CDS spreads are used as the monthly data series.

[5] See Hull et al. (2004) and Ericsson et al. (2009) among others as examples.

countries because dates of contract initiation are different. Sovereign CDSs with less than 3 years are excluded from the empirical works, and the final sample set contains 31 countries. Table 2 presents the list of sample sovereigns, classified by developed/developing countries, with their corresponding geographical regions.

Table 3 presents the basic statistics of CDS spreads for the 31 countries. The CDS spreads is quoted at base point over the principal amount and therefore, does not require adjustments from risk-free rate. The lowest CDS spread are found in Germany and France, which are only 11.41 and 11.69, respectively. By contrast, the largest CDS spreads fall on Argentina and Venezuela, which are 967.55 and 741.00, respectively. Also, Argentina and Brazil have the largest standard deviations during the sample period.

4.2. ECM outcomes for all sovereigns

Table 4 presents the estimation results of ECMs for all sovereigns with Panel A showing the first step pooled OLS results of level regressions (equations 1 and 3). Panel B shows the second step GMM results of first-difference regressions (equations 2 and 4) where both models of one lagged term and two lagged terms of $\Delta Rating_t$ are separately presented. At this empirical application, k is set as 1 based on the usual AR(1) specification in time series analysis and h is set as 2 due to the rigidity of rating series discussed in literature review.

In Panel A, the estimates of intercepts and explanatory variables are highly statistically significant away from zero in both simple regression models. For example, in the first column, when CDS_t is regressed against $Rating_t$, the estimates of intercept and $Rating_t$ are 585.90 and -46.36, respectively, with t-statistics as 43.09 and -32.10. The significant negative estimate of -46.358 confirms the long-term inverse relationship between the two series of CDS spreads and credit rating scores. This is also true when using CDS_t to explain $Rating_t$ in the second column, where the coefficient of CDS_t is significantly estimated as -0.006.

In Panel B of Table 4, the first two columns show the results of second-step dynamic panel regressions for models with ΔCDS_t as the dependent variable, where the first model has the error correction term, ΔCDS_{t-1}, and $\Delta Rating_{t-1}$ as explanatory variables and the second one has one additional regressor of $\Delta Rating_{t-2}$. In the first model, the coefficients of error correction term and ΔCDS_{t-1} are respectively estimated as -0.069 and 0.175, both highly significant, where the estimate of $\Delta Rating_{t-1}$ is insignificant and equal to -9.038. The results show that, first, as expected, the error correction term is negatively and significantly estimated, and it means that the lagged errors between the two series are able to correct the current change of CDS spreads. Second, the ΔCDS_t series is positively serial correlated, a characteristic consistent with most financial assets. At last, statistically, there is no impact from lagged change of ratings on the dependent ΔCDS_t. The result is somehow not surprising given the fact that rating score is a persistent series of integrals and most data of $\Delta Rating_t$ would be zero, the impacts from such variable in one lag are difficult to be detected.

The second model has one additional explanatory variable, $\Delta Rating_{t-2}$, than the first model has. Except for the intercept, all estimated results for the overlapping variables (i.e. the error correction term, ΔCDS_{t-1}, and $\Delta Rating_{t-1}$) are close between the two models, where the signs and significances of the estimates are identical with similar magnitudes. The estimate of the additional $\Delta Rating_{t-2}$ variable is, a little puzzlingly, negative and statistically significant. This result implies that the change of ratings series two month earlier generates significant impacts on the current level of ΔCDS_t, which is not affect by change of ratings series in previous month. This interesting dynamics may be caused by the unique attribute of the $\Delta Rating_t$ series as highly persistent with majority data of zero.

In Panel B of Table 4, the third and fourth columns share similar structures with first two columns but have $\Delta Rating_t$ as the dependent variable. Focusing on the error correction terms, their estimates are again significantly negative for both models; confirming the short-run convergence between the two series. The coefficients of ΔCDS_{t-1} in both models, as expected, are estimated negatively significant; confirming interactive relations between the first-differences of the two series and consistent directions in measuring credit quality changes. The coefficients of $\Delta Rating_{t\text{-}1}$ are statistically equal to zero for both models, and the coefficient of $\Delta Rating_{t\text{-}2}$ in fourth column is significant. Analogous to the analyses droved from first two columns, the characteristics of $\Delta Rating_t$ series may contribute to its serial correlated dynamics observed from the empirical findings.

