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Macroprudential Modeling Based on Spin Dynamics in a Supply Chain Network

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July 2018

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Abstract

The economic crisis of 2008 showed that conventional microprudential policy to ensure the soundness of individual banks was not sufficient, and prudential regulations to cover the whole financial sector were desired. Such regulations attract increasing attention, and policy related to those regulations is called macroprudential policy, which aims to reduce systemic risk in the whole financial sector by regulating the relationship between the financial sector and the real economy. In this paper, using a spin network model, we study channels of distress propagation from the financial sector to the real economy through the supply chain network in Japan from 1980 to 2015 and discuss good indicators for macroprudential policy. First, an estimation of the exogenous shocks acting on the communities of real economy in the supply chain network provides us evidence of the channels of distress propagation from the financial sector to the real economy through the supply chain network. Furthermore, causal networks between exogenous shocks and macroeconomic variables clarified the characteristics of the lead–lag relationship between exogenous shocks and macroeconomic variables as the bubble burst. In summary, monitoring temporal changes of exogenous shocks and the causal relationship among the exogenous shocks and macroeconomic variables will provide good indicators for macroprudential policy.

Keywords: Macroprudential policy, Supply chain network, Spin network model, Causal network, Exogenous shock, Macroeconomic variables, Community detection

JEL classification: E50, G01, L14

[1]This study was conducted as part of the project "Large-scale Simulation and Analysis of Economic Network for Macro Prudential Policy" undertaken at the Research Institute of Economy, Trade and Industry (RIETI). This research was also supported by MEXT as Exploratory Challenges on Post-K computer (Studies of Multi-level Spatiotemporal Simulation of Socioeconomic Phenomena). The present study was supported in part by the Ministry of Education, Science, Sports, and Culture, Grants-in-Aid for Scientific Research (B), Grant No. 17904923 (2017-2019) and (C), Grant No. 26350422 (2014-16). This study was supported by the Joint Research Program of KIER, Kyoto University.

1. Introduction

The economic crisis of 2008 showed that conventional microprudential policy to ensure the soundness of individual banks was not sufficient, and prudential regulations to cover the whole financial sector were desired. Such regulations attract increasing attention, and policy related to such regulations is called macroprudential policy, which aims to reduce systemic risk in the whole financial sector by regulating the relationship between the financial sector and real economy.

In this paper, using a spin network model, we study channels of distress propagation from the financial sector to real economy through the supply chain network in Japan from 1980 to 2015 and discuss a good indicator for macroprudential policy. Section 2 presents a literature survey of preceding studies. Section 3 explains methodologies used in the analysis, and Section 4 describes the data analyzed. Section 5 shows various results and discusses policy implications. Finally, Section 6 concludes the paper.

2. Literature Survey

Numerous preceding studies have tried to explain the characteristics of the stock market using spin variables in econophysics literature. First, we note some content and mathematical description from previous studies [1,2]. In particular, we note studies by Kaizoji and Sornette [3–10] in which strategies (buy or sell) of investors are modeled as spin variables, with stock price varying depending on differences in the number of spin-ups. In addition, the feedback effect on investor's decision-making through neighbor's strategies can explain bubble formation and crash. For instance, temporal evolution is simulated by adding random components in Sornette and Zhou's study [6]. Most papers adopt two-state spin variables; however, Vikram and Sinha's study adopts three-state spin variables [8]. Note that the purpose of these studies was to reproduce the scaling law and not to explain phase transition.

On the other hand, literature in economics journals aims to explain the optimality of investors' decision-making [7]. Phase transition is discussed starting with discrete choice theory in the study by Nadal et al. [10]. Many papers have similar discussions of phase transition, with slight variations in optimization and profit maximization. Although empirical studies using real data are relatively few, the market crashes of Wall Street in 1929, 1962, and 1987 and the crash of the Hong Kong Stock Exchange in 1997 were studied in Johansen, Ledoit, and Sornette's study [9]. Note that elaborate theoretical studies exist on phase transition effects on networks and the thermodynamics of networks [11–14].

Furthermore, there exist preceding studies on macroprudential policy, which mainly focus on time series analyses of macroeconomic variables [15–17].

3. Methodologies

3.1 Spin Network Model

Stock price $p_{i,t}$ $(i = 1, \cdots, N, t = 1, \cdots, T)$ is assumed to be a surrogate variable to indicate the soundness of each company and bank. Spin variable $s_{i,t}$ was estimated from the log return of daily stock price, $r_{i,t}$:

$$s_{i,t} = +1 \qquad (r_{i,t} = \ln(p_{i,t}) - \ln(p_{i,t-1}) \geq 0) \tag{1}$$

$$s_{i,t} = -1 \qquad (r_{i,t} = \ln(p_{i,t}) - \ln(p_{i,t-1}) < 0) \tag{2}$$

Here spin-up: $s_{i,t} = +1$ means company i is in good condition; on spin-down: $s_{i,t} = -1$ means company i is in bad condition. Macroscopic order parameter $\mathrm{M} = \sum_i s_i$ is an indicator of the soundness of the macro economy. This is regarded as an extreme simplification to capture the soundness of the economy. In addition to this simplification, spin variables include noise information because we have various distortions in the stock market caused by irrational decision-making by investors.

