Spillover effects across credit spreads in Korean bond market

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Abstract

Following Diebold and Yilmaz (2009, 2012) with generalized forecast error variance decompositions, we measure spillover effects across the credit spreads of different bond ratings in Korea. The estimation results suggest that approximately 35 percent of the fluctuations in credit spreads are explained by spillover effects. We also find asymmetry in the spillover effects: a shock to a credit spread tends to spillover more strongly into lower-rated spreads than into higher rated spreads. Rolling regression and sub-sample results reveal that spillover effects are stronger during the period of financial crisis.

Keywords: spillover effect, credit spread, generalized forecast error variance decomposition

JEL Classification: G11, G12

1 Introduction

Credit rating agencies assess the creditworthiness of bond issuers and assign credit ratings to bonds. Credit spreads, defined by the difference between yields on bonds of different credit ratings, reflect risk premium asso-

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ciated with probability of future default or liquidity. Fluctuations in credit spreads, therefore, are known to be market assessment for future economic activity and widely used for empirical factor in asset pricing models.[3]

In empirical studies, credit spread is often defined by the difference between yield on BBB-rated bond and yield on government bond. The credit spread defined in this way, however, can be broken down into several subdivided credit spreads which have one notch difference in credit ratings. For example, the spread between AAA-rated corporate bond and government bond is the highest rated spread while the spread between BBB and AA- is the low rated spread.

These subdivided credit spreads tend to move together due to common shocks. In addition, the co-movement of credit spreads can be driven by spillover effects: shocks on a subdivided individual spread can be spilled over into other spreads of different bond ratings. Looking into the joint dynamics of the subdivided credit spreads thus provides a deeper understanding of the movements in credit spread and corporate bond market.

The purpose of this paper is to examine the spillover effects across credit spreads in the Korean corporate bond market. Following Diebold and Yilmaz (2012), we employ generalized forecasting error variance decomposition which is invariant to the variable ordering. This approach enables us to compute the spillover effect of a particular credit spread from and to other credit spreads of different ratings. In particular, we attempt to uncover the direction of spillovers by comparing the spillover effect to higher-rated bond spread and the spillover effect to lower-rated bond spread. In addition, we examine the changing magnitude and direction of the spillover effects over time. We find that the spillover effects are strengthened during the global financial crisis.

This paper is organized as follows. Section 2 describes Diebold and Yilmaz (2009, 2012)'s approach to estimate spillover effects through a generalized forecast error variance decomposition developed by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998). Section 3 presents the estimated total spillover effect and the direction of the spillovers according to credit ratings from the full sample. Section 4 examines the

3 Estrella and Mishkin (1998), Stock and Watson (2003), Gilchrist and Zakrajsek (2012) among others stressed that credit spread is a good leading indicator for future economic activity. Fama and French (1993), Hahn and Lee (2006) use credit spread as a pricing factor in explaining cross-section of stock returns.

changes in spillover effects with rolling sample regressions, structural break tests and comparisons of subsample estimation results. Section 5 concludes.

2 Methodology

Consider a vector autoregressive model,

$$X_t = \sum_{j=1}^{p} \Phi_j X_{t-j} + e_t, \tag{1}$$

where $X_t = (X_{1t}, X_{2t}, \cdots, X_{mt})'$ is an $m \times 1$ vector of credit spreads and Φ_j is $m \times m$ coefficient matrix. We assume that $\mathrm{E}(e_t) = 0$, $\mathrm{E}(e_t e_t') = \Omega$ for all t.

Under the assumption that X_t is stationary, (1) can be rewritten as the infinite moving average representation,

$$X_t = \sum_{j=0}^{\infty} A_j e_{t-j}, \tag{2}$$

where $A_j = \Phi_1 A_{j-1} + \Phi_2 A_{j-2} + \cdots + \Phi_p A_{j-p}$ and $A_0 = I_m$.

To measure the spillover effects, Diebold and Yilmaz (2012) employ generalized forecast error variance decomposition of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998). An important advantage of this approach is that it is invariant to variable ordering and thus enables us to examine directions of the spillover effects.

Assuming that e_t has a multivariate normal distribution, Pesaran and Shin obtain the generalized impulse response function by

$$GI(h) = \Omega_{jj}^{-1/2} A_h \Omega \nu_j, \tag{3}$$

where ν_j is an $m \times 1$ selection vector with unity as its j-th element and zeros elsewhere.