In sum, based on regression outcomes generated from the entire sample, the results of first step regressions show that the credit ratings and CDS spreads significantly interact with each other in the long-run and in the same direction in measuring change of credit quality. Second, the significant and negative estimates of the error correction terms in the second step regression show that the two first-difference series converge in the short-run. Third, the first-differences of both rating series and CDS spreads are serial correlated, and lagged first-difference of CDS spreads in one period explain the current difference of ratings series while lagged difference of ratings in two periods explain the current difference of CDS spreads; implying a two-way causality. Therefore, despite credit ratings series being rigid in its nature of design and CDS data provide prompt information, significant long-run interdependence and short-run convergence between the two variables are documented.

4.3. ECM outcomes for sub-samples

Neighbor sovereigns often have common economic characteristics; Kose et al. (2003) document the differences regarding macroeconomic aggregates and properties of business cycle across regions. Therefore, the application of ECM regression is conducted for sub-samples by both regions and level of development to see if the relationships between CDS spreads and credit ratings change across sovereigns with different properties. Four sub-samples of regions are categorized: Africa, Asia, Europe, and South America and two sub-samples of developed and developing countries are grouped according to IMF classification. The outcomes of sub-samples in regions will first be discussed, and since there are only two African sovereigns in the sample, results of sub-sample of Africa will be presented at last.

Table 5 shares the same structure with Table 4 and presents the outcomes for sub-sample of Asia with nine sovereigns. From Panel A, all coefficients are significantly estimated, and the estimates of regressors in both models are also negative. From Panel B, the coefficients of error correction terms are significantly estimated only for models with ΔCDS_t as dependent variable but not for ones with $\Delta Rating_t$ as dependent variable. The result is contrary to ones from entire sample and suggests only the first-difference of CDS spreads series converges to the equilibrium established from the first step regression. No other coefficients of regressors are estimated statistically significant; implying neither of ΔCDS_t nor $\Delta Rating_t$ is serial correlated and no causality is generated in the short-run between the two series. One can then argue that since ratings change is infrequent and only ΔCDS_t converges, it is rational to observe the short-run change of credit quality according to data of CDS market for Asian sovereigns.

Table 6 presents the outcomes for sub-sample of Europe with thirteen sovereigns. From Panel A, the long-run interdependence is confirmed between CDS spreads and credit ratings with the estimates of regressors in both models are significant. From Panel B, the coefficients of error correction terms are all significantly and negatively estimated; a result that is consistent with all sovereigns and suggesting the two first-difference series converge in the short-run. In addition to the error correction term, both series are explained only by lagged ΔCDS_t, showing that ΔCDS_t is serial correlated and leads the difference of credit ratings series in the short-run. For European countries, while the two series interact with each other, CDS data react to change of credit quality faster than ratings.

Table 7 presents the outcomes for sub-sample of America with seven sovereigns. From Panel A, all coefficients are again significantly estimated, and the estimates of regressors in both models are negative; confirming the long-run interdependence between CDS spreads and credit ratings and their consist direction in measuring credit changes. From Panel B, the coefficients of error correction terms are all significantly and negatively estimated; suggesting the two first-difference series also converge in the short-run. The ΔCDS_t is serial correlated and explained by lagged $\Delta Rating_t$ in two periods, these results are consistent with ones from entire sample. The $\Delta Rating_t$, on the other hand, is only significantly explained by $\Delta Rating_{t-2}$; an observation contrary to the ones from previous samples showing one-way causality from ratings to CDS spreads.

Table 8 presents the outcomes for sub-sample of Africa with two sovereigns. Results of Panel A confirm the long-run interdependence between CDS spreads and credit ratings. From Panel B, similar to sub-sample of Asia, only the coefficients of error correction terms for models with ΔCDS_t as dependent variable are significantly estimated but not for models with $\Delta Rating_t$ as dependent variable. The result implies that only the first-difference of CDS spreads series converges to the equilibrium established from the long-run regression. No causality is observed in the short-run for the two African sovereigns.

