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Abstract

The purpose of the paper is to show how widening credit spreads in "unstable periods" influence the primary markets, the lending markets, and production activities, in comparison with stable periods. The MS-SBVAR identifies the 2008 global financial crisis and the 2011 great East Japan earthquake as unstable periods. During unstable periods, negative shocks influence industrial activities and bond issuance, while outstanding loans are affected by positive shocks, which results from the banks in Japan remaining their financial health. In addition, marginal research is conducted, using a "modified credit spread," which eases the excess impact of the great East Japan earthquake on credit spreads. It is confirmed that the results are constant, although the regime of the disturbance terms corresponds to other events.

1 Introduction

Financial systems play a primary role in the economy. In particular, corporate bonds, along with the direct finance market, have been growing in Japan. The corporate bond market consists of the primary market, where firms issue bonds, and the secondary market, where institutional investors trade bonds.

However, the financial system may not function well during "unstable periods." For instance, a financial crisis might alter the economic fundamentals. The studies about the global financial crisis suggest that the responses of the financial systems and the production sectors might differ. Regarding bank lending, Bassett, et al. (2014) observed that a worsening credit supply reduced real GDP and U.S. lending. In the production sector, Caldara, Dario, et al. (2016), suggested that in the case of a global financial crisis, financial and economic uncertainty contributes to a drop in industrial production and in stock prices. Additionally, Naifar (2011) reported industrial production and credit default swaps as an indicator of default risk from 2006 to 2009 has highly negative-correlation only during the 2008 financial crisis in Japan.

An "unstable period" in the paper is defined as when a sudden and drastic widening of credit spreads in the secondary market changes the behavior of financial systems and industrial production. Credit spreads mean the difference in yield between Japanese Governmental Bonds (JGB) and straight corporate bonds (SB) with the same maturity.

$$CS_{i,t} = SB_{i,t} - JGB_{i,t} \tag{1}$$

For each variable, i denotes maturity at time t. The few studies that discuss credit spreads in the Japanese secondary market include the following. Nakashima and Saito (2009) opined credit spreads reflect the debt-to-equity ratios, the volatility of firms' value, and the term to maturity at the firm level, and market liquidity. Shirasu (2014) documented that Japanese bond spreads are affected by credit risk, macroeconomics, market liquidity, the primary bondholders, and the issuer's liquidity. Therefore, credit spreads includes not only firms' credit situations but the whole financial condition, and widening credit spreads imply financial condition is unpreferable.

This paper aims to research the response of the primary bond, banking, and production sectors to the widening credit spreads between financially unstable periods and stable periods. To capture the difference of changes in financial sector and production sector between two periods, a Markov Switching Structural Bayesian VAR (hereafter, MS-SBVAR) is implemented to allow time variation in the multivariate time series model, and investigates relationships between corporate bond, average loan balances, and industrial production. The model was developed by Hamilton (1989), Chib (1996), and Kim and Nelson (1999). Sims,

et al. (2008) relaxed the model for the multivariate MS-SBVAR.

Our results verify that the MS-SBVAR identifies the global financial crisis and the great East Japan earthquake as unstable periods, and others as stable periods. Furthermore, different responses of variables is found to widening credit spreads between the two periods. A novelty of this paper is that observation of the responses to the shocks from Japan's primary market to the secondary market, and the MS-SBVAR identifies two static yet clearly different financial conditions in responding to credit spreads in Japan.

This paper proceeds as follows. Section 2 introduces the methodology and selects the best-fit models. Section 3 provides the estimated results and analyzes and interprets the estimated impulse response functions. Section 4 researches the secondary market responses to three variables, using a "modified credit spread" to remove the excessive impact of the 2011 earthquake on credit spreads. Section 5 provides a conclusion.

2 Methodology

2.1 Data

To discuss the state-dependent relationships between financial systems and industrial production, the following variables are used: credit spreads (CS) as a secondary market and financial stress indicator, outstanding of straight bonds (SB) as a primary market indicator, average loan balances (LV) as a banking sector indicator, and the index of industrial production (IIP) as a production sector indicator. The data sample runs from January 2000 to June 2017. The data frequency is monthly, and details of data follows:

- Industrial production (IIP): the logarithm of the seasonally adjusted industrial production (May, 2010 =100) (Source: Ministry of Economy and Industry)
- Average loan balance (LV): the logarithm of banks' and credit unions' average loan balances (Source: Bank of Japan)
- Outstanding straight bonds (SB): the logarithm of outstanding straight bonds (Source: Japan Securities Dealers Association)
- Credit spreads (CS): 1-year A-rated credit spreads, rated by Rating & Investment Information (Source: Japan Securities Dealers Association)

2.2 Model

A class of MS-SBVAR models, developed by Sims, et al. (2008), is the following structural VAR models that allows structural shocks and coefficients to change independently in accordance with unobserved state

variables:

$$y_t' A_0\left(s_t^c\right) = \sum_{i=1}^{\rho} y_{t-i}' A_i\left(s_t^c\right) + C\left(s_t^c\right) + \epsilon_t' \Xi^{-1}\left(s_t^v\right) \tag{2}$$

- y denotes $n \times 1$ vector of endogenous variables.

  In this paper, MS-SBVAR orders $y \equiv [IIP, LV, SB, CS]'$, discussed further in the later identification section. ρ stands for lag length.

- $A_0\left(k\right)$: $n \times n$ matrix of parameters, describing contemporaneous relationships between the elements of y_t.

- $A_i\left(k\right)$: $n \times n$ regular matrix of the endogenous variables.

- ϵ_t: $n \times n$ unobservable disturbance terms

- $\Xi\left(k\right)$: $n \times n$ diagonal matrix

- $s_t = (s_t^c, s_t^v)$: composite Markov process with s_t^c and s_t^v as independent regime variable. Both are latent variables. s_t^v corresponds to variances in the disturbance term, and s_t^c corresponds to the constant term and coefficients.

- $q_{i,j}$: probability of s_t=i and s_{t+1}=j

  s_t evolves according to a first-order Markov process with the following state probabilities:

$$q_{i,j} = Pr\left(s_t = i | s_{t-1} = j\right)\left(q_{i,j} \geq 0 \sum_{i \in H} q_{i,j} = 1\right)$$

- Q: Markov transition matrix

  The general form is expressed as follows:

$$Q = \left(q_{i,j}\right)_{i \in H} = \begin{bmatrix} q_{1,1} & \left(1-q_{2,2}\right)/2 & \cdots & 0 & 0 \\ 1-q_{1,1} & q_{2,2} & \ddots & \vdots & \vdots \\ 0 & \left(1-q_{2,2}\right)/2 & \ddots & \left(1-q_{k-1,k-1}\right)/2 & 0 \\ \vdots & \vdots & \ddots & 1-q_{k-1,k-1} & 1-q_{k,k} \\ 0 & 0 & \cdots & \left(1-q_{k-1,k-1}\right)/2 & q_{k,k} \end{bmatrix} \tag{3}$$

In our estimation[1], VAR imposes two assumptions, identification and normalization. Identification is the restriction on the contemporaneous coefficient matrix A_0 to understand the relationships among endogenous variables. The Choleski decomposition is used on a variance-covariance matrix in this paper, and A_0 is set as an upper triangular matrix. Recursive identification schemes, including the Choleski decomposition, assume that variables are ordered, along with exogeneity of variables. For instance, the variable ordered first is

[1]Results are estimated by "ms-sbvar," based on Sims, et al. (2008), using Dynare open software. For the estimation, the codes of Lhuissier (2017) is referred, available on his homepage (http://www.stephanelhuissier.eu).

assumed to be contemporaneously uncorrelated to all other variables in an upper triangular matrix A_0. This paper orders IIP, LV, SB, CS for the following reasons:

- Credit Spreads(CS): Credit spread, which responds simultaneously to all other variables, is ordered last, because it is forward-looking and includes information about the future economy.
- Outstanding Straight Bonds (SB) and Average Loan Balance (LV): In general, firms raise funds by issuing bonds or by borrowing from banks. Hosono, et al (2013) verifies a hold-up hypothesis between lending and bond issuance in Japan. Because of imperfect contracts, banks exclusively hold information about borrowers and exploit firms' profits when the hypothesis is verified. Therefore, firms prefer issuing bonds under this condition, and LV orders before SB.
- Industrial Production (IIP): Following Leeper, et al (1996), the production sector does not respond contemporaneously with other variables and, therefore, orders first in our model.