The generalized forecast error variance decomposition, which is used to compute spillover effects, can be derived from the generalized impulse response function. The proportion of the h-step ahead forecast error variance of X_i accounted for by the innovations of X_j is written as

$$\theta_{ij}^{0}(h)=\Omega_{ii}^{-1}\sum_{s=0}^{h}\left(\nu_i' A_s \nu_j\right)^2/\sum_{s=0}^{h}\nu_i' A_s \Omega A_s' \nu_j,\ i,\ j=1,\ 2,\ \cdots,\ m. \quad (4)$$

Since $\sum_{j=0}^{m}\theta_{ij}^{0}(h)\neq 1$, each entry of $\theta^{0}(h)=\left[\theta_{ij}^{0}(h)\right]$ is normalized by the row sum as

$$\theta_{ij}(h)=\theta_{ij}^{0}/\sum_{j=0}^{m}\theta_{ij}^{0}. \quad (5)$$

Now, we have $\sum_{j=1}^{m}\theta_{ij}(h)=1$ and $\sum_{i,j=1}^{m}\theta_{ij}(h)=m$, implying that each row sum of $\theta(h)$ is one and the total sum of the elements in $\theta(h)$ equals the number of the variables in the system.

Diebold and Yilmaz (2012) define the total spillover index as the ratio of the sum of off-diagonal elements to the sum of all the elements in the matrix of $\theta(h)$. It measures the contribution of shocks across different credit spreads to the total forecast error variance.

$$\text{Total Spillover Index}=\frac{\sum_{i,j=1,i\neq j}^{m}\theta_{ij}}{\sum_{i,j=1}^{m}\theta_{ij}}\times 100. \quad (6)$$

As the generalized variance decomposition is invariant to the variable ordering, Diebold and Yilmaz also calculate directional spillovers. The spillover effect to X_i from all other credit spreads X_js can be written as

$$SI(i,\ .)=\frac{\sum_{j=1,j\neq i}^{m}\theta_{ij}}{\sum_{i,j=1}^{m}\theta_{ij}}=\frac{\sum_{j=1,j\neq i}^{m}\theta_{ij}}{m}$$

Similarly, the spillover effect from X_i to all other credit spreads X_js is

$$SI(.,\ j)=\frac{\sum_{i=1,i\neq j}^{m}\theta_{ij}}{\sum_{i,j=1}^{m}\theta_{ij}}=\frac{\sum_{i=1,i\neq j}^{m}\theta_{ij}}{m}$$

Given the directional spillover effects, the net spillover effect of X_i can be calculated by the difference of the spillovers to X_js and the spillovers from X_js.

Net spillover effect $= SI(.,\ i)-SI(i,\ .)$

3 Empirical results for the full sample

3.1 Data

We use the bond yield data with the same maturity (3-year) but different credit ratings compiled by KIS pricing. The data include yield on Korean government bond (GB) and yields on eight corporate bonds (AAA, AA+, AA, AA-, A+, A, A-, BBB+). The Korean government bond is of the highest quality with lowest credit risk and thus regarded as effectively credit-risk-free. (AAA)-rated bond is the second lowest credit risk one while (BBB+)-rated bond is the riskiest bond in the data.

The credit spreads are defined by the difference between yields on bonds of one notch difference in credit ratings. For example, X_1 is the spread between yields on AAA-rated corporate bond and government bond and X_2 is the spread between yields on (AA+)-rated and AAA-rated bonds. X_8 is the yield spread between (BBB+)-rated and (A-)-rated corporate bonds. Thus, X_1 is the yield spread between highest-rated bonds while X_8 is the spread between lowest-rated bonds. The definitions of credit spreads are given in Table 1.

Table 1 . Definitions of credit spreads

	definition
X_1	(AAA)-rated bond – government bond
X_2	(AA+)-rated bond – (AAA)-rated bond
X_3	(AA)-rated bond – (AA+)-rated bond
X_4	(AA-)-rated bond – (AA)-rated bond
X_5	(A+)-rated bond – (AA-)-rated bond
X_6	(A)-rated bond – (A+)-rated bond
X_7	(A-)-rated bond – (A)-rated bond
X_8	(BBB+)-rated bond – (A-)-rated bond

The sample period is from January 3 2001 to September 10 2014. We construct weekly data by selecting Wednesday yield spreads. When spreads for Wednesday are not available due to a holiday, we select Thursday spread. If the Thursday is also a holiday, we select Tuesday spread.