Table 9 shares the same structure with Tables 4 to 8 and presents the outcomes for sub-sample of developed countries with ten sovereigns. We observe same results from Panel A comparing to previous tables where all coefficients are significantly estimated, and the estimates of regressors in both models are negative. From Panel B, the coefficients of error correction terms are all significantly and negatively estimated; suggesting the two first-difference series converge in the short-run. The ΔCDS_t is serial correlated and cannot be explained by lagged $\Delta Rating_t$, and the $\Delta Rating_t$ cannot be explained by any of regressor except the error correction terms. The results of Panel B are analog to ones of Asian sub-sample, and CDS data should be more useful to public in revealing credit quality change.

Table 10 presents the outcomes for sub-sample of developing countries with twenty-one sovereigns. Results of all estimates from both panels, in term of sign and statistical significance, are consistent with ones from entire sample. Thus, long-run interdependence between CDS spreads and credit ratings is found, as well as their short-run convergences. Both ΔCDS_t and $\Delta Rating_t$ are significantly explained by $\Delta CDS_{t\text{-}1}$ and lagged $\Delta Rating_t$ in two periods; implying their serial correlations and two-way causality.

In sum, consistent with results of all sovereigns, the outcomes of first step regressions confirm the long-run interdependence and inverse relations between CDS spreads and ratings series regardless how the sub-sample is grouped. The short-run dynamics, on the other hand, vary across sub-samples by regions where the convergence of ΔCDS_t is found for all sub-samples but convergence of $\Delta Rating_t$ is only found for American and European sovereigns. The short-run two-way causality is not observed for any sub-sample by regions but for sub-sample of developing countries.

4.4. Regression outcomes by Poisson regression

As discussed in previous sections, there are some unique characteristics of the credit ratings time series. First, it is a count variable with only integrals between 0 and 16. Second, it is highly persistent, even for monthly data. According to the S&P's *Sovereign Rating and Country T&C Assessment Histories*, the average frequency in adjusting the ratings of a particular sovereign is about one year. In fact, many of the sample sovereigns in this study have had the same ratings for over two years during the sample period. Therefore, such count variable in a regression framework often requires special treatment, especially when their forecasting is needed. To ensure nonnegative predictions, Poisson regression is often applied in modeling the expected value of dependent variable as an exponential function.[6] Quasi-maximum likelihood estimation should be adopted to generate the estimates of Poisson regression. The first-step regression of the ECM with credit ratings as dependent variable, i.e. the equation (1), can be estimated under the Poisson regression to confirm robustness of our

[6] A detail discussion and specification test for Poisson regression please see Lee (1986).

OLS results.[7]

Table 11 presents regression outcomes of equation (1) by Poisson regression for all sovereigns, as well as for all sub-samples. The first column shows the results of entire sample where both coefficients of intercept and CDS_t are significantly estimated. The estimate of CDS_t is -0.0019, and the negative estimation confirms the inverse relation between $Rating_t$ and CDS_t. The rest of table shows similar observations for sub-samples: first, the intercept coefficients are all significantly estimated with positive sign and similar magnitude. Second, the coefficients of CDS_t are all significantly and negatively estimated; suggesting that $Rating_t$ and CDS_t generally measure change of credit quality in same direction. These findings are all in line with those reported form OLS results.

5. Concluding Remarks

This study presents the first research applying time series method to investigate the interdependence between credit ratings and CDS spreads for sovereigns. Total of 31 countries with CDS data available for at least three years between January 2001 and February 2010 are applied as sample. The credit ratings are transformed into a count variable with corresponding scores and used in a two step framework of error correction model. The error correction term is designed to capture the short-run convergence between changes of ratings and CDS spreads. The linear regression results of the count variable are robust to alternative application by Poisson regression.