Secondary, normalization is required. Waggoner and Zha(2003) point out that incorrect normalization on VAR leads to a misinterpretation of the impulse response function analysis. To prevent this problem, this paper imposes $diag\left(A\left(s_t\right)\right) > 0$, where $diag\left(X\right)$ describes the diagonal of matrices in X.

2.3 Model Selection

In this paper, the best-fit model is compared among several models, using the marginal data density (hereafter, MDD) as the criteria. The MDD, a likelihood function, integrates whole parameters, as in the following equation:

$$p\left(Y_T\right) = \int p\left(Y_T|\theta\right) p\left(\theta\right) d\theta \tag{4}$$

$p\left(Y_T|\theta\right)$ is a likelihood function and $p\left(\theta\right)$ is prior. The larger value of the likelihood function is preferable. Chib's (1995) method is employed for constant parameter modeling and Sims, et al (2008) for time-variant models (see the Appendix for details). For the first step, the lag order of MS-SBVAR is chosen, using time-invariant model $M_{constant}$. Table 1 reports MDD of $M_{constant}$ with each lag. $\rho = 3$ and $\rho = 4$ shows the largest MDD. $\rho = 3$ is selected to reduces the cost of calculation. Next, various models with $\rho = 3$ are estimated. Table 2 reports each MDD of various time-variant models. Compared to the time-invariant model, time-variant models improve MDD by more than 10. M_{2c2v} has the largest MDD among the models and it is selected as the best fit.

Table 1: MDD of $M_{constant}$ with Each Lag

ρ	3	4	5	6	7
log MDD	2729.7	2729.7	2708.6	2687.8	2679.1

Table 2: MDD of Time-Variant Models with ρ=3

Model	Description	Log MDD
M_{1c1v}	Time-invariant model	2729.7
M_{1c2v}	2-regimes in shock variances	2862.7
M_{1c3v}	3-regimes in shock variances	2920.5
M_{2c2v}	2-regimes in all equation coefficients and 2-regimes in shock variances	2924.7
M_{2c3v}	2-regimes in all equation coefficients and 3-regimes in shock variances	2898.9

3 Estimated Results and Analysis

3.1 Posterior Distribution

Figure 6, 7 shows the estimated probabilities from the best fit M_{2c2v}. The generated probabilities are smoothed by Kim's (1994) method. In this section, we arbitrarily segregate each regime for analysis. Probabilities in Figure 6, 7 are clearly equal to either 1 or 0. Statistically speaking, the regimes are clearly identified. $s_t^c = 1$ corresponds to the coefficients, and $s_t^v = 2$ corresponds to the variance of disturbance term, showing high probabilities in two periods from January 2008 to January 2009, and from March 2011 to August 2011. The former is the time of the global financial crisis, and the latter is the time of the great East Japan earthquake.

$$A_0(s_t^c = 1) = \begin{bmatrix} 202.11 & -6.50 & 14.98 & 11.39 \\ 0 & 387.15 & 48.43 & -30.51 \\ 0 & 0 & 366.94 & -35.72 \\ 0 & 0 & 0 & 24.42 \end{bmatrix} \quad A_0(s_t^c = 2) = \begin{bmatrix} 54.99 & 21.88 & -83.62 & -12.52 \\ 0 & 526.21 & -204.78 & -259.44 \\ 0 & 0 & 441.76 & 193.22 \\ 0 & 0 & 0 & 44.50 \end{bmatrix}$$

The contemporaneous coefficient matrix $A_0(s_t^c)$ is reported above for both stable and unstable periods. Coefficients, beginning in the left column, list IIP, LV, SB, and CS equations. The absolute value of the coefficients in the equation of CS in unstable periods are larger than in a stable period, which indicates that the secondary market substantially responses to other variables in the unstable periods. Table 3, 4 report relative shock variance in each regime. All values in $s_t^v = 2$ except IIP in $A_0(s_t^c = 2)$ are larger than in $s_t^v = 1$. From these fact, $s_t^c = 1$ is defined as the high-coefficient-stress period, and $s_t^v = 2$ as the high-volatility period. Furthermore, the duration, in which $s_t^c = 1$ and $s_t^v = 2$ overlap, are defined as unstable period, and, $s_t^c = 2$ and $s_t^v = 1$ are defined as stable period.

Q has latent variables s_t^c and s_t^v in our model. The model is expressed as

$$Q = Q^c \otimes Q^v = \begin{bmatrix} q_{1,1}^c & 1 - q_{2,2}^c \\ 1 - q_{1,1}^c & q_{2,2}^c \end{bmatrix} \otimes \begin{bmatrix} q_{1,1}^v & 1 - q_{2,2}^v \\ 1 - q_{1,1}^v & q_{2,2}^v \end{bmatrix} \tag{5}$$

Q_c is the transition matrix which governs the coefficients and Q_v is the transition matrix which governs the

Table 3: The Relative Shock Variance $A_0\,(s_t^c = 1)$ Diagonal Components are Normalized to 1

	IIP	LV	SB	CS
$s_t^v = 1$	1.845.E-02	1.900.E-03	2.264.E-03	2.221.E-01
$s_t^v = 2$	1.903.E-02	2.706.E-03	4.132.E-03	3.003.E+00

Table 4: The Relative Shock Variance $A_0\,(s_t^c = 2)$ Diagonal Components are Normalized to 1

	IIP	LV	SB	CS
$s_t^v = 1$	4.948.E-03	2.583.E-03	2.725.E-03	4.093.E-02
$s_t^v = 2$	3.227.E-03	3.678.E-03	4.975.E-03	5.535.E-01

variance of disturbance term.

$$Q_c = \begin{bmatrix} 0.976 & 0.083 \\ 0.023 & 0.916 \end{bmatrix} \quad Q_v = \begin{bmatrix} 0.980 & 0.053 \\ 0.009 & 0.946 \end{bmatrix} \tag{6}$$

Equation 6 reports the value of the transition matrix. The probability of high stress coefficient periods ($q_{22}^c = 0.976$) is 6% lower than the probability of low stress coefficient periods ($q_{11}^c = 0.916$). The former lasts for 11.90 months, and the latter lasts for 41.66 months[2]. Regarding volatility, the probability of high volatility periods ($q_{22}^v = 0.946$) is 3.4% lower than the probability of low volatility periods ($q_{11}^c = 0.980$). The former lasts for 18.51 months, and the latter lasts for 50 months. This is consistent with the fact that unstable periods are not long-lasting.