The spin variables of companies interact with spins of other companies through the supply chain network and interact with banks through the lending network. Those interactions between companies and banks are mathematically expressed as Hamiltonian. A Hamiltonian is written as follows:

$$H = -\sum_{i\in C} H_C s_i - \sum_{i\in B} H_B s_i - \sum_{i\in C, j\in C} J_C a_{ij} s_i s_j - \sum_{i\in C, j\in B} J_{CB} a_{ij} s_i s_j \tag{3}$$

where H_C and H_B are the exogenous shocks acting on companies and banks, respectively. a_{ij} represents elements of adjacency matrix A of the supply chain network treated as a binary directed network. Interactions between banks, represented as

$$\sum_{i\in B, j\in B} J_{BB} a_{ij} s_i s_j, \tag{4}$$

are observed as described in Section 4.3. In this paper, however, the interactions between banks were ignored because of lack of data. If we identify the community structure of a supply chain network, the Hamiltonian is rewritten as follows:

$$H = -\sum_{C\in Comm} \sum_{i\in C} H_C s_i - \sum_{i\in B} H_B s_i - \sum_{C\in Comm} \sum_{i\in C, j\in C} J_C a_{ij} s_i s_j$$
$$- \sum_{C\in Comm} \sum_{i\in C, j\in B} J_{CB} a_{ij} s_i s_j \tag{5}$$

Here, interaction between companies belonging to different communities is assumed to be minor enough to be neglected.

When spins are set on exogenous shock H_{ext}, an effective shock of

$$H_{eff} = H_{ext} + H_{int} \tag{6}$$

acts on each spin. By calculating interaction H_{int} considering nearest neighbor interactions in the Hamiltonian of Eq. (3), exogenous shock H_{ext} was estimated using the mean-field approximation by assuming a lattice-type configuration,

$$\frac{M}{N\mu} = \tanh\left(\frac{\mu H_{ext}}{kT} + \frac{zJ}{kT}\frac{M}{N\mu}\right), \tag{7}$$

or considering the nearest neighbor companies in the supply chain network

$$\frac{M}{N\mu} = \tanh\left(\frac{\mu H_{ext}}{kT} + \frac{zJ}{kT}\frac{\frac{1}{z}\Sigma_{ij}(a_{ij}+a_{ji})s_i}{N\mu}\right), \tag{8}$$

where T represents temperature as a measure of the activeness of the economy, which is considered proportional to the GDP per capita, and z is the average value of the sum of in-degree and out-degree. We note that if supply chain network data are not available, the value of z is not known, and therefore exogenous shock H_{ext} cannot be estimated.

3.2 Causal Networks

The next step is interpreting the estimated exogenous shocks using macroeconomic variables. Vector $X(t)$ consists of the estimated exogenous shocks and macroeconomic variables. Explained variable vector $X(t)$ is modeled using a vector autoregression model (e.g., the VAR (1) model):

$$X(t) = A'(1)X(t-1) + U(t), \tag{9}$$

where $A'(1)$, $X(t-1)$, and $U(t)$ represent the regression coefficient matrix, explanatory variable vector, and error vector, respectively. Note that the explanatory variable vector leads the explained variable vector by a time step. If the time series is monthly, the former leads the latter by one month. Estimated elements of $A'(1)$ are considered statistically significant if the p-value of the estimation is less than a specified value—e.g., $\mathrm{p} < 0.1$. Statistically significant element a'_{ij} provides us a link from variable $\mathrm{x}_j(t-1)$ to $\mathrm{x}_i(t)$. This link is interpreted as a causal relationship. We construct a causal network whose nodes are x_i and links from node j to i are a_{ij}:

$$a_{ij} = \begin{cases} 1 & (\mathrm{p} < 0.1 \text{ for } \mathrm{a}'_{ji}) \\ 0 & \text{(otherwise)} \end{cases} \tag{10}$$

However, in this study, we treat the network as a binary network by ignoring link weights. The shortest path length from the most leading node to node x_i provides us a lead–lag relation between the most leading node and node x_i. If the path length is small, node x_i is considered the relatively leading node. On the other hand, if the path length is large, node x_i is considered the relatively lagging node. Similarly, the in-degree and out-degree of nodes provide information about the role of nodes in a network. For instance, the in-degree of a node corresponds to the number of explanatory variables of the node while the out-degree of a node corresponds to the number of explained variables of the node.

4. Data

4.1 Stock Price

Stock price is the daily time series for the period January 1, 1980–December 31, 2015. Spin variable $s_{i,t}$ was estimated using Eqs. (1) and (2). Order parameters for real economy and financial sector are magnetizations, which is the sum of spin variables for companies $\sum_{i \in C} s_i$ and banks $\sum_{i \in B} s_i$. Temporal changes of order parameters for real economy (companies) and the financial sector (banks) are shown in Fig. 1 and Fig. 2, respectively. Symbols in Figs. n1, b1, c1, n2, c2, b2, c3, and b3 show "Normal period: 1980–1985," "Bubble period: 1985–1989," "Asset bubble crisis: 1989–1993," "Normal period: 1993-1997," "Financial crisis: 1997–2003," "Bubble period: 2003–2006," "US subprime loan crisis and the Great East Japan Earthquake: 2006–2012," and "BOJ monetary easing: 2013–present," respectively.