A few observations are in order. First, the results of first step regressions show that the credit ratings and CDS spreads significantly move along with each other in the same direction when measuring change of credit quality. That is, the two variables are interdependent with

[7] Note that the OLS estimation for equation (1) is unbiased and asymptotically efficient even with such count variable. The application of ECM in this study is designed in linear concept; therefore, it is best to use OLS results to carry out the main empirical works.

each other in the long-run. Second, the coefficient estimates of the error correction terms in the second step regression are significantly and negatively obtained for all sovereigns together; implying that the two series generally converge in the short-run. Third, the first-differences of both series are serial correlated for entire sample, and the direction of causality among them depends on sample characteristics. For all sovereigns, the lagged first-differences of CDS spreads and credit ratings significantly explain current differences of CDS spreads and ratings; showing a two-way causality in the short-run. For sub-samples by regions, one-way causality from ratings to CDS spreads is found for South American sovereigns and from CDS spreads to ratings is observed for European sovereigns. No causality in the short-run is shown for Asia, African, and developed samples, and two-way causality is observed for developing countries.

Since long-run interdependence and short-run convergence between ratings and CDS spreads are documented, CDS market provides as reliable information as credit ratings for credit quality change. Given the fact that credit ratings series is rigid in its nature of design and only series of CDS spreads converge in the short-run for sub-samples including developed countries and South American sovereigns, capital market participants and policy regulators should observe the short-run change of credit quality according to data of CDS market. Fund managers and bond holders should consider CDS data as primary benchmark of credit quality when constructing investment principles and conducting fund distributional decisions. The dynamics lead to the differences of relationships between credit ratings and CDS spreads across sovereigns in the short-run remain unaddressed and should be areas worth for future exploration.

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Table 1

Numerical Scores of Credit Ratings by Standard & Poor’s

Credit Ratings	Scores
AAA	16
AA+	15
AA	14
AA-	13
A+	12
A	11
A-	10
BBB+	9
BBB	8
BBB-	7
BB+	6
BB	5
BB-	4
B+	3
B	2
B-	1
CCC+	0

This table presents the numerical scores of credit ratings issued by the Standard & Poor’s, and the scores are assigned based on Reinhart (2002).

Table 2
Sample Sovereigns

Classifications	Sovereigns	Regions
Developed Countries		
	Czech Republic	Europe
	France	Europe
	Germany	Europe
	Greece	Europe
	Italy	Europe
	Japan	Asia
	Portugal	Europe
	Slovakia	Europe
	South Korea	Asia
	Spain	Europe
Developing Countries		
	Argentina	South America
	Brazil	South America
	Bulgaria	Europe
	Chile	South America
	China	Asia
	Colombia	South America
	Egypt	Africa
	Hungary	Europe
	Indonesia	Asia
	Malaysia	Asia
	Mexico	South America
	Peru	South America
	Philippines	Asia
	Poland	Europe
	Romania	Europe
	Russia	Europe
	South Africa	Africa
	Thailand	Asia
	Turkey	Asia
	Venezuela	South America
	Vietnam	Asia

This table lists the sample sovereigns with regions, and the nations are classified into developed and developing countries according to IMF classification.