3.2 Impulse Response

Using the impulse response, credit-spreads shocks versus other variables are analyzed in respective regimes. The impulse response functions show how one variable's shocks in one disturbance term of one variable affect other variables.

Before viewing the results, we note that our assumptions about the relationship of variables, in both stable and unstable financial situations, could be made by referring to similar studies using MS-SBVAR in Europe and in the U.S., (Hubrich and Tetlow (2015), Hartmann, et al (2015), and Lhuissier (2017)). The variables are not affected by the widening credit spreads during stable periods. In unstable periods, the variables are affected by negative shocks. Banks holding 40% of outstanding bonds in Japan might suffer a loss from a widening credit spread. Simultaneously, a widening credit spreads informs borrowers about economic conditions. In this situation, banks might take funds back from borrowers, or stop new financings. Firms are forced to cancel new issues for constraint on the primary market. Under these conditions, the macroeconomic outlook turns negative and industrial production decreases.

[2]Average duration of state i is calculated by $E\,(D_i) = \frac{1}{1-q_{ii}}$

Figure 12 reports the responses to widening credit spreads during both stable and unstable periods. Each period shows a remarkably different response. In a stable period, outstanding corporate bonds keeps increasing over the entire period. The average loan balances decline for six months after the shock, but industrial production increases during the same six-month period. During an unstable period, SB, in the short run, experiences a subtle negative shock, but this turns positive in the long run. Surprisingly, LV is positive for the first six months and remains the credible interval on the zero boundary. Industrial production plunges instantly and remains below zero for eight months. The response of variables counters our assumption from the previous studies.

Our prior assumption was that credit shocks would never affect other variables during a stable period and would decline during an unstable one. However, the impulse responses in this research display that SB and IIP are positive and LV is negative in the former case, while SB and IIP are negative and LV is positive in the latter case. In the following sections, we interpret this response in detail and investigate the cause.

3.2.1 Interpretation

The research above proves that the global financial crisis and the great East Japan earthquake are identified as unstable period. In stable period, the impulse responses in this research display that SB and IIP are positive and LV is negative. Credit spreads shocks have a positive effect on average loan balances and a negative effect on the outstanding straight bonds and industrial production during an unstable period. We now interpret these responses in detail.

Although the previous studies in Europe and in the U.S. have noted that credit spread shocks during stable periods have minimal effects to other variables, a widening credit spreads significantly affect the others in our research. This is interpreted as the result from the monetary policy that lowers JGB yields during stable periods. The changes in the JGB yields, conducted by BoJ, are greater than those in corporate bonds, then credit spreads relatively widen. Regarding the monetary policy from an issuer's viewpoint, Graham and Harvey, (2001), Bancel and Mittoo (2004), and Barry (2005) prove that the dollar amount of issues increases when yields are lower than in the past. These facts support our interpretation of the impulse response in primary market during stable periods. When fundraising is conducted by issuing bonds smoothly, firms are disincentivized to lend from banks. Additionally, industrial production is activated in stable periods when the economic outlook is favorable.

In unstable periods, our research indicates that positive shock has affected lending and negative shock

has affected corporate bond issuance for the first six months. This is because banks in Japan stay healthy and continue to lend during unstable periods. In the primary market, institutional investors are unwilling to marginally invest, and firms cut down on issuing bonds. As seen in Figure 12, the impulse response of SB is positive eight months after a credit spread shock. This is interpreted as a reverse effect, due to a strong demand from firms that had postponed issuances. In the production sector financing constraints and future declines in demand suppress production activities.

The 2008 global financial crisis and the 2011 great East Japan earthquake are captured as financial instability by the MS-SBVAR. The former was a financial crisis that originated in the U.S., and the latter was a natural disaster. Both negatively affected the production sectors and the financial markets. Although we interpreted the impulse response above, it is unsure that it is consistent with the facts. Next, we will confirm the interpretation by checking the facts.

The 2008 global financial crisis reduced firms' industrial production, which acts as a proxy variable for the production sector, fell drastically in comparison to Europe and the U.S. Imports declined by approximately 25%, mostly from Europe and from the U.S., in the first quarter of 2009. As Figure 10 shows, corporate bonds rated below "A" could not be issued. Regarding bank lending, lending increased in Japan, although Ivashina and Scharfstein (2010) documented that new financing in the fourth quarter in 2008 decreased by 47% in the U.S. compared with the previous quarter. Uchino (2011) found that banks remained financially healthy during the 2008 crisis, and that firms shifted from issuing bonds to bank borrowings.

The 2011 earthquake in Japan caused a tsunami and disabled a nuclear generator in Fukushima. Production activities ceased not only where the earthquake hit but all over Japan. Turmoil is also created in the corporate bond market. Electric power bonds accounted for 21% of the total outstanding Japanese corporate bonds in March 2011. After the earthquake, the heightened credit risk in the electric power industry widened the credit spreads for the entire market. Furthermore, the uncertain outlook for nuclear generation restrained further marginal investment in electronic power companies. As a result, the issuance of new electric power bonds was suspended for 11 months except for a few issues. Figure 11 presents the changes in long-term debt, versus electric power firms' public bond issuance. The figure indicates that the electric power sector borrowed more from financial institutions after 2011. Those changes are interpreted as the shift of fundraising method from public bond issuance to bank lending in the electric power sector.

In summary, these separate 2008 and 2011 disasters are consistent with the interpretation of estimated impulse response. The reactions from the financial and production sectors during these unstable periods

differ from their respective reactions in stable periods. Firms, locked out of the primary market, borrowed from financial institutions, along with a decline in the production sector. However, the impact of the wider credit spreads may be overstated, since the physical damage to electric power firms primarily widened the A-rated credit spreads. Therefore, our credit spreads are modified to confirm the conclusions in the next section.

4 Modified Credit Spreads

As reported in the previous section, a nuclear disaster occurred at Tokyo Electric Power Co.'s (TEPCO) Fukushima 1st Nuclear Power Plant on March 11, 2011. Before the earthquake, TEPCO was one of the largest bond issuers in Japan. TEPCO bonds totaled 4.974 trillion yen, accounting for 0.5% of Japan's total outstanding corporate bonds in 2010). The disaster raised TEPCO's yield sharply, and the company's credit rating was downgraded from AA- to A on April 7th, 2011, and to B on October 7th. Since the data is end-of-month one, TEPCO's bond existed in A-rate and might influence on whole A-rated credit for 6 months. TEPCO's impact was reflected in a credit spread. increase, from 0.408% in March, 2011 to 0.83% in April, 2011, which shrank approximately 1% when TEPCO's rating was lowered to BBB. TEPCO's situation clearly skewed all A-rated fixed-income securities. A modified credit spreads was implemented to ease TEPCO's impact. Following Okimoto and Takaoka (2017), the Thomson Reuters Bond Credit Curve[3] is applied to modify credit spreads after January 2011. CS_t^X denotes credit spreads rated by X at time t and n is sample size.

$$CS_t^{modified} = CS_t^{Reuter} + CS_t^{R\&I} \frac{1}{n} \Sigma \frac{CS_t^{R\&I} - CS_t^{Reuter}}{CS_t^{R\&I}} \tag{7}$$

The MS-SBVAR with $[IIP, LV, SB, MCS]'$ is estimated, with others constant. Figure 8, 9 displays the probability of each Markov Switching process' estimated regime from model M_{2c2v} with modified credit spread. The regime of coefficient $s_t^c = 1$ responds to the duration from May 2008 to June 2009 and from March 2011 to August 2011. By contrast, the variance of disturbance period $s_t^v = 2$ corresponds to the collapse of the IT bubble (October 2001 to January 2012); the global financial crisis (June 2008 to January 2010); the European debt crisis (April 2012 to August 2012); and implementation of quantitative and qualitative monetary easing with negative interest rates (January 2016 to September 2016). From these facts, $s_t^c = 1$ is regarded as a high-coefficient-stress period and $s_t^v = 2$ as a high-volatility period. The impulse responses in high-coefficient-stress period and low-coefficient stress period differ minimally from the original (Figure 13).