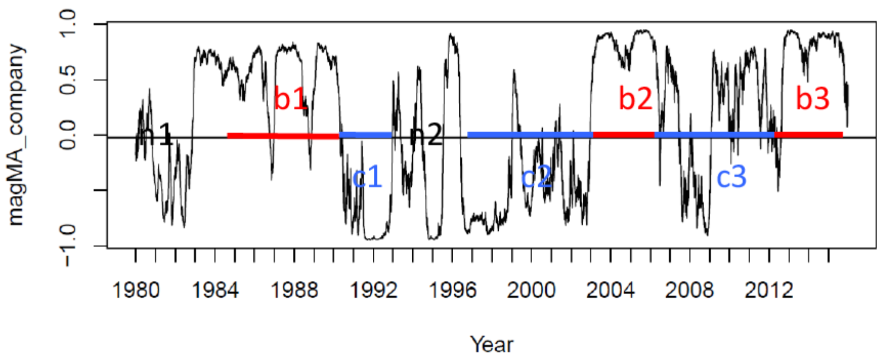

Fig. 1 Order Parameter of the Real Economy (companies)

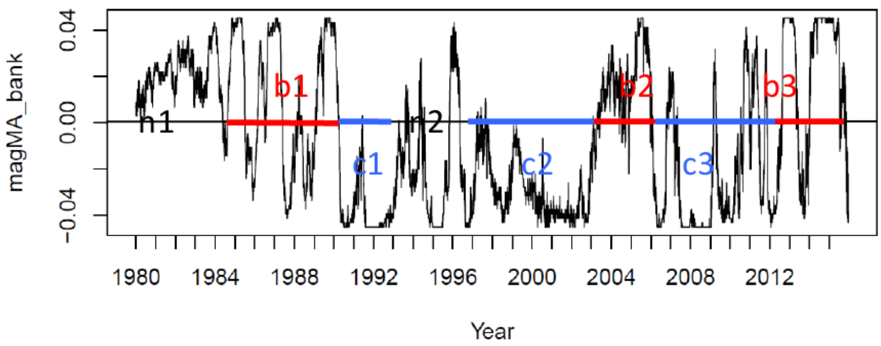

Fig. 2 Order Parameter of the Financial Sector (banks)

4.2 Supply Chain Network and Lending Network

Data were prepared by Tokyo Shoko Research, Ltd. Although the data include listed companies, unlisted companies, and banks, only listed companies and banks are included in this study.

4.3 Balance Sheet Data of Banks

Data are prepared by Nikkei NEEDS. Temporal changes in the shares of some assets relative to the total assets of each bank are shown from 1980 to 2015 in figs. 3 to 5. Here, bank IDs were assigned in the order megabanks; first-kind of regional banks, trust banks; and second-kind regional banks. We confirm that bank assets change to reflect changes in macro monetary policy. A call loan, in Fig. 3, is the amount of lending by first-kind regional banks to megabanks and trust banks. This relationship among banks is understood as the interaction between banks in Eq. (4). The amount and share of call loans reached a peak around 1990 and then decreased to the present. Call money represented in Fig. 4 is mainly the borrowing of megabanks and trust banks. Amount and share of call money reached a peak around 1990 and decreased to the present. It particularly decreased during periods of economic crisis. Recent government bonds owned by megabanks and trust banks especially increased as shown in Fig. 5. This reflects monetary easing that was conducted by the Bank of Japan (BOJ).

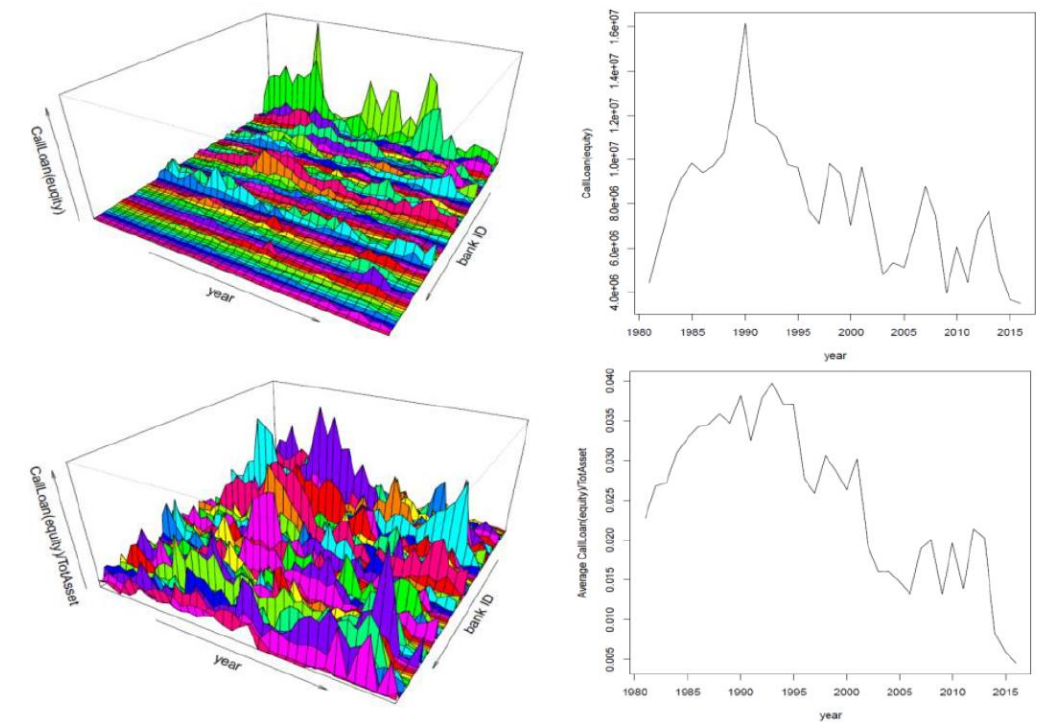

Fig. 3 Call Loan (Lending)