Table 2 shows the summary statistics for the period from January 2001 to September 2014. First, the mean of X_8, the spread between the lowest-rated bonds(A- and BBB+), is 1.462 percent, which is much higher than means of other spreads. The mean of X_1 (spread between AAA and GB) is also high, suggesting that even the highest quality corporate bonds are exposed to substantial credit risk relative to the government bond. An interesting finding from Table 2 is that the means are quite low and almost the same for X_2, X_3, and X_4 (spreads between AAA, AA+, AA, AA-), but the mean is increasing in the credit ratings from X_5 to X_8(spreads between A+, A, A-, BBB+). The volatility of spreads, measured by standard deviation, for X_8 is also several times higher than other spreads. Skewness and Kurtosis, however, are higher for spreads between higher-rated bonds.

Table 2. Summary statistics (full sample)

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Mean	0.527	0.080	0.086	0.084	0.143	0.157	0.226	1.462
Median	0.400	0.060	0.070	0.070	0.110	0.160	0.240	1.030
Maximum	3.410	0.870	0.760	0.770	0.640	0.420	0.520	3.070
Minimum	0.130	0.010	0.020	0.030	0.030	0.030	0.030	0.280
Standard dev.	0.422	0.087	0.095	0.088	0.111	0.087	0.127	1.045
Skewness	3.014	5.394	4.825	5.234	1.933	0.800	0.045	0.342
Kurtosis	16.246	40.548	28.472	36.073	7.178	3.557	1.874	1.335

3.2 Spillover table

Table 3 reports the estimated spillover effects for the full sample period.[4] The upper-left 8×8 block in Table 3 represents the forecast error variance decompositions. Each element of this block corresponds to θ_{ij} which measures the magnitude of the spillover effect from credit spread X_j to credit spread X_i as explained in the previous section.

The rightmost column of Table 3 is the row sum of the off-diagonal elements, representing the directional spillover effect to X_i from all other credit spreads X_js. Similarly, the ninth row is the column sum of the off-diagonal elements indicating directional spillover effect from X_i to all

4 The forecasting horizon is set to be five weeks. We include two lagged variables in the VAR model following Schwarz information criterion.

other credit spreads X_js. Numbers in parentheses in the ninth row denote the ratios of the off-diagonal column sums to the total (diagonal and off-diagonal) column sums. The bottom row of Table 3 is the net spillover, which is the difference between the column sum in the ninth row and the row sum in the rightmost column. The total spillover index appears in the lower right corner of Table 3. It is the ratio of the total off-diagonal column sum (or row sum) relative to the total column sum (or row sum).

Table 3. Spillover table (full sample)

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	From others
X_1	0.60	0.13	0.06	0.10	0.05	0.01	0.03	0.02	0.40
X_2	0.12	0.63	0.09	0.05	0.06	0.03	0.02	0.00	0.37
X_3	0.05	0.14	0.53	0.09	0.14	0.01	0.01	0.03	0.47
X_4	0.09	0.11	0.21	0.46	0.06	0.03	0.00	0.03	0.54
X_5	0.06	0.10	0.17	0.07	0.56	0.04	0.00	0.00	0.44
X_6	0.07	0.02	0.05	0.04	0.11	0.69	0.01	0.01	0.31
X_7	0.06	0.05	0.05	0.00	0.04	0.02	0.77	0.00	0.23
X_8	0.03	0.00	0.01	0.01	0.00	0.01	0.01	0.93	0.07
To	0.49	0.56	0.64	0.36	0.46	0.14	0.08	0.10	2.82
others	(0.446)	(0.469)	(0.547)	(0.436)	(0.450)	(0.164)	(0.096)	(0.097)	(0.352)
Net	0.09	0.19	0.17	–0.18	0.02	–0.17	–0.15	0.02	

The total spillover index for the full sample period is 2.82 or 35 percent (2.82/8=0.35), implying that approximately 1/3 of the total variance of the forecast errors is accounted for by the spillovers of shocks to other credit spreads.[5] The remaining 65 percent of the total variance is explained by idiosyncratic shocks to each credit spread.[6] Considering that shocks affect interest rates with different credit ratings simultaneously, the 35 percent of the spillover index is not small.