Table 3

Summary Statistics of CDS Spreads

Sovereigns	Mean	S.D.	Minimum	Maximum	N	Sample Period
Argentina	967.55	1,132.63	193.18	4,201.61	57	2005.06-2010.02
Brazil	562.33	732.60	62.16	3,790.00	101	2001.10-2010.02
Bulgaria	206.86	181.56	13.42	697.50	113	2000.10-2010.02
Chile	63.89	58.54	13.17	266.56	86	2003.01-2010.02
China	49.78	47.39	10.13	248.34	86	2003.01-2010.02
Colombia	280.13	169.63	77.40	805.00	86	2003.01-2010.02
Czech	62.31	69.59	3.41	305.00	46	2006.05-2010.02
Egypt	236.27	163.51	42.00	633.25	41	2006.10-2010.02
France	11.69	16.40	1.75	84.33	84	2003.04-2010.02
Germany	11.41	14.85	3.01	87.17	84	2003.04-2010.02
Greece	52.69	83.25	5.55	383.00	84	2003.03-2010.02
Hungary	92.92	125.48	11.00	563.60	96	2002.03-2010.02
Indonesia	250.43	147.29	100.20	708.89	61	2005.01-2010.02
Italy	33.31	44.41	5.68	182.25	84	2003.04-2010.02
Japan	18.46	22.78	2.17	97.31	86	2003.01-2010.02
Malaysia	82.93	66.06	12.88	296.39	101	2001.10-2010.02
Mexico	147.45	97.03	28.56	462.10	101	2001.10-2010.02
Peru	202.45	110.11	62.17	570.89	77	2003.10-2010.02
Philippines	322.77	142.95	101.25	617.50	95	2002.04-2010.02
Poland	57.71	63.47	8.13	366.00	113	2000.10-2010.02
Portugal	26.53	35.99	4.09	161.06	84	2003.03-2010.02
Romania	177.84	162.56	17.75	723.56	89	2002.10-2010.02
Russia	304.44	270.70	38.73	1,017.50	113	2000.10-2010.02
Slovakia	47.32	47.81	6.00	211.67	101	2001.10-2010.02
South Africa	142.62	89.76	25.06	459.93	113	2000.10-2010.02
South Korea	80.53	84.67	14.28	432.48	97	2002.02-2010.02
Spain	29.20	39.65	2.63	138.00	71	2004.04-2010.02
Thailand	80.80	61.97	26.94	298.34	95	2002.04-2010.02
Turkey	449.86	307.18	122.94	1,281.25	113	2000.10-2010.02
Venezuela	741.00	657.88	121.97	3,218.04	86	2003.01-2010.02
Vietnam	208.77	138.54	54.25	529.61	46	2006.05-2010.02

This table presents the summary statistics of CDS spreads for the 31 sample sovereigns. S.D. stands for standard deviations.

Table 4

Estimation Results of ECM for All Sovereigns

Panel A	CDS_t		$Rating_t$	
Intercept	585.904	***	9.695	***
	(43.094)		(132.81)	
$Rating_t$	-46.358	***		
	(-32.095)			
CDS_t			-0.006	***
			(-32.095)	

Panel B	ΔCDS_t				$\Delta Rating_t$			
Intercept	-0.763		0.197		0.017		0.018	
	(-0.403)		(0.103)		(4.65)		(4.743)	
$\hat{e}_{t-1}$	-0.069	***	-0.073	***	-0.006	***	-0.006	***
	(-10.65)		(-11.086)		(-5.684)		(-5.746)	
ΔCDS_{t-1}	0.175	***	0.176	***	-8.6×10^{-5}	**	-9.2×10^{-5}	**
	(9.127)		(9.107)		(-2.336)		(-2.490)	
$\Delta Rating_{t-1}$	-9.038		-9.984		-0.022		-0.023	
	(-0.894)		(-0.987)		(-1.135)		(-1.176)	
$\Delta Rating_{t-2}$			-52.744	***			-0.039	**
			(-5.243)				(-2.047)	
Observations	2,628		2,597		2,628		2,597	

This table presents the estimation results of error correction models for the entire sample. Panel A shows the first step OLS results of level regressions, and Panel B shows the second step GMM results of first-difference regressions. The numbers in parentheses are *t* statistics, and *, **, *** indicate statistical significances in 1%, 5%, and 10% levels, respectively.

Table 5

Estimation Results of ECM for Sovereigns in Asia

Panel A	CDS_t		$Rating_t$	
Intercept	487.079	***	9.850	***
	(37.821)		(81.686)	
$Rating_t$	-40.200	***		
	(-26.693)			
CDS_t			-0.012	***
			(-26.693)	

Panel B	ΔCDS_t		$\Delta Rating_t$	
Intercept	-0.474	-0.419	0.016	0.016
	(-0.243)	(-0.212)	(2.713)	(2.597)
$\hat{e}_{t-1}$	-0.070 ***	-0.071 ***	-0.003	-0.004
	(-5.323)	(-5.321)	(-1.499)	(-1.497)
$\Delta CDS_{t\text{-}1}$	0.030	0.036	-3.0×10^{-5}	-3.0×10^{-5}
	(0.848)	(0.997)	(-0.317)	(-0.294)
$\Delta Rating_{t\text{-}1}$	-12.125	-12.082	-0.011	-0.011
	(-1.003)	(-0.996)	(-0.296)	(-0.286)
$\Delta Rating_{t\text{-}2}$		-7.445		0.039
		(-0.614)		(1.085)
Observations	762	753	762	753

This table presents the estimation results of error correction models for the sample sovereigns in Asia. Panel A shows the first step OLS results of level regressions, and Panel B shows the second step GMM results of first-difference regressions. The numbers in parentheses are *t* statistics, and *, **, *** indicate statistical significances in 1%, 5%, and 10% levels, respectively.