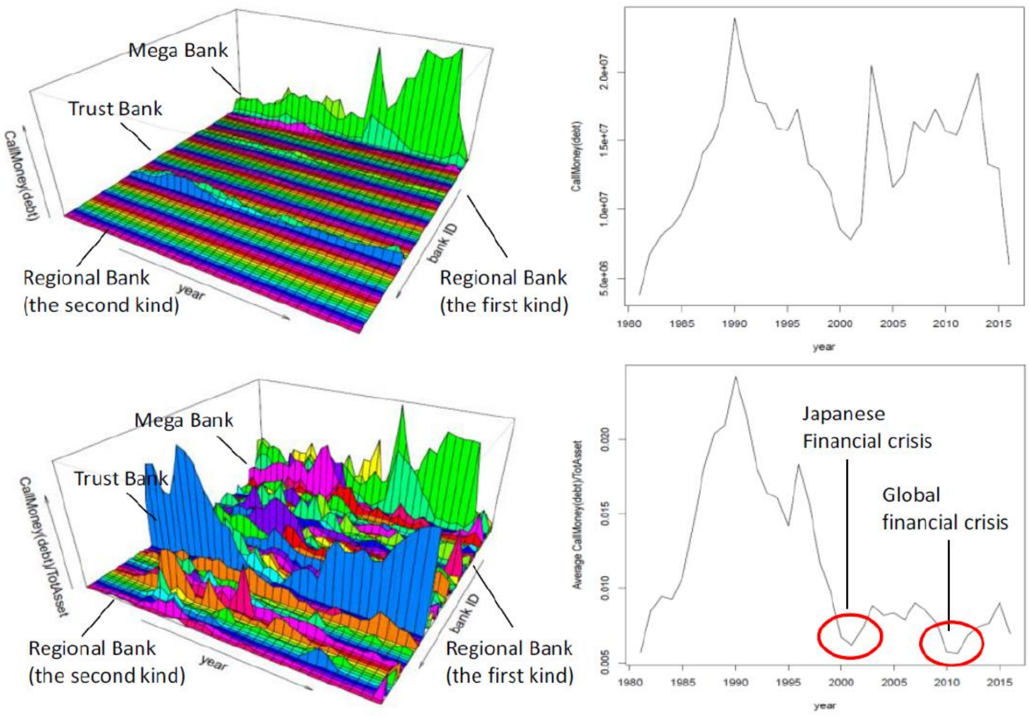

Fig. 4 Call Money (Borrowing)

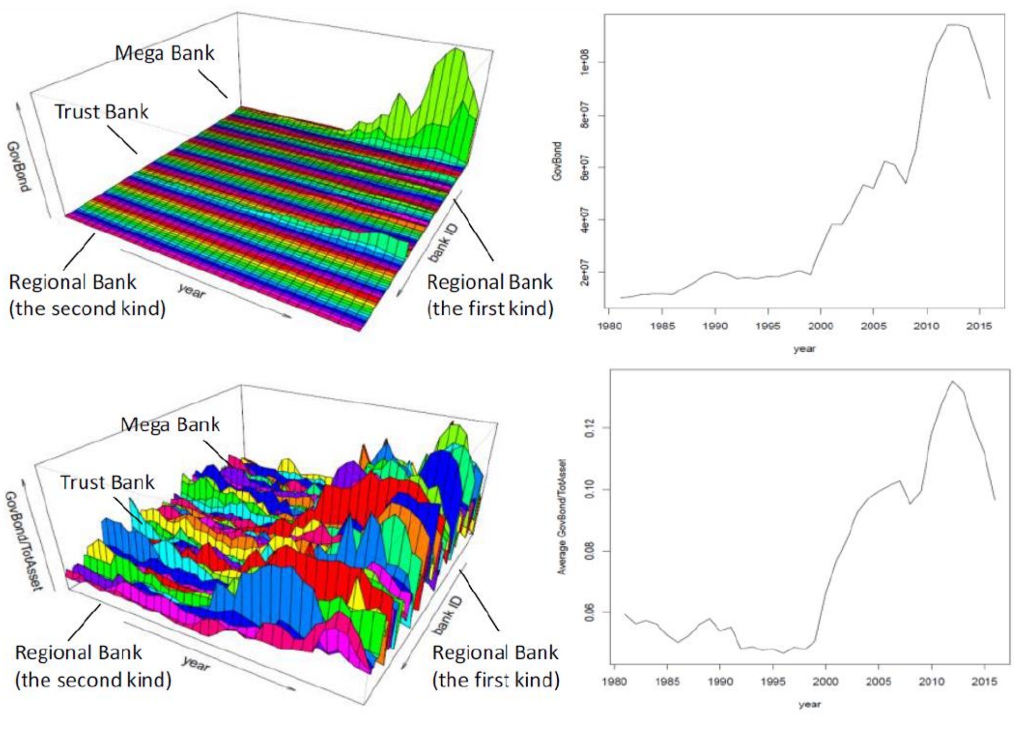

Fig. 5 Government Bond

4.4 Macroeconomic Variables

By considering capital-adequacy rules, monetary policy, and bank assets, we focus on the following monthly macroeconomic variables from October 1985 to December 2015: (1) Monetary base “mb”; (2) Short-term government bond (1-year) “nbond1yr”; (3) Long-term government bond (10-year) “nbond10yr”; (4) Call rate “callrate”; (5) Exchange rate “exchgrate”; (6) Money stock “m2cd”; (7) Bank lending “banklend”; (8) Other bank assets “banketc”; (9) Government debt “govdebt”; (10) Residential land price “landprice”; (11) Residential house price “houseprice”; and (12) Number of bankruptcies “bnkrpt.” Temporal change in these macroeconomic variables is shown in Fig. 6. Correlation coefficients were estimated among these macroscopic variables. High correlation was obtained for the following combinations: “nbond1yr” and “callrate” (0.991), “houseprice” and “landprice” (0.946), “govdebt” and “m2cd” (0.962), “banketc” and “m2cd” (0.945), and “nbond10yr” and “callrate” (0.938), where the numbers in parentheses are the correlation coefficients. Because of high correlation for these combinations, “nbond1yr,” “houseprice,” “govdebt,” “banketc,” and “nbond10yr” were removed from the analysis below. Considering these results, we determine vector $X(t)$ in Eq. (9) as follows:

$$X(t) = \begin{bmatrix} \text{EF\_bank}(t),\ \text{EF\_comm4}(t),\ \text{EF\_comm5}(t), \\ \text{EF\_comm11}(t),\ \text{EF\_comm15}(t),\ \text{EF\_comm23}(t), \\ \text{mb}(t),\ \text{callrate}(t),\ \text{exchgrate}(t),\ \text{m2cd}(t), \\ \text{banklend}(t),\ \text{landprice}(t),\ \text{bnkrpt}(t) \end{bmatrix}^T. \quad (11)$$

Note that estimated exogenous shocks are daily although macroeconomic variables are monthly. We sum up the exogenous shocks for each month to fit the time step of macroeconomic variables.

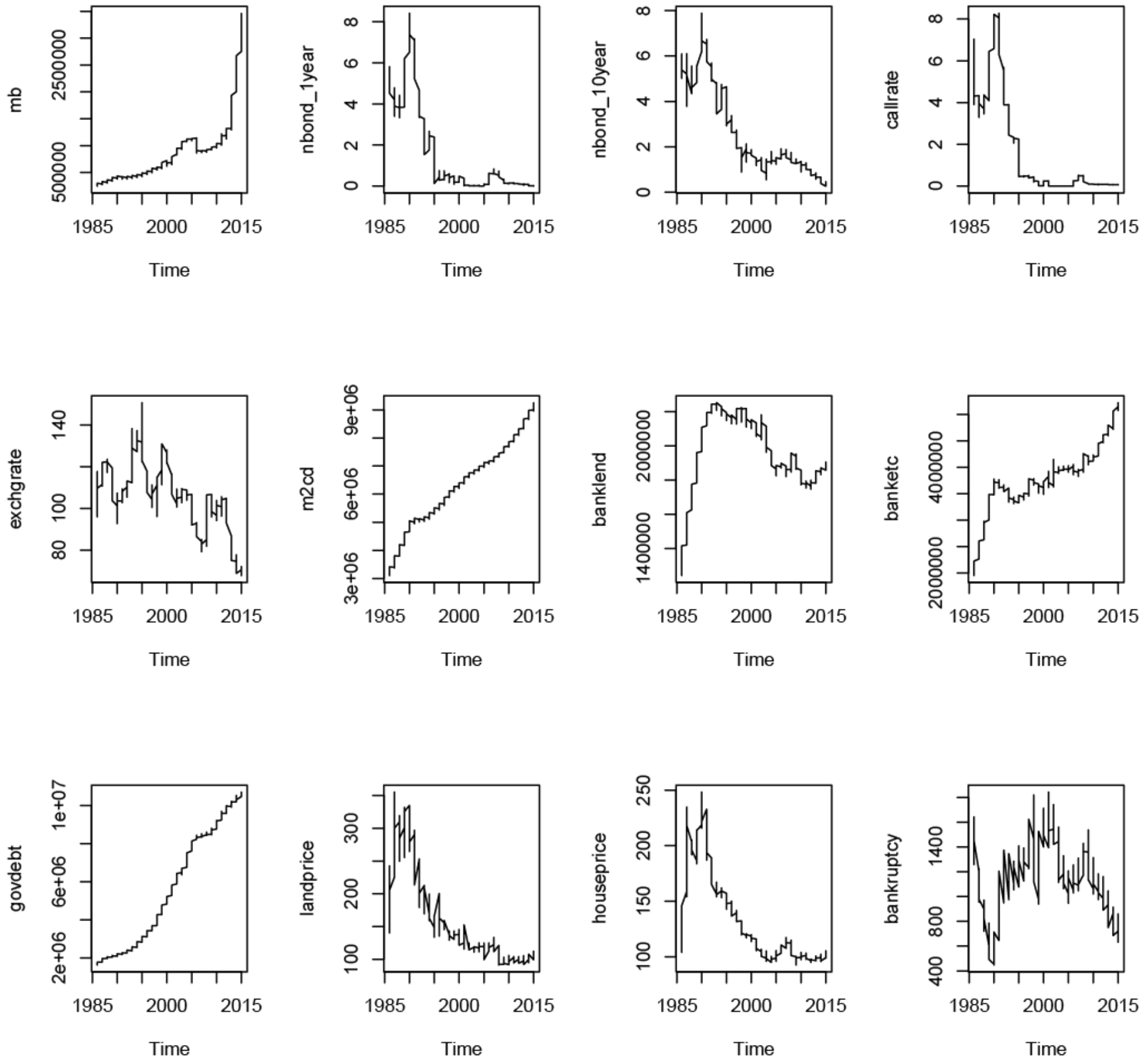

Fig. 6 Temporal change in Macroeconomic Variables

5 Results and Discussions

5.1 Spin Correlation and Temperature

Spin correlations of the supply chain network and lending network are shown in figs. 7 and 8, respectively. These figures show that correlation strength is normal<bubble<crisis. Bank–company correlation is weaker compared with company–company correlation. As an analogy of magnetic materials, Eq. (3) shows that the system is in either a ferromagnetic phase or a paramagnetic phase when s_i and s_j are parallel, if J_C>0 and J_{CB}>0. Here, ferromagnetic phase means that macroscopic order parameter M is preserved even after removing exogenous shock H_{ext}. On the other hand, paramagnetic phase means that M becomes zero after removing H_{ext}. We expect to find a paramagnetic phase in the actual economy. Companies compete to obtain better economic performance; therefore, once the bad effect from H_{ext} is removed, M increases toward zero.