The rightmost column of Table 3 shows that the directional spillover effect from other spreads is largest for X_4 as 54 percent of forecast error variance of X_4 is explained by other spreads. In contrast, it turns out that the spillover effect from others is smallest for X_8, the credit spread between the lowest-rated bonds. Interestingly, the magnitude of directional

5 The total (diagonal and off-diagonal) sum of the elements is equal to the number of variables.

6 We believe that the 35 percent of spillover is never small once we consider that macroeconomic news are priced simultaneously and instantaneously across the bonds of different credit ratings.

spillover effects from others exhibits a hump-shape along the credit ratings.[7] The spillover effects are increasing in credit ratings up until X_4 and then start decreasing as credit ratings get lower.

The magnitude of directional spillover effects to others, shown in the ninth row, also exhibits a hump-shape along the credit ratings. The spillover effect to others peaks at 55 percent for X_3 and dropped to a low of about 10 percent for X_7 and X_8. It is noteworthy that X_8 has the smallest spillover effects both 'from others' and 'to others'. This result suggests that the lowest-rated credit spread is determined independently relative to other credit spread.

3.3 Decomposition of total spillover index

Since the total spillover index is the sum of elements in the off-diagonal block of the matrix, we can divide the total spillover index into some partial sums of the elements based on certain criteria. This exercise of decomposition tells us more about the contribution of credit ratings on spillover effects across different credit spreads.

First, we decompose the 8×8 matrix in Table 3 into the upper-right triangular part and the lower-left triangular part. Given the ordering of the credit spreads in Table 3, an element in the upper-right triangle, θ_{ij} (i¡j), implies a spillover effect from a lower-rated credit spread, X_j, to a higher-rated credit spread, X_i. The sum of the element in the upper-right triangle relative to total sum of the elements in the matrix can be called 'low-to-high' spillover index and is expressed as

$$SI(i<j)=\frac{\sum_{i,j=1,i<j}^{m}\theta_{ij}}{\sum_{i,j=1}^{m}\theta_{ij}}\times 100.$$

In a similar way, an element in the lower-left triangle, θ_{ij}(i¿j), means a spillover effect from a higher-rated spread, X_j, to a lower-rated credit spread, X_i. This can be called 'high-to-low' spillover index which is written as

7 One possible explanation is that medium-rated bond divides the bonds into high quality and low quality bonds and investors are more sensitive to fluctuations in the medium-rated bond yield. Thus, marginal effects of idiosyncratic shocks can be larger for medium-rated spread which leads to a hump-shaped spillover.

$$SI(i>j)=\frac{\sum_{i,j=1,i>j}^{m}\theta_{ij}}{\sum_{i,j=1}^{m}\theta_{ij}}\times 100.$$

Comparing the magnitude of these two spillover indexes, 'low-to-high' and 'high-to-low', we can determine the overall direction of spillovers along the credit ratings. When 'low-to-high' spillover effect is larger than 'high-to-low' effect, a shock to a credit spread X_i tends to spill-over more strongly into the higher-than-X_i-rated spreads rather than lower-than-X_i-rated spreads.

Second, we classify the credit spreads into the spreads of high grade bonds and the spreads of low grade bonds. In this paper, the high grade bonds include government bonds, AAA-rated bonds, and AA-rated bonds, while the low grade bonds are A-rated and BBB-rated bonds. Given this classification, we can partition the 8×8 matrix of forecast error variance in Table 3 to four 4×4 submatrices according to credit ratings. The first partitioned submatrix is the upper-left 4×4 matrix. The off-diagonal elements of this submatrix, θ_{ij}, $1\leq i\leq 4$, $1\leq j\leq 4$, $i\neq j$, represent the spillover effects within the four credit spreads of high grade bonds. The second submatrix is the lower-right 4×4 submatrix, of which off-diagonal elements, θ_{ij}, $5\leq i\leq 8$, $5\leq j\leq 8$, $i\neq j$, reflect the spillover effects within low grade spreads. The elements in the upper-right (lower-left) submatrix indicate the spillover from low (high) grade spreads to high (low) grade spreads.

Table 4 presents the decomposed total spillover index. Because the number of elements of the partitioned matrices is not the same, the average values of the elements are also reported in parentheses. In panel A, we find that 'low-to-high' spillover index is 13.8 percent and 'high-to-low' spillover index is 21.4 percent.[8] This result suggests that the spillover effects from higher-rated spreads are stronger than the spillover effects from lower-rated spreads. Panel B provides the decomposition of total spillover index based on the grade of bonds. The result shows that spillover effects are relatively stronger within the high grade spreads, accounting for about 44 percent of the total spillover index. The spillover effects from high grade spreads to low grade spreads are also strong. In contrast, the spillover effects within low grade spreads and from low to high grade spreads are relatively weak.