[3]The index is provided from August 2010 and bond yields are smoothed by B-spline curve

5 Conclusion

The purpose of the paper is to assess how widening credit spreads during stable and unstable periods influence primary bond markets, lending markets, and production activities. The MS-SBVAR identifies the 2008 global financial crisis and the 2011 great East Japan earthquake as unstable periods. The shocks by widening credit spread in each period are different. In a stable period, the monetary policy might widen credit spreads. Corporate bonds and industrial production see positive effects, while average loan balances decline. In unstable periods, higher credit spreads indicate unfavorable economic conditions, which negatively affect industrial activities and bond issuance. Interestingly, it is found that a widening credit spreads increased lending. In addition, the marginal research is concluded with modified credit spreads, which eases the impact of the great East Japan earthquake on financial markets. The results are constant, although the regime of the disturbance period responds to other events.

However, further research is needed. First, a financial shift from bonds to banks, which we observed during unstable periods, might not happen during times of serious financial instability. For instance, commercial banks suffering a deterioration of shareholders' equity, limited lending during the 1991- 93 collapse of Japan's real estate bubble. Production could also be affected, as it occurred. Secondary, the relationship between demand and supply in the primary market both in stable and unstable periods is unclear. In other words, our study uses limited empirical research and does not provide a theoretical interpretation. It is still open question "which is the determinants of issue amounts, whether the risk capacity of investors on the demand side, or the investment interest of issuers on the supply side." Hence, additional theoretical research is required.

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Appendix

A MS-SBVAR

A.1 Assumption for Estimation

Conditional posterior ϵ_t is assumed as

$$p\left(\epsilon_t|Y_{t-1},S_t,\theta,q\right)=normal\left(\epsilon_t|O_n,I_n\right) \tag{A-1}$$

where O_n: $n\times 1$ vector of 0, I_n: $n\times n$ identity matrix, and θ denotes all coefficients in the model without q:

$$\theta=\{A,F,\Xi\}$$

$$A=\{A\left(1\right),...,A\left(h\right)\},F=\{F\left(1\right),...,F\left(h\right)\},\Xi=\{\Xi\left(1\right),...,\Xi\left(h\right)\}$$

As disturbance terms defined above, this assumption is equivalent to

$$p\left(y_t|Y_{t-1},S_t,\theta,q\right)=normal\left(y_t|\mu_t\left(k\right),\Sigma_t\left(k\right)\right) \tag{A-2}$$

$$\mu_t\left(k\right)=\left(F\left(k\right)A^{-1}\left(k\right)\right)'x_t\quad \Sigma\left(k\right)=\left(A\left(k\right)\Xi^2\left(k\right)A'\left(k\right)\right)^{-1}$$

In short, y_t is mean values explained by coefficients and explanatory variables at t with variance of disturbance terms.

A conditional likelihood function, which follows a normal distribution (Equation A-1) with mean $\mu_t\left(k\right)$, variance $\Sigma\left(k\right)$, represents

$$p\left(y_t|Y_{t-1},S_t,\theta,q\right)=\frac{1}{\left(2\pi\right)^{\frac{n}{2}}\left|\Sigma\left(k\right)\right|^{\frac{1}{2}}}\exp\left(-\frac{1}{2}\left(y_t-\mu\left(s_t\right)\right)'\Sigma^{-1}\left(s_t\right)\left(y_t-\mu\left(s_t\right)\right)\right) \tag{A-3}$$

As n is sufficiently large, $\frac{1}{\left(2\pi\right)^{\frac{n}{2}}}\approx 1$ and the equation in exp is expanded:

$$p\left(y_t|Y_{t-1},S_t,\theta,q\right)=\left|A\left(s_t\right)\Xi\left(s_t\right)\right|\exp\left(-\frac{1}{2}\left(y_t'A\left(s_t\right)-x_t'F\left(s_t\right)\right)\Xi^2\left(s_t\right)\left(A'\left(s_t\right)y_t-F'\left(s_t\right)x_t\right)\right) \tag{A-4}$$

$$p\left(y_t|Y_{t-1},S_t,\theta,q\right)=\left|A\left(s_t\right)\right|\prod_{j=1}^{n}\left|\xi_j\left(s_t\right)\right|\exp\left(-\frac{\xi_j^2\left(s_t\right)}{2}\left(y_t'a_j\left(s_t\right)-x_t'f_j\left(s_t\right)\right)\right) \tag{A-5}$$

Hence, the overall likelihood function of Y_T is given by

$$p\left(Y_T|\theta,q\right)=\prod_{t=1}^{T}[\sum_{s_t\in H}p\left(y_t|Y_{t-1},\theta,q,s_t\right)p\left(s_t|Y_{t-1},\theta,q\right)] \tag{A-6}$$

A.1.1 Time-Variant Restriction

As estimated sample numbers and latent variables increase, computational processes exponentially swell (the curse of dimensionality). To deal with this issue, time-variant restriction is imposed as follows:

$$F\left(s_t^c\right)=G\left(s_t^c\right)+\bar{S}A\left(s_t^c\right) \tag{A-7}$$

$$\bar{S}=\left[I_n,0_{(m-n)\times n}\right]$$

$g_j\left(S_t^c\right)$ is the jth column of $G\left(S_t^c\right)$, which consists of a time varying factor $g_{\delta_j(h)}$ and a regime-independent

factor g_{Ψ_j}, are expressed by

$$diag\left(g_j\left(1\right)',..,g_j\left(h\right)'\right)=diag\left(\left[g'_{\delta_j(1)},...,g'_{\delta_j(h)}\right]'\right)diag\left(g_{\Psi_j}\right) \tag{A-8}$$

A.1.2 Identification Restriction

MS-SBVAR representing a simultaneous equation itself would not be identified without any restriction. Following Waggoner and Zha(2003), $\mathbb{R}_j\left[a_j \quad f_j\right]'=0$ is applied as linear restriction. where $\mathbb{R}_j$ is any $(n+\rho n+m)\times(n+\rho n+m)$ matrix and is not full of rank. To deal with over-parameterization, $a_j\left(k\right)$ and $f_j\left(k\right)$ are given by[4]

$$a_j\left(k\right)=U_jb_j\left(k\right) \tag{A-9}$$

$$f_j\left(k\right)=V_jg_j-W_jU_jb_j\left(k\right) \tag{A-10}$$

where U_j: $n\times$ orthonormal matrix of q_j, Vj: $(\rho n+m)\times$ orthonormal matrix of r_j, W_j: $(\rho n+m)\times n$ free parameter matrix.