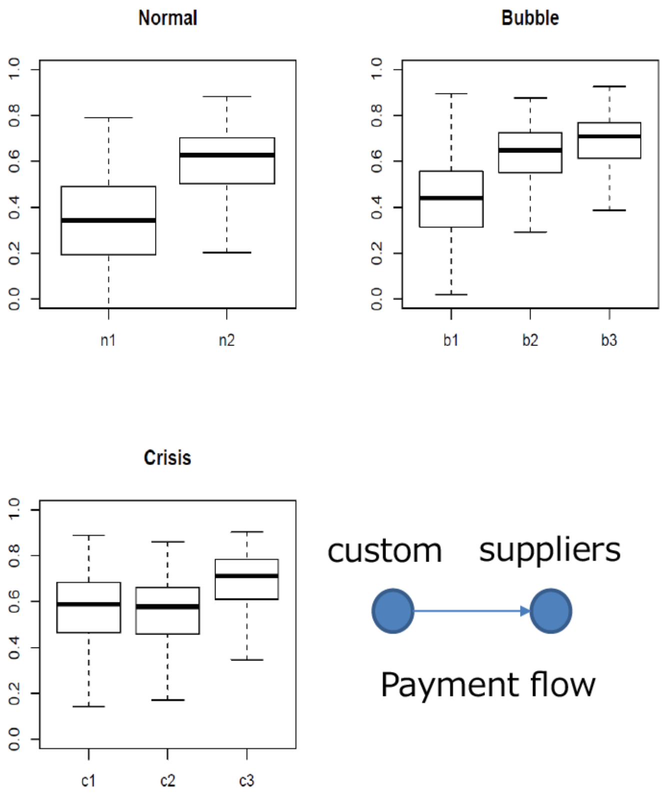

Fig. 7 Spin Correlation of the Supply Chain Network

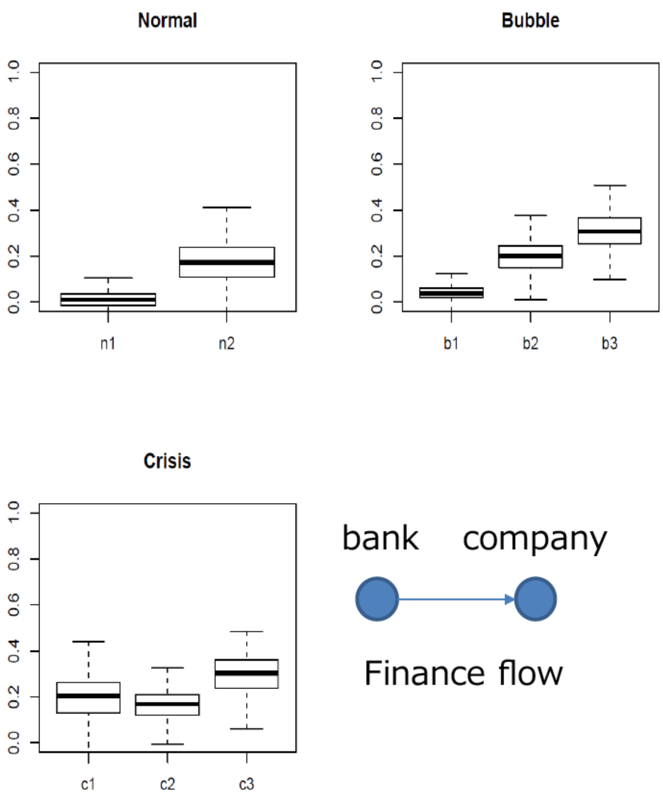

Fig. 8 Spin Correlation of the Lending Network

At the critical point of phase transition, we have $zJ/kT_C = 1$. Thus, when $\mathrm{T} < T_C$, $zJ/k\mathrm{T} > 1$ is satisfied and the system is in a ferromagnetic phase. Alternatively, when $\mathrm{T} > T_C$, $zJ/k\mathrm{T} < 1$ is satisfied and the system is in a paramagnetic phase. With the assumption of $H_{ext} = 0$ in normal economic period n1, we obtain $zJ/k\mathrm{T} \approx 0.85$. Therefore, the system is in a paramagnetic phase.

Simple statistical mechanical calculation shows that distribution of N_+/N_- will be a Boltzmann distribution for a non-interacting spin system, where N_+ and N_- are the number of up-spins and down-spins, respectively. However, because the actual system has interactions between spins, we need to estimate slope parameter $1/kT$ of the N_+/N_- distribution. The distributions and estimated temperatures of the supply chain network in each period are presented in Fig. 9. Temperature is a measure of the activeness of economy, which is considered proportional to the GDP per capita. The results show that variations in temperature during the period are relatively minor, and therefore, the system can be said to be in a paramagnetic phase throughout the observed period.