8 The sum of the 'low-to-high' effect and the 'high-to-low' effect is equal to the total spillover index.

Table 4. Decomposition of spillover effects

Panel A	
Low-to-High	0.138 (0.040)
High-to-low	0.214 (0.061)
Panel B	
Within high grade	0.154 (0.103)
From low grade to high grade	0.067 (0.033)
From high grade to low grade	0.101 (0.051)
Within low grade	0.030 (0.020)

4 Changes in the spillover effects

4.1 Rolling regression

Diebold and Yilmaz (2009, 2012) assess the stability of the total spillover index to find that spillovers across different financial markets are stronger during the periods of financial turmoil. Following Diebold and Yilmaz, we also examine whether the spillover effects across credit spreads are stable over time. To do this, we estimate the models using 2-year (104 weeks) rolling samples to construct a time series of the total spillover indexes.

Figure 1. Total spillover indexes from rolling regressions

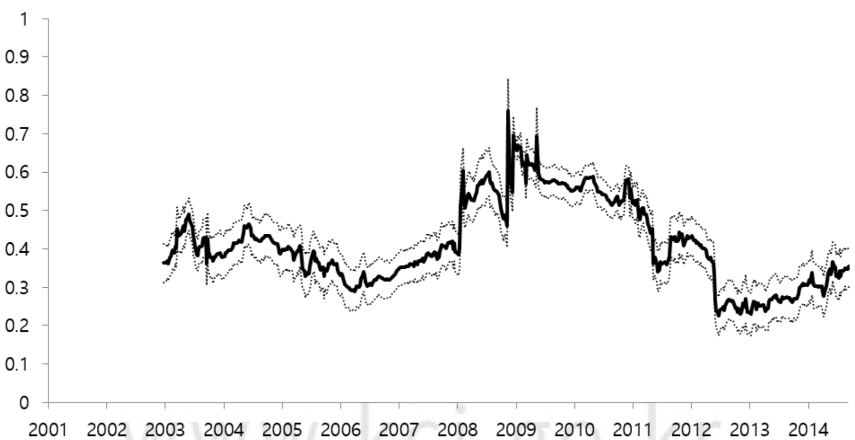


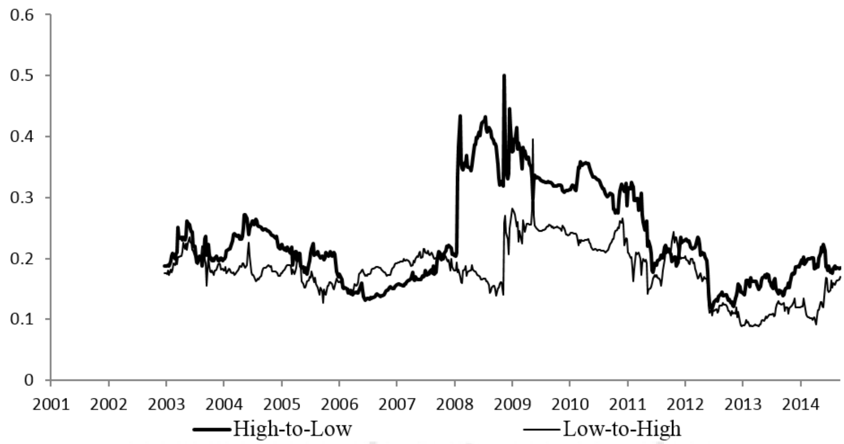
Figure 1 illustrates the time series of the total spillover indexes from 2-year rolling regressions. The dates in the x-axis are the last observations in each rolling sample. Overall, the total spillover index is relatively stable between 0.3 and 0.5 until 2007 but jumps to 0.6 in early 2008 and then jumps again to over 0.7 in late 2008.[9] Since then the total spillover index has declined back to the pre-crisis level.

In the previous section, the total spillover index was decomposed into 'low-to-high' spillover index and 'high-to-low' spillover index. In the 2-year rolling regression, we also construct the time series of the 'low-to-high' and the 'high-to-low' spillover indexes. Figure 2 depicts the two directional spillover effects.

Until 2007, 'high-to-low' spillover index fluctuates below 0.3 but suddenly jumps to 0.6 in early 2008 and 0.75 in late 2008 before it decreases to hit the bottom of 0.12 percent in mid-2012. Overall, the 'high-to-low' index goes hand in hand with the total spillover index, explaining most of the large swings of total spillover index.