Substitute Equation A-9 , A-10 into Equation A-6 and transform it to the following form:

$$p\left(y_t|Y_{t-1},S_t,\theta,w\right)=\left|A\left(k\right)\right|\prod_{j=1}^{n}\left|\xi_j\left(k\right)\right|\exp\left(\left(-\frac{\xi_j\left(k\right)}{2}\left(y_t'U_jb_j\left(k\right)-x_j'\left(V_jg_j-W_jU_jb_j\left(k\right)\right)\right)^2\right)\right) \tag{A-11}$$

$$p\left(y_t|Y_{t-1},S_t,\theta,w\right)=\left|A\left(k\right)\right|\prod_{j=1}^{n}\left|\xi_j\left(k\right)\right|\exp\left(\left(-\frac{\xi_j\left(k\right)}{2}\left(y_t'+x_j'W_j\right)U_jb_j\left(k\right)-x_j'U_jg_j\right)^2\right) \tag{A-12}$$

A.2 Settings of Priors

- The Prior of a_j,g_j follows normal distribution below:

$$p\left(a_j\left(k\right)\right)=normal\left(a_j\left(k\right)|0,\tilde{\Sigma}_{a_j}\right) \tag{A-13}$$

$$p\left(g_{\psi_j}\right)=normal\left(g_{\psi_j}|0,\tilde{\Sigma}_{g_{\psi_j}}\right) \tag{A-14}$$

Sims (1992) points out that large share of the sample period fluctuation accounts for deterministic components in multi-variate time series model without dummy observations in the prior. To confront this, Sims and Zha (1998) suggest $n+1$ dummy observations from variables, introduced in part of the prior. Let VAR model with mth equations, i any value up to m, s any value described with $j=1,...,m$, lag $l=1,.,p$ and, constant periods, dummy observation on overall equation are given by

$$Y_dA_0=X_d\left(G_\Psi+\hat{S}A\left(k\right)\right)+\hat{E}_d \quad Y_d=\left\{y\left(i.j\right)\right\},\ \ X_d=\left\{x\left(i.s\right)\right\} \tag{A-15}$$

where Y_d: $(n+1)\times n$ dummy observation matrix, X_d: $(n+1)\times m$ dummy observation matrix, G_Ψ: $(\rho n+m)\times n$ matrix comprised of g_Ψ, $\bar{E}_d$: $(n+1)\times n$ matrix.

[4]Refer to Appendix D in Sims et al.(2008) for transformation of equations and proof in detail.

Given Equation A-13 , Equation A-14 , and Equation A-15 , the prior is transformed as follows:

$$p\left(a_j\left(k\right)\right) = normal\left(a_j\left(k\right)|0, \tilde{\Sigma}_{a_j}\right) \tag{A-16}$$

$$p\left(g_{\psi_j}\right) = normal\left(g_{\psi_j}|0, \tilde{\Sigma_{g_{\psi_j}}}\right) \tag{A-17}$$

$$\bar{\Sigma}_{g_{\psi_j}} = I_{h_1} \otimes \bar{\Sigma}_g, \quad \bar{\Sigma}_g = \left(X_d' X_d + \tilde{\Sigma}_g^{-1}\right)^{-1}$$

- The Prior of g_{ψ_j}, b_j, ψ_j: linear restriction $a_j\left(k\right) = U_j b_j\left(k\right), g_{\psi_j} = \Psi_j \psi_j$ and Equation A-16 , Equation A-17 leads to

$$p\left(b_j\left(k\right)\right) = normal\left(b_j\left(k\right)|O, \bar{\Sigma}_{b_j}\right) \quad \bar{\Sigma}_{b_j} = \left(U_j' \Sigma_{a_j}^{-1} U_j\right)^{-1} \tag{A-18}$$

$$p\left(\psi_j\right) = normal\left(\psi_j|O, \bar{\Sigma}_{\psi_j}\right) \quad \bar{\Sigma}_{\psi_j} = \left(\Psi_j' \Sigma_{\psi_j}^{-1} \Psi_j\right)^{-1} \tag{A-19}$$

- The Prior of δ_j follows a normal distribution:

$$p\left(\delta_j\left(k\right)\right) = normal\left(\delta_j\left(k\right)|0, \tilde{\Sigma}_{\delta_j(k)}\right) \quad \bar{\Sigma}_{\delta_j(k)} = \sigma_\delta^2 I_{r_{\delta,j}} \tag{A-20}$$

- The Prior of ξ_j follows a Gamma distribution:

$$p\left(\xi_j^2\left(k\right)\right) = gamma\left(\xi_j^2\left(k\right)|\bar{\alpha_j}, \bar{\beta_j}\right) = \frac{1}{\Gamma\left(\bar{\alpha_j}\right)} \bar{\beta_j}^{\bar{\alpha_j}} x^{\bar{\alpha_j}-1} e^{-\beta_j x} \tag{A-21}$$

- The Prior of q_j follows a Dirichlet distribution:

$$p\left(q_j\right) = dirichlet\left(q_j|\alpha_{1,j}, ..., \alpha_{k,j}\right) = \left(\frac{\Gamma\left(\Sigma_{i\in H}\alpha_{i,j}\right)}{\prod_{i\in H}\Gamma\left(\alpha_{i,j}\right)}\right) \prod_{i\in H}\left(q_{i,j}\right)^{\alpha_{i,j}-1} \tag{A-22}$$

Following Litterman (1986), the hyperparameter of $\bar{\Sigma}_{b_j}$ is set where MDD of the constant VAR model is maximized. In an optimization of MDD, we refer to the value from previous studies.[5]

A.3 Conditional Posterior

1. $p\left(\theta|Y_T, q, S_T\right)$

   To approximate the joint posterior density $p\left(\theta, w|Y_T\right)$, alternatively sampling from the following conditional posterior:

$$p\left(b_j|y_t, S_t, b_i\left(k\right)\right) \tag{A-23}$$

$$p\left(g_j\left(k\right)|y_t, S_t\right) \tag{A-24}$$

$$p\left(\xi_j^2\left(k\right)|y_t, S_t\right) \tag{A-25}$$

[5]In estimations, hyperparameters are set to μ_1=0.70: overall tightness of the random walk prior on A_0, F, μ_2=0.30: relative tightness of the random walk prior on F, μ_3=0.1: relative tightness of random walk prior on the constant periods, μ_4=1.0: erratic sampling effects on lag coefficients, μ_5=2.0: belief about unit roots, μ_6=2.0: belief in cointegration. The prior on $\delta(i, j, s_t)$ for each i, j and s_t is set to a normal distribution with mean 0 and a standard deviation of 50. The prior on each element of the diagonal of $\Xi^2(s_t)$ is a gamma distribution, represented by Gamma$(\bar{\alpha}, \bar{\beta})$ with $\bar{\alpha} = 1$ and $\bar{\beta} = 1$.