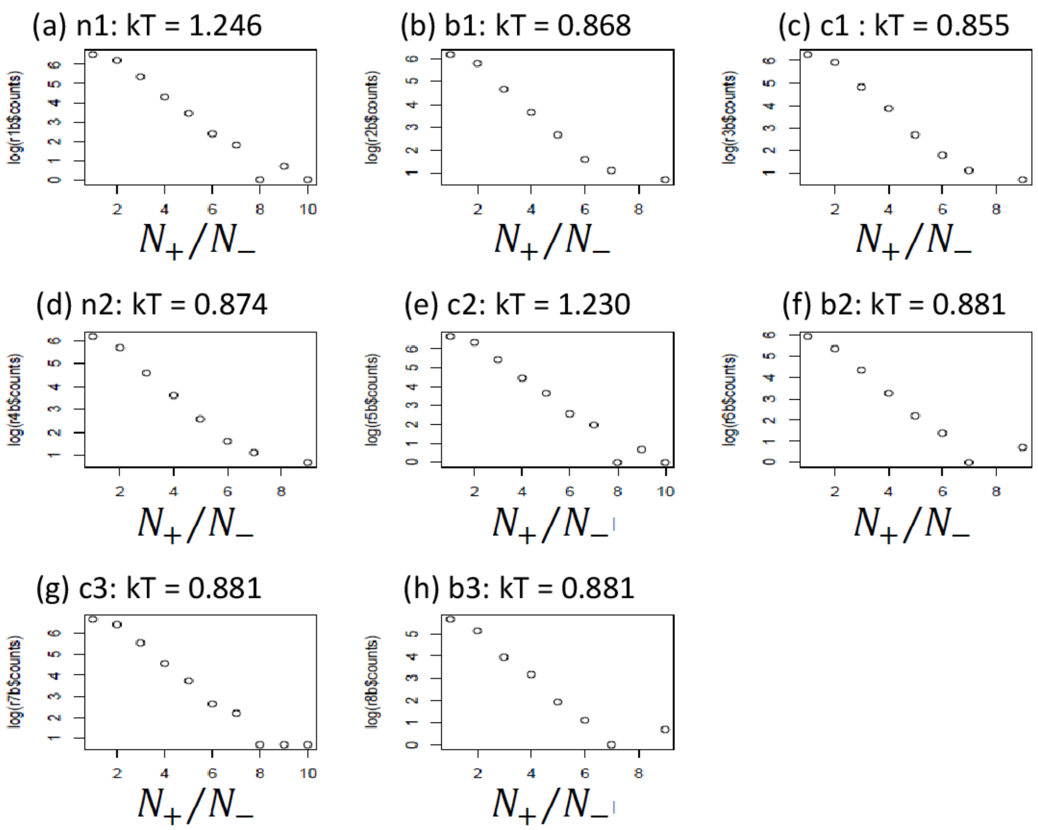

Fig. 9 Temperature of the Supply Chain Network

5.2 Community Structure of the Supply Chain Network

The community structure of the supply chain network was identified, and the results are shown in Fig. 10. Panel (a) is a dendrogram of the network. This depicts that five major communities are identified with fairly large values of modularity. The five major communities shown in panels (b)–(f) are C_4: “agriculture, forestry and fisheries, mining, construction, transportation equipment, precision machinery”; C_5: “petroleum and coal, rubber, ceramic, steel, non-ferrous metal, metal product”; C_{11}: “textile, pulp and paper”; C_{15}: “chemical, pharmaceutical product, wholesale and retail trade, real estate”; and C_{23}: “machinery, electric machinery,” respectively.