Table 6

Estimation Results of ECM for Sovereigns in Europe

Panel A	CDS_t	$Rating_t$
Intercept	374.294 ***	12.038 ***
	(35.138)	(122.333)
$Rating_t$	-26.362 ***	
	(-27.773)	
CDS_t		-0.015 ***
		(-27.773)

Panel B	ΔCDS_t		$\Delta Rating_t$	
Intercept	-0.213	-0.071	0.013	0.012
	(-0.233)	(-0.077)	(2.223)	(2.136)
$\hat{e}_{t-1}$	-0.0573 ***	-0.056 ***	-0.010 **	-0.010 **
	(-7.379)	(-7.074)	(-4.857)	(-5.147)
ΔCDS_{t-1}	0.230 ***	0.237 ***	-5.2×10^{-4} ***	-6.5×10^{-4} ***
	(8.101)	(8.192)	(-2.971)	(-3.671)
$\Delta Rating_{t-1}$	-5.655	-5.488	-0.034	-0.039
	(-1.173)	(-1.134)	(-1.158)	(-1.313)
$\Delta Rating_{t-2}$		-4.138		-0.029 **
		(-0.864)		(-1.005)
Observations	1,136	1,123	1,136	1,123

This table presents the estimation results of error correction models for the sample sovereigns in Europe. Panel A shows the first step OLS results of level regressions, and Panel B shows the second step GMM results of first-difference regressions. The numbers in parentheses are *t* statistics, and *, **, *** indicate statistical significances in 1%, 5%, and 10% levels, respectively.

Table 7

Estimation Results of ECM for Sovereigns in South America

Panel A	CDS_t		$Rating_t$	
Intercept	984.454	***	6.836	***
	(20.663)		(53.483)	
$Rating_t$	-100.151	***		
	(-13.846)			
CDS_t			-0.002	***
			(-13.846)	

Panel B	ΔCDS_t				$\Delta Rating_t$			
Intercept	-2.641		1.916		0.028		0.032	
	(-0.331)		(0.239)		(2.989)		(3.359)	
$\hat{e}_{t-1}$	-0.080	***	-0.089	***	-0.007	**	-0.008	**
	(-5.242)		(-5.843)		(-2.069)		(-2.207)	
ΔCDS_{t-1}	0.194	***	0.194	***	-7.6×10^{-5}		-7.8×10^{-5}	
	(4.690)		(4.739)		(-1.574)		(-1.610)	
$\Delta Rating_{t-1}$	-7.832		-13.008		-0.029		-0.032	
	(-0.219)		(-0.368)		(-0.699)		(-0.760)	
$\Delta Rating_{t-2}$			-154.629	***			-0.122	**
			(-4.416)				(-2.942)	
Observations	580		573		580		573	

This table presents the estimation results of error correction models for the sample sovereigns in South America. Panel A shows the first step OLS results of level regressions, and Panel B shows the second step GMM results of first-difference regressions. The numbers in parentheses are *t* statistics, and *, **, *** indicate statistical significances in 1%, 5%, and 10% levels, respectively.

Table 8

Estimation Results of ECM for Sovereigns in Africa

Panel A	CDS_t	$Rating_t$
Intercept	448.493 ***	8.253 ***
	(7.796)	(52.587)
$Rating_t$	-36.852 ***	
	(-4.945)	
CDS_t		-0.004 ***
		(-4.945)

Panel B	ΔCDS_t		$\Delta Rating_t$	
Intercept	0.634	0.809	0.014	0.014
	(0.201)	(0.250)	(1.430)	(1.437)
$\hat{e}_{t-1}$	-0.074 **	-0.075 ***	-0.004	-0.004
	(-2.603)	(-2.625)	(-0.447)	(-0.458)
ΔCDS_{t-1}	0.185 **	0.187 **	-1.0×10^{-4}	-1.0×10^{-4}
	(2.285)	(2.280)	(-0.415)	(-0.405)
$\Delta Rating_{t-1}$	-0.760	-0.996	-0.013	-0.013
	(-0.028)	(-0.036)	(-0.151)	(-0.153)
$\Delta Rating_{t-2}$		-1.917		-0.012
		(-0.069)		(-0.138)
Observations	150	148	150	148