(a) $p\left(b_j|y_t, S_t, b_i\left(k\right)\right)$

Reproduce Equation A-23 by employing the MetroPolis-Hastings method:

$$p\left(b_j|y_t, S_t, b_i\left(k\right)\right) = \exp\left(-\frac{1}{2}b_j'\left(k\right)\bar{\Sigma}_{b_j}^{-1}b_j\left(k\right)\right) \times \prod_{t\in t:s_t=k}\left[\left|A_0\left(k\right)\right|\exp\left(\left(-\frac{\xi_j\left(k\right)}{2}\left(y_t'a_j\left(k\right)-x_j'\left(k\right)\right)^2\right)\right)\right] \tag{A-26}$$

(b) $p\left(g_j\left(k\right)|y_t, S_t\right)$ Equation A-24

Generate Equation A-24 from a multi-variate normal distribution:

$$p\left(g_j\left(k\right)|y_t, S_t\right) = normal\left(g_j\left(k\right)|\tilde{\mu}_{g_j(k)}, \tilde{\Sigma}_{g_j(k)}\right) \tag{A-27}$$

(c) $p\left(\xi_j^2\left(k\right)|y_t, S_t\right)$

Generate Equation A-25 from a Gamma distribution:

$$p\left(\xi_j^2\left(k\right)|y_t, S_t\right) = gamma\left(\xi_j^2\left(k\right)|\tilde{\alpha}_j\left(k\right), \bar{\beta}_j\left(k\right)\right) \tag{A-28}$$

$$\tilde{\alpha}_j\left(k\right) = \bar{\alpha}_j + \frac{T_{2,k}}{2}$$

$$\tilde{\beta}_j\left(k\right) = \bar{\beta}_j + \frac{1}{2}\sum_{t\in t:s_{2t}=k}\left(y_t'a_j\left(s_t\right)-x_t'f_j\left(s_t\right)\right)^2$$

$T_{2,k}$ denotes $\{t : s_{2t} = k\}$

2. $p\left(S_T|Y_T, q, \theta\right)$

Due to computation costs, it is getting difficult to sample latent variable s_t at the same time with other estimation as sample size T is large. A multi-move sampler is employed in order to sample efficiently. The free parameter s_T is sampled from

$$p\left(s_t|y_t, S_t\right) = \sum_{S_{t+1}\in H} p\left(S_t|Y_T, \theta, q, s_{t+1}\right)p\left(S_{t+1}|Y_T, \theta, q\right) \tag{A-29}$$

3. $p\left(q|Y_T, S_T, q, \theta\right)$

The posterior of q_j follows

$$p\left(q_j|Y_t, S_t\right) = \prod_{i=1}^{h}\left(q_{i,j}\right)^{n_{i,j}+\beta_{i,j}-1} \tag{A-30}$$

Figure 1: A-rated One-Year Credit Spreads (Source: Datastream)

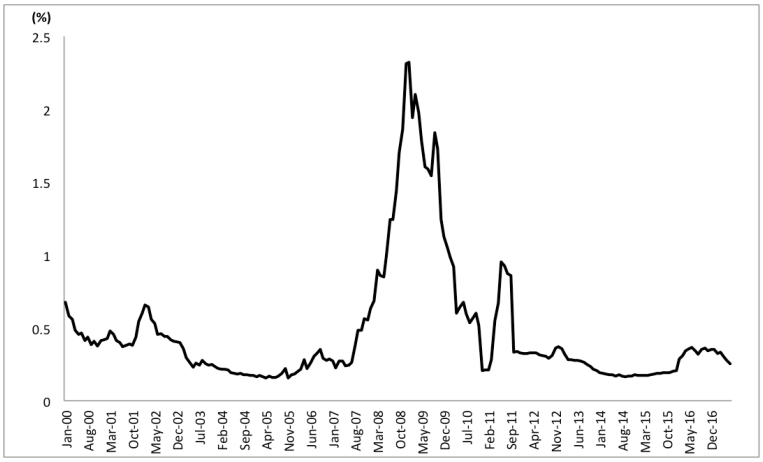


Figure 2: Outstanding of Straight Bonds (Source: Japan Securities Dealers Association)

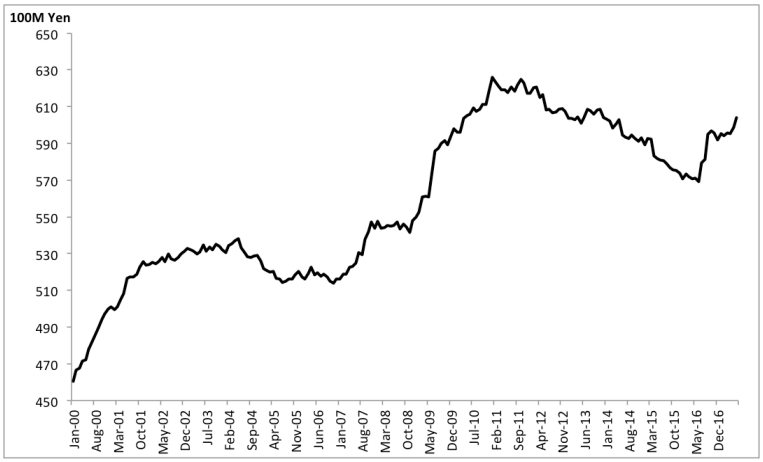


Figure 3: Average Loans Outstanding (Source: Bank of Japan)

Figure 4: Industrial Production (Source: Ministry of Economy, Trade and Industry)

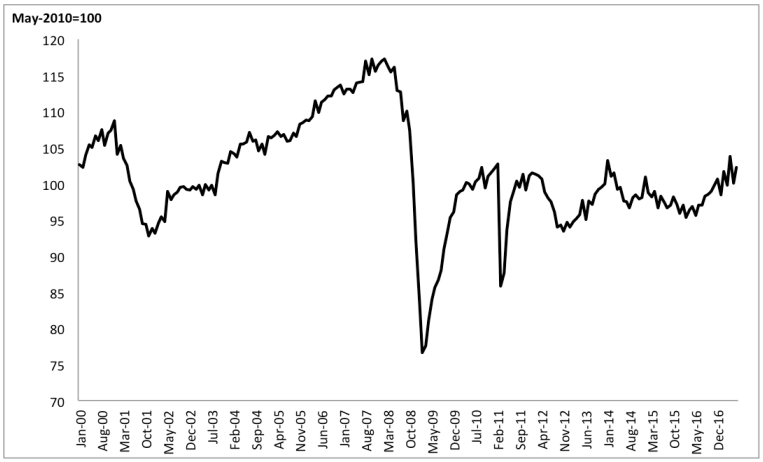


Figure 5: Modified Credit Spreads (Source: DataStream)