In contrast, the 'low-to-high' spillover effect has been relatively stable over the entire sample period. Although 'high-to-low' effect is skyrocketed in 2008, the 'low-to-high' effect was low and even decreasing. The 'low-to-high' index jumps at the end of 2008 but not exceed 0.3 except for the very short period in mid-2009.

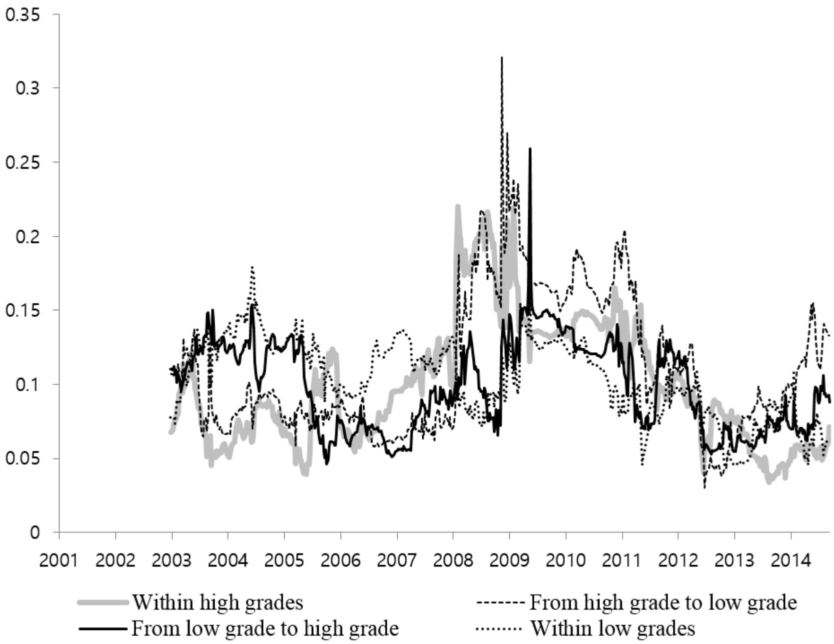
Figure 2. 'High-to-low' and 'low-to-high' spillovers



9 Peng and Ng(2012) report that crashes are easier to transmit during financial turmoil.

Figure 3 shows the decomposed spillover index based on the grades of bonds. Consistent with Figure 2, both the spillover effects within high grades and the spillover effect from high grades to low grades increase rapidly in 2008 and early 2009. Meanwhile, the spillovers within low grades and the spillover effects from low grades to high grades remain relatively stable during the entire sample period.

Figure 3. Spillovers based on the grades of bonds



4.2 Tests for structural break

Rolling sample regressions in Figure 1, Figure 2, and Figure 3 strongly indicate that spillover effect may not be stable over time. To investigate this issue in a more formal way, we employ Bai and Perron (2003) procedure to test for structural breaks in the estimated spillover index. Bai and Perron procedure starts with double maximum tests (unweighted UDmax test and weighted WDmax test) for the null hypothesis of no structural break versus an unknown number of structural changes. Once the null hypothesis is rejected, the next step in the procedure is to determine the number of structural breaks. Bai and Perron propose a test for the null hypothesis of l changes against the alternative hypothesis of l+1 breaks, labelled SupF˙T (l+1|l). A sequential application of this test, starting from SupF˙T (2|1), allows us to identify the number of structural changes in the time series.

Table 5 reports the Bai-Perron test statistics with 5% critical values and Table 6 presents the estimated break dates. Both UDmax and WD-max test statistics strongly reject the null hypothesis of no structural changes for total spillover index. Given these test results, we sequentially conduct SupF˙T (l+1|l) tests. The SupF˙T (2|1) test result suggests that there exist more than single structural break in the total spillover index. The SupF˙T (3|2) test statistics, however, cannot reject the null hypothesis of two structural breaks. From these results, we conclude that the total spillover index has two structural break dates, which are January 16 2008 and May 4 2011.

Bai-Perron test results also indicate two structural breaks in both the 'low-to-high' and the 'high-to-low' spillover indexes. The estimated break dates, however, are not the same between two indexes. The break dates for 'high-to-low' index are January 16 2008 and April 6 2011 which are almost identical to the break dates for the total spillover index. The break dates for 'low-to-high' are, in contrast, November 5 2008 and March 14 2012, which are one year after the 'high-to-low's break dates. Bai-Perron test also shows that the 'within high grade' and the 'from high grade to low grade' spillover indexes have two structural breaks, but the 'from low grade to high grade' and the 'within low grade' indexes have only one break, broadly consistent with Figure 3.