This table presents the estimation results of error correction models for the sample sovereigns in Africa. Panel A shows the first step OLS results of level regressions, and Panel B shows the second step GMM results of first-difference regressions. The numbers in parentheses are *t* statistics, and *, **, *** indicate statistical significances in 1%, 5%, and 10% levels, respectively.

Table 9

Estimation Results of ECM for Developed Sovereigns

Panel A	CDS_t		$Rating_t$	
Intercept	146.259 ***		13.437 ***	
	(14.705)		(143.453)	
$Rating_t$	-8.484 ***			
	(-11.158)			
CDS_t			-0.016 ***	
			(-11.158)	

Panel B	ΔCDS_t		$\Delta Rating_t$	
Intercept	0.853	0.862	0.004	0.004
	(1.411)	(1.408)	(0.663)	(0.681)
$\hat{e}_{t-1}$	-0.053 ***	-0.051 ***	-0.009 ***	-0.009 ***
	(-4.331)	(-4.119)	(-3.522)	(-3.539)
ΔCDS_{t-1}	0.269 ***	0.270 ***	-8.0×10^{-5}	-7.0×10^{-5}
	(7.599)	(7.539)	(0.252)	(0.226)
$\Delta Rating_{t-1}$	-2.513	-2.477	-0.008	-0.008
	(-0.633)	(-0.616)	(-0.227)	(-0.234)
$\Delta Rating_{t-2}$		5.963		-0.009
		(1.504)		(-0.268)
Observations	801	791	801	791

This table presents the estimation results of error correction models for the sample sovereigns that are developed countries. Panel A shows the first step OLS results of level regressions, and Panel B shows the second step GMM results of first-difference regressions. The numbers in parentheses are *t* statistics, and *, **, *** indicate statistical significances in 1%, 5%, and 10% levels, respectively.

Table 10

Estimation Results of ECM for Developing Sovereigns

Panel A	CDS_t	$Rating_t$
Intercept	758.777 ***	7.647 ***
	(37.966)	(117.794)
$Rating_t$	-75.347 ***	
	(-27.282)	
CDS_t		-0.004 ***
		(-27.282)

Panel B	ΔCDS_t		$\Delta Rating_t$	
Intercept	-1.490	0.159	0.023	0.024
	(-0.549)	(0.058)	(4.858)	(4.982)
$\hat{e}_{t-1}$	-0.074 ***	-0.079 ***	-0.009 ***	-0.009 ***
	(-9.006)	(-9.459)	(-4.415)	(-4.352)
ΔCDS_{t-1}	0.178 ***	0.178 ***	-9.0×10^{-5} **	-9.0×10^{-5} **
	(7.688)	(7.693)	(-2.215)	(-2.372)
$\Delta Rating_{t-1}$	-9.355	-10.885	-0.024	-0.025
	(-0.691)	(-0.804)	(-1.027)	(-1.067)
$\Delta Rating_{t-2}$		-67.032 ***		-0.046 **
		(-4.983)		(-1.978)
Observations	1,827	1,806	1,827	1,806

This table presents the estimation results of error correction models for the sample sovereigns that are developing countries. Panel A shows the first step OLS results of level regressions, and Panel B shows the second step GMM results of first-difference regressions. The numbers in parentheses are *t* statistics, and *, **, *** indicate statistical significances in 1%, 5%, and 10% levels, respectively.