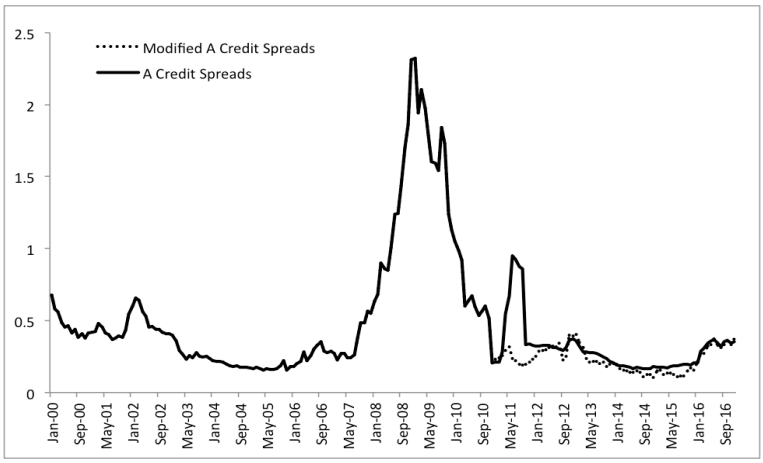


Figure 6: The Posterior s_t^v with Credit Spread

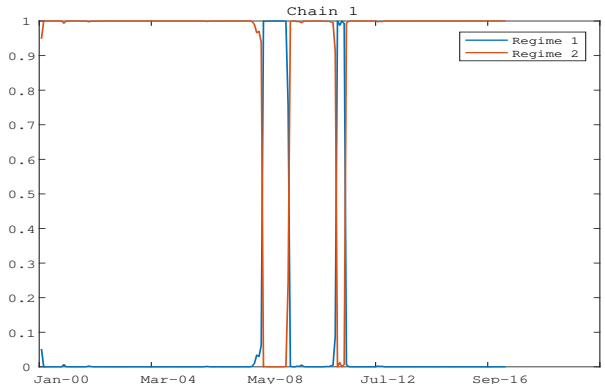


Figure 7: The Posterior s_t^c with Credit Spread

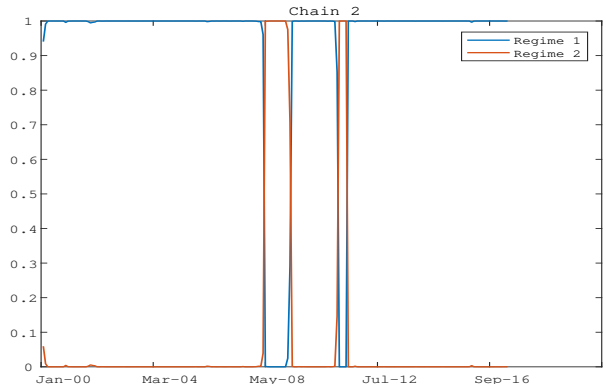


Figure 8: The Posterior s_t^v with Modified Credit Spread

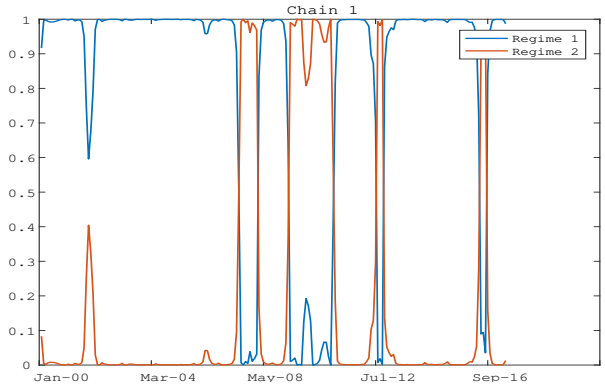


Figure 9: The Posterior s_t^c with Modified Credit Spread

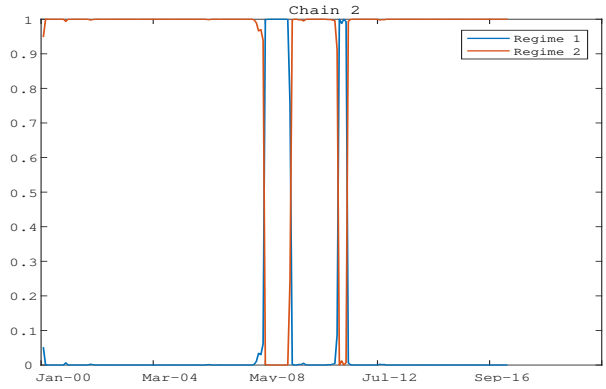


Figure 10: Amount of Issues for A-rated and BBB-rated Bonds (Source: Japan Securities Dealers Association)

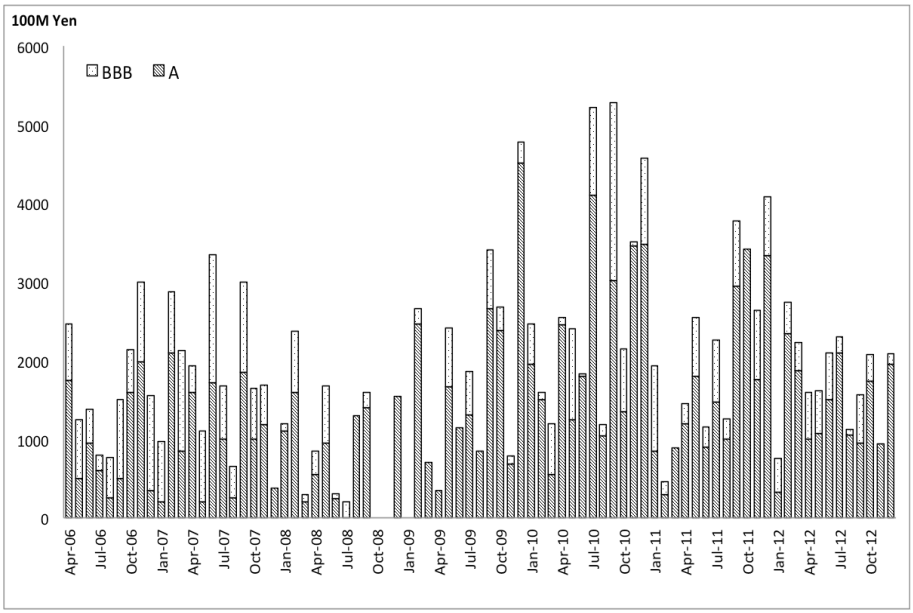


Figure 11: Changes in Issues of Electric Power Companies and Long-Term Debt from the Previous Year (Source: Japan Securities Dealers Association)