Table 5. Bai-Perron test result for the total spillover index

	UDmax	WDmax	SupF˙T (2|1)	SupF˙T (3|2)
Total spillover index	66.46	114.28	16.82	4.26
Low-to-High	49.46	73.90	14.67	1.93
High-to-low	56.35	109.17	37.05	0.73
Within high quality	65.17	143.01	15.63	3.81
From low quality to high quality	112.35	161.74	12.78	4.63
From high quality to low quality	43.69	95.87	3.12	–
Within low quality	21.92	35.11	4.43	–
5% critical values	(8.88)	(9.91)	(10.13)	(11.14)

Table 6. Estimated break dates of spillover indexes

Spillover index	Break dates
Total spillover index	2008.1.16, 2011.5.4
Low-to-High	2008.11.5, 2012.3.14
High-to-low	2008.1.16, 2011.4.6
Within high quality	2007.9.5, 2011.7.6
From low quality to high quality	2008.1.23, 2011.4.13
From high quality to low quality	2012.3.14
Within low quality	2010.10.13

4.3 Subsample results

Next, we split the full sample into three subsamples according to the structural break test results for the total spillover index. The first subsample period is from January 3 2001 to January 9 2008, the second period is from January 16 2008 to April 27 2011, and the last one is from May 4 2011 to September 10 2014. Then we estimate the VAR models and compute the spillover tables for each subsample.

Table 7, Table 8, and Table 9 report the spillover tables for three subsamples. Consistent with Figure 1, the total spillover effect is strong in the second subsample period of global financial crisis from January 2008 to April 2011. The total spillover index is relatively low at 19.2 percent 'before the crisis' period, jumps to 48.6 percent 'during the crisis' period, and declines back to 18.9 percent 'after the crisis' period.

The directional spillover effects from other spreads in the rightmost columns show quantitatively different but qualitatively similar patterns across three subsample periods. The 'from others' spillover effect is relatively large for medium-rated credit spread and relatively small for high-rated and low-rated spreads. For example, it is largest for X_7 (30 percent) followed by X_5 (28 percent) before the crisis period, for X_4 (67 percent) during the crisis period, and for X_4 (27 percent) after the crisis period.

The directional spillover effects to others, however, do not exhibit a clear pattern across the subsamples. The 'to others' effect is relatively large for medium-rated X_4 (25.6 percent) and X_6 (25.9 percent), but also large for X_7 (25.5 percent) and X_8 (25.0 percent) before the crisis period. During the crisis period, however, the 'to others' spillover effect is largest for X_1 (58.6 percent). After the crisis period, X_6 has the largest 'to others' spillover effect.

Table 7. Spillover table (2001.1.3-2008.1.9)

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	From others
X_1	0.89	0.01	0.01	0.02	0.00	0.01	0.02	0.04	0.11
X_2	0.01	0.85	0.01	0.01	0.01	0.10	0.00	0.01	0.15
X_3	0.00	0.01	0.85	0.09	0.01	0.01	0.03	0.00	0.15
X_4	0.01	0.01	0.07	0.77	0.03	0.01	0.08	0.01	0.23
X_5	0.01	0.02	0.01	0.06	0.72	0.04	0.02	0.12	0.28
X_6	0.02	0.00	0.00	0.03	0.01	0.87	0.02	0.03	0.13
X_7	0.02	0.03	0.01	0.04	0.02	0.12	0.70	0.05	0.30
X_8	0.04	0.00	0.00	0.01	0.06	0.01	0.07	0.80	0.20
To	0.11	0.09	0.11	0.27	0.14	0.31	0.24	0.27	1.54
others	(0.107)	(0.095)	(0.119)	(0.256)	(0.167)	(0.259)	(0.255)	(0.250)	(0.192)
Net	0.00	-0.06	-0.04	0.04	-0.13	0.18	-0.06	0.07	

Table 8. Spillover table (2008.1.16-2011.4.27)