Table 11

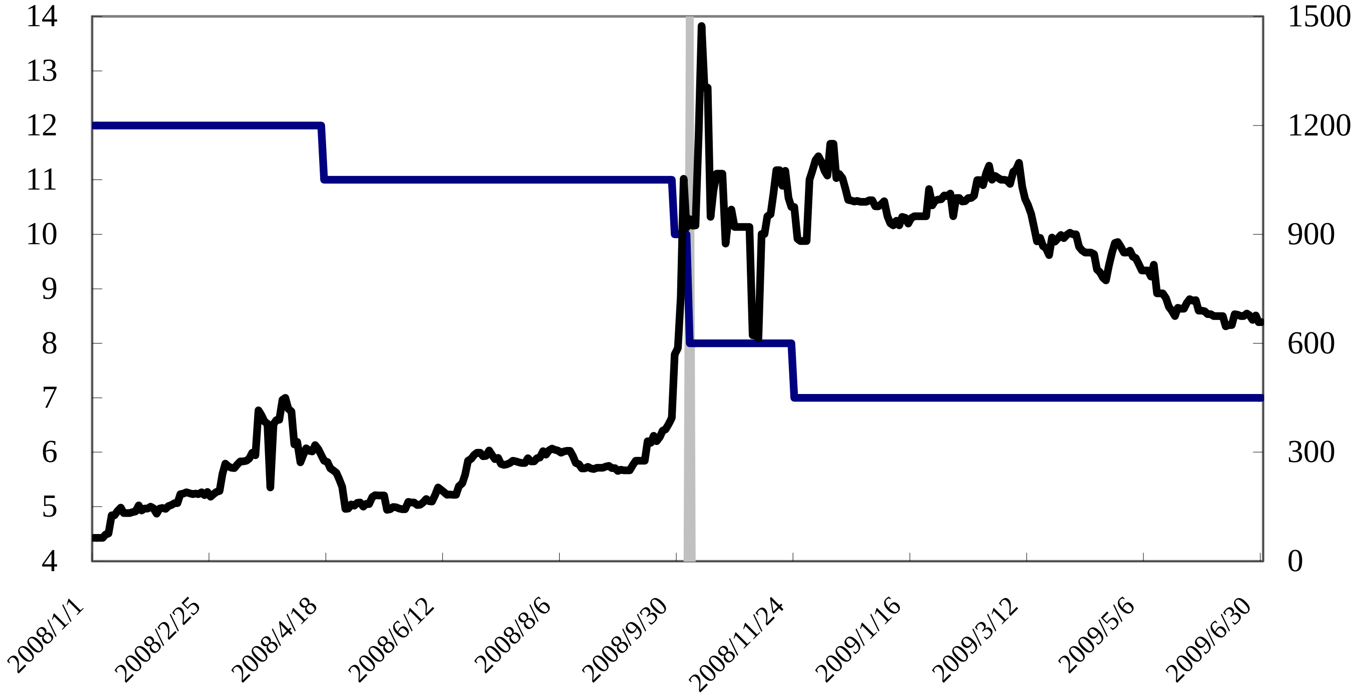
Results of Poisson Regression

	All	America	Asia	Europe	Africa	Developed	Developing
Intercept	2.4042	2.0269	2.3862	2.5237	2.1157	2.6017	2.1536
	[84,748]	[8,339]	[19,969]	[57,256]	[1,791]	[49,412]	[31,777]
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
CDS_t	-0.0019	-0.0009	-0.0025	-0.0022	-0.0005	-0.0014	-0.0013
	[1,631]	[210.96]	[595.84]	[575.39]	[4.150]	[48.35]	[688.00]
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0417)	(<0.0001)	(<0.0001)
Pearson χ^2	6,467	660	581	867	25.92	315	1,809
Log Likelihood	27,721	2,852	6,783	17,151	1,212	16,431	11,746

This table presents the estimation results of Poisson regression with credit ratings series, $Rating_t$, as the dependent variable. The numbers in brackets and parentheses are χ^2 statistics and *p*-values, respectively.

Figure 1

Series of Credit Rating and CDS Spreads for the Republic of Iceland



This figure presents the series of credit ratings and CDS spreads for the Republic of Iceland between January 2008 and June 2009. Based on ratings issued by Standard & Poor's, the series of credit ratings (the blue line) are transferred into numerical variable according to Table 1 and follows the left hand axis. The series of CDS spreads (the black line) follows the right hand axis. The gray area indicates October 6, 2008, when the Prime Minister of Iceland, Geir H. Haarde, addressed to the nation regarding the financial deterioration of Iceland.