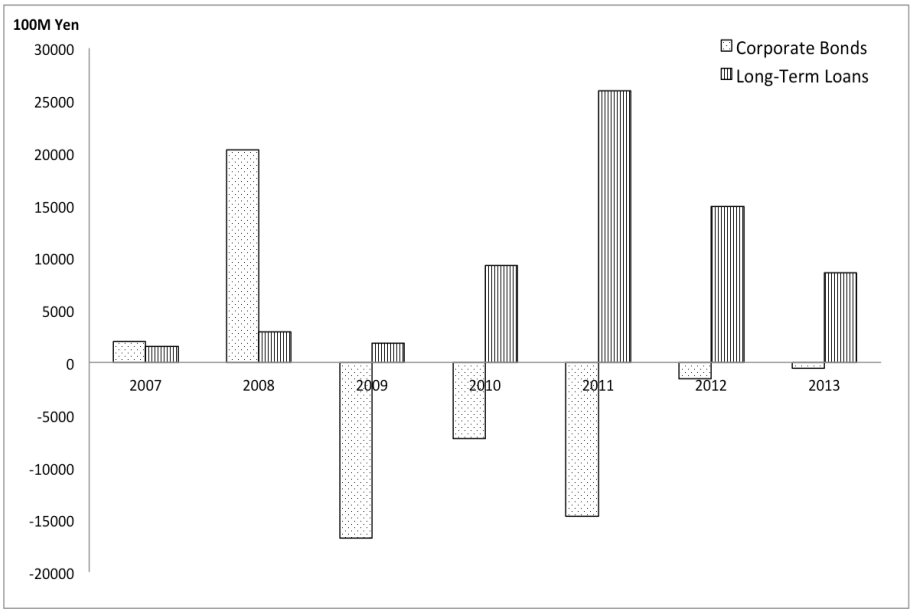
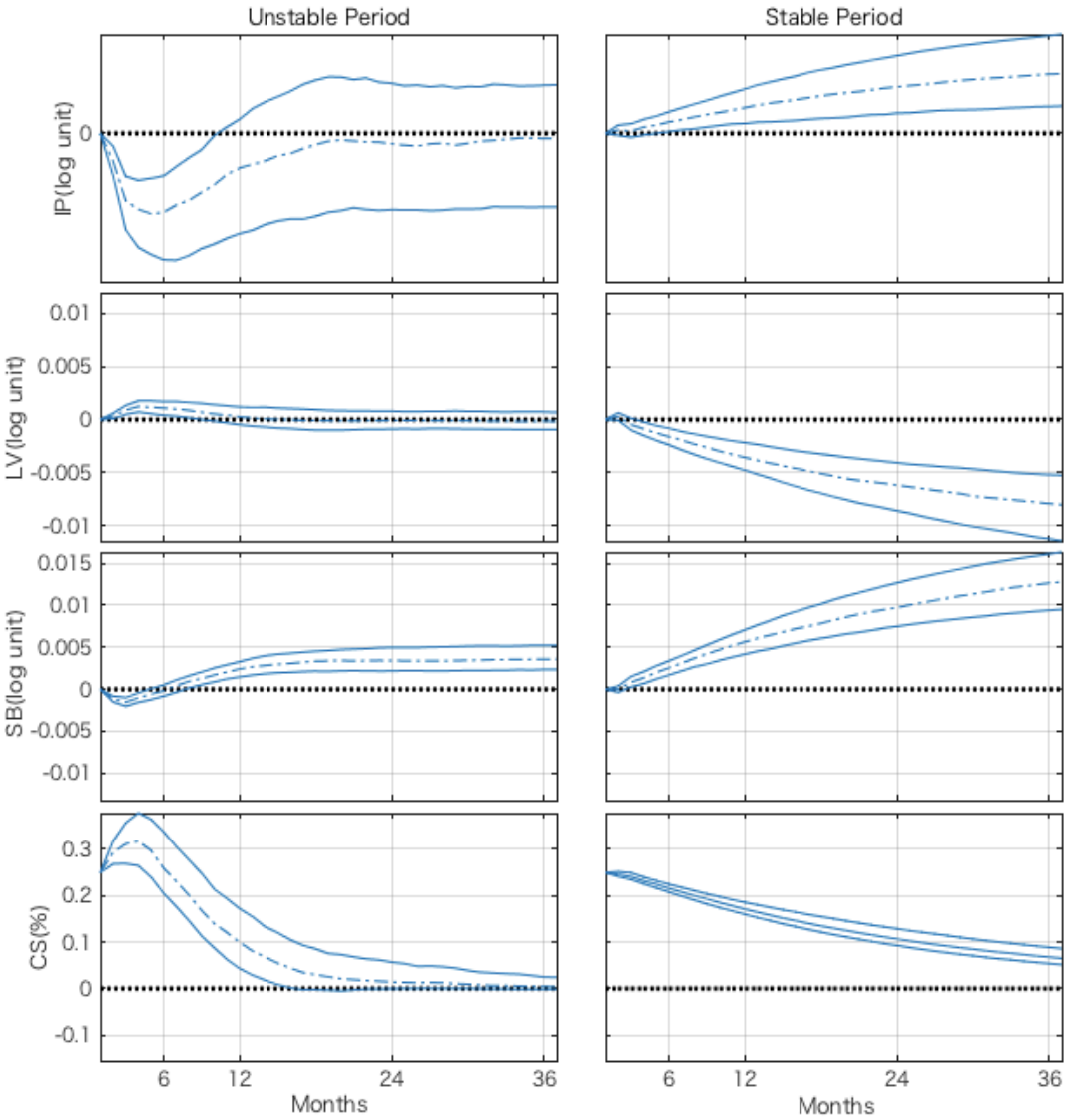
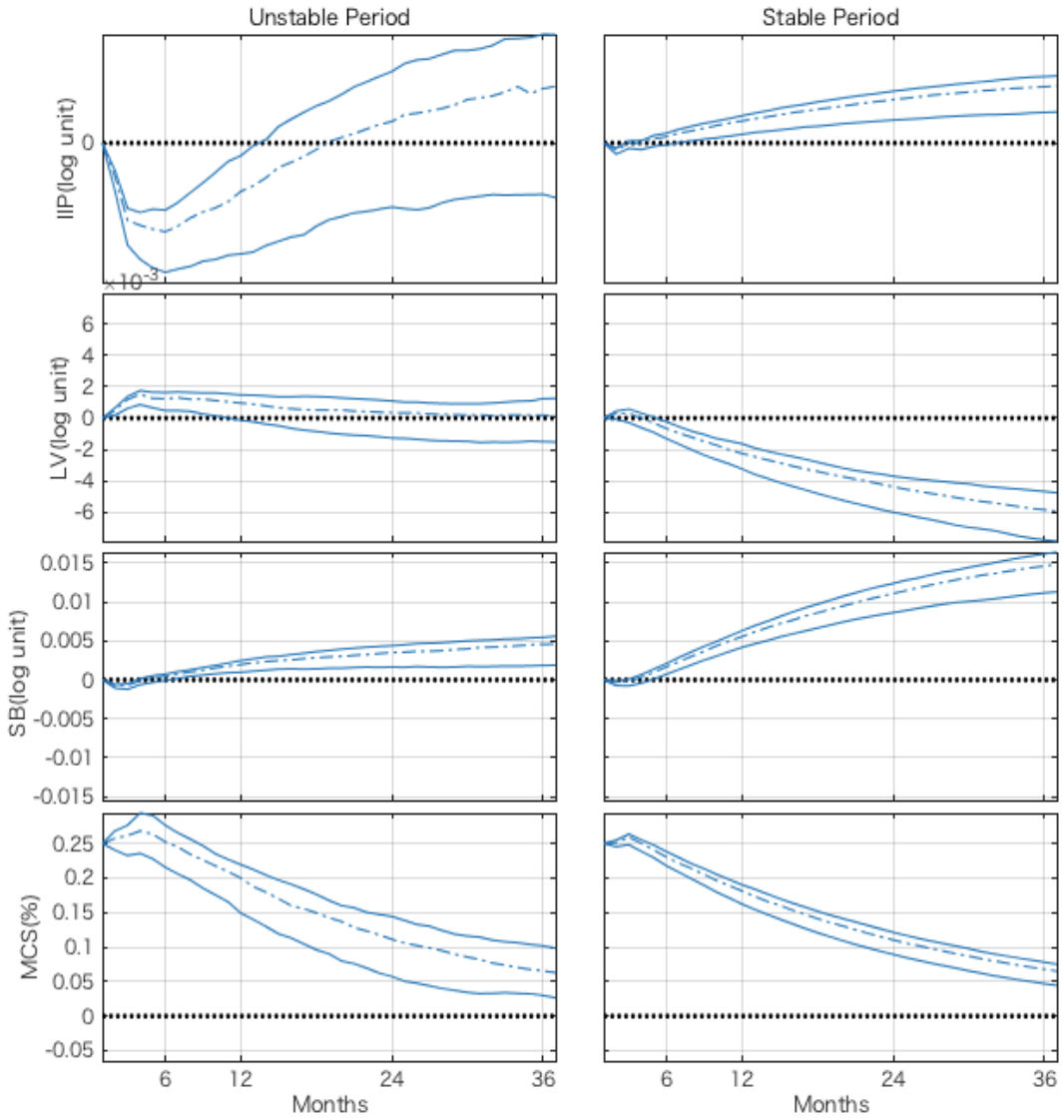


Figure 12: Impulse Response to a of Credit Spread Shock



Impulse response from an identified MS-SBVAR on an unstable regime (first column) and a stable regime (second column). The median is the dotted lines. A 70% credible interval in the solid lines is in each column.

Figure 13: Impulse Response to a Modified Credit Spread Shock



Impulse response from an identified MS-SBVAR on an unstable regime (first column) and a stable regime (second column). The median is the dotted lines. A 70% credible interval in the solid lines is in each column.