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	From others
X_1	0.59	0.16	0.02	0.07	0.05	0.04	0.06	0.01	0.41
X_2	0.22	0.57	0.02	0.05	0.05	0.04	0.04	0.02	0.43
X_3	0.08	0.08	0.43	0.03	0.11	0.03	0.08	0.17	0.57
X_4	0.15	0.15	0.07	0.33	0.04	0.04	0.11	0.09	0.67
X_5	0.08	0.05	0.16	0.05	0.44	0.02	0.05	0.15	0.56
X_6	0.13	0.04	0.04	0.04	0.13	0.54	0.05	0.01	0.46
X_7	0.14	0.03	0.12	0.04	0.10	0.06	0.48	0.03	0.52
X_8	0.02	0.08	0.07	0.03	0.04	0.02	0.01	0.73	0.27
To	0.83	0.58	0.51	0.31	0.53	0.24	0.41	0.49	3.89
others	(0.586)	(0.505)	(0.543)	(0.480)	(0.544)	(0.305)	(0.460)	(0.401)	(0.486)
Net	0.42	0.15	-0.06	-0.36	-0.03	-0.22	-0.11	0.22	

Table 9. Spillover table (2011.5.4-2014.9.10)

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	From others
X_1	0.83	0.03	0.01	0.00	0.08	0.01	0.00	0.03	0.17
X_2	0.07	0.89	0.01	0.01	0.00	0.00	0.02	0.00	0.11
X_3	0.06	0.02	0.84	0.01	0.01	0.03	0.02	0.01	0.16
X_4	0.03	0.04	0.01	0.73	0.03	0.14	0.01	0.01	0.27
X_5	0.04	0.01	0.00	0.13	0.77	0.03	0.01	0.01	0.23
X_6	0.02	0.01	0.02	0.07	0.01	0.82	0.04	0.01	0.18
X_7	0.00	0.02	0.00	0.01	0.02	0.11	0.80	0.05	0.20
X_8	0.06	0.02	0.02	0.02	0.00	0.01	0.05	0.81	0.19
To	0.29	0.15	0.08	0.26	0.15	0.32	0.15	0.11	1.52
others	(0.260)	(0.142)	(0.084)	(0.261)	(0.165)	(0.282)	(0.162)	(0.125)	(0.189)
Net	0.12	0.03	–0.08	–0.01	–0.07	0.14	–0.05	–0.08	0.00

Table 10 reports the decomposition of total spillover index for three subsamples. Panel A shows that both 'low-to-high' and 'high-to-low' spillover indexes are higher during the period of the financial crisis than other sample periods. Comparing 'low-to-high' and 'high-to-low' indexes, we find that 'high-to low' effect is higher than 'low-to-high' effect only in the second sample period of 'during the crisis.' Before and after the crisis, the two spillover effects are low and not much different from each other. Before the crisis period, the 'low-to-high' spillover is even slightly higher than 'high-to-low'.

We can also confirm these findings in Panel B. All the decomposed spillover indexes increase during the crisis period and decrease after the crisis period. During the crisis period, within high grade and from high grade to low grade spillovers are relatively strong. Before and after the crisis period, however, there is no evidence that these two spillover indexes are relatively higher. Indeed, within low grade spillover effect is even stronger than other directional effects before the crisis period and there are no significant differences among the four spillover effects after the crisis period.

Table 10. Decomposition of spillover effects

	2001.1.3-2008.1.9	2008.1.16-2011.4.27	2011.5.4-2014.9.10
Panel A			
Low-to-High	0.100 (0.029)	0.205 (0.059)	0.079 (0.023)
High-to-low	0.091 (0.026)	0.281 (0.080)	0.110 (0.032)
Panel B			
Within high grades	0.032 (0.022)	0.138 (0.092)	0.038 (0.025)
From low grade to high grade	0.047 (0.023)	0.122 (0.061)	0.052 (0.026)
From high grade to low grade	0.040 (0.020)	0.141 (0.070)	0.059 (0.029)
Within low grades	0.073 (0.049)	0.085 (0.057)	0.041 (0.028)

5 Concluding remarks

Spillover effects across financial markets have been of great concern to market participants. Measuring spillover effects, therefore, is important to understand the interconnectedness of the markets and the co-movement of asset prices. Following the approach of Diebold and Yilmaz with generalized forecast error variance decompositions, this paper estimates spillover effects across the credit spreads of different ratings in Korea.

Empirical results suggest that approximately 35 percent of the fluctuations in credit spreads are explained by spillover effects. We also find asymmetry in the spillover effects. A shock to a credit spread tends to spillover more strongly into lower-rated spreads than into higher rated spreads. Empirical results also suggest that spillover effects are strong during the period of financial crisis, consistent with previous research.

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