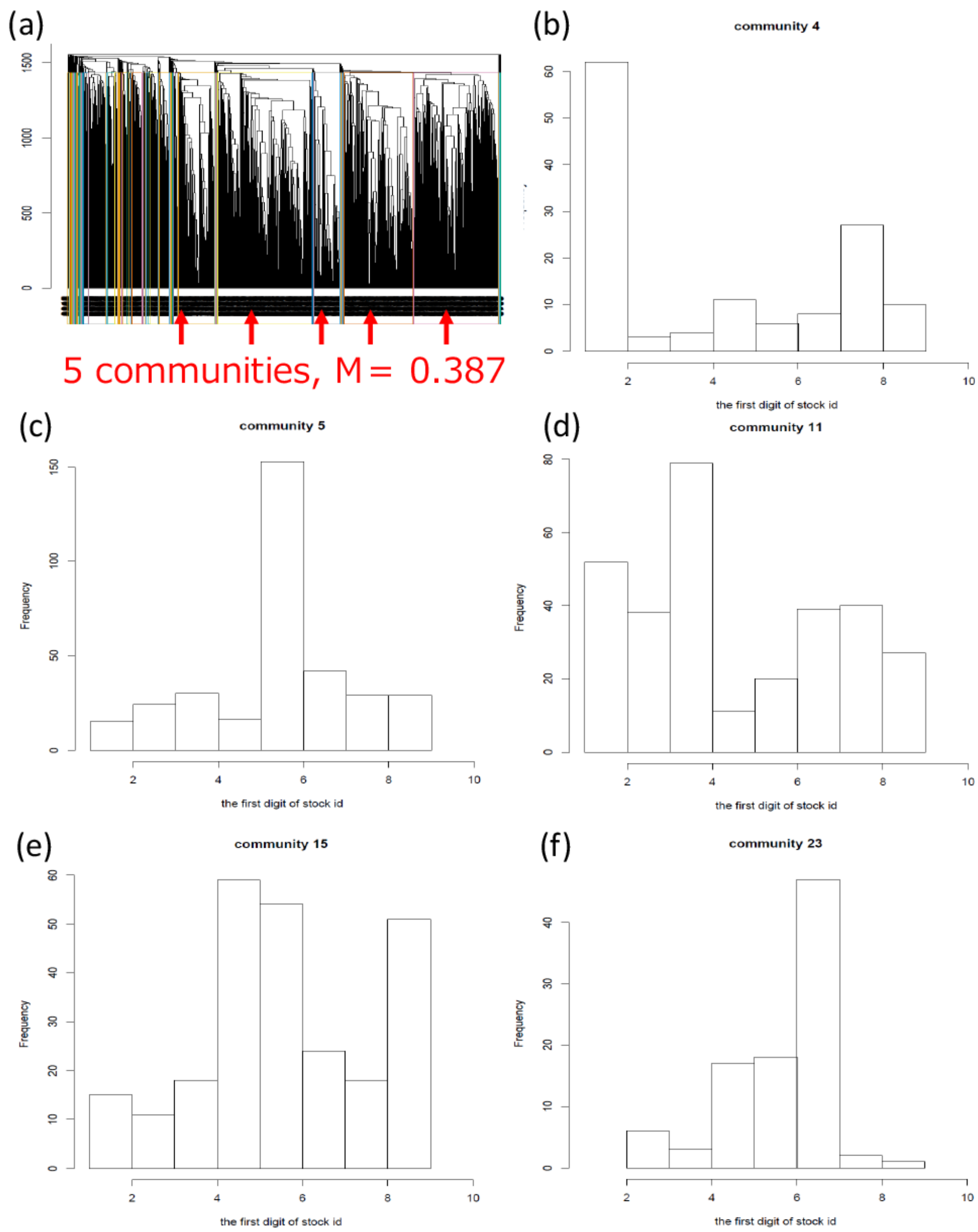

Fig. 10 Community Structure of Supply Chain Network

5.3 Exogenous Shock

Exogenous shock was estimated using Eq. (8), and the major mode of exogenous shock was extracted using random matrix theory for the correlation of exogenous shock and bank spins. The major mode of exogenous shock acting on the financial sector is shown in Fig. 11. The obtained exogenous shock acting on the financial sector indicates large negative shocks at the beginnings of T_{c1} (1989) and T_{c2} (1997) but no large negative shock at period T_{c3} (2008). This means that the effect of the US subprime loan crisis on the Japanese economy was introduced through shocks to real economy (e.g., the sudden decrease of exports to the US), not through shocks in the financial sector directly.

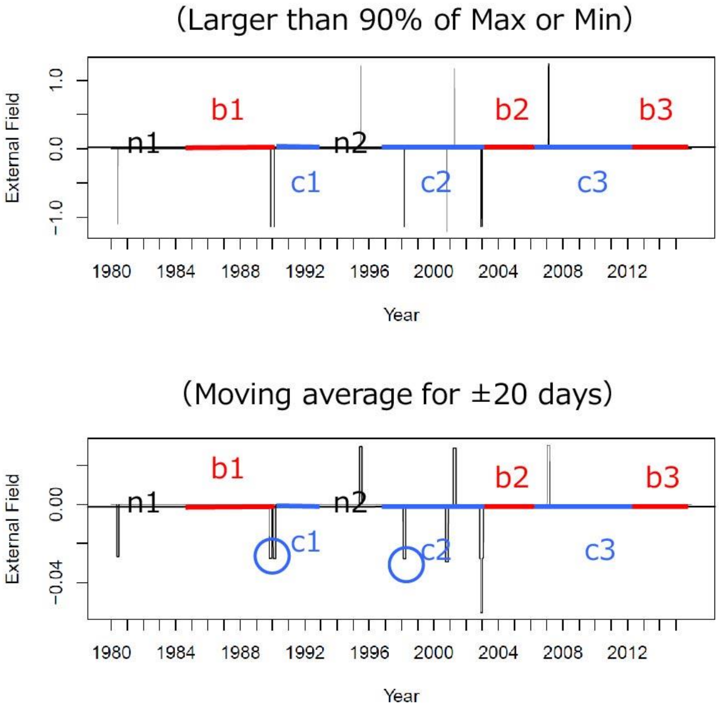

Fig. 11 Exogenous shock acting on the Financial Sector

Exogenous shock was estimated using Eq. (8), and the major mode of exogenous shock was extracted using random matrix theory to determine correlation of the exogenous shock and company spins in each community.

The major mode of exogenous shock acting on community C_4 is shown in Fig. 12. For community C_4, no large negative shock was obtained at the beginnings of T_{c1} (1989) and T_{c2} (1997). We note that M~−1 is observed for these communities at the beginnings of T_{c1} (1989) and T_{c2} (1997). This is interpreted as evidence of channels of distress propagation from the financial sector to real economy through the supply chain network in Japan from 1980 to 2015. Note that we show a negative shock from the US subprime loan crisis (c3) although the shock is not significant.

The major mode of exogenous shock acting on community C_5 is shown in Fig. 13. For community C_5, no large negative shock was obtained at the beginnings of T_{c1} (1989) and T_{c2} (1997). We note that M~−1 is observed for these communities at the beginnings of T_{c1} (1989) and T_{c2} (1997). This is interpreted as evidence of the channels of distress propagation from financial sector to real economy through the supply chain network in Japan from 1980 to 2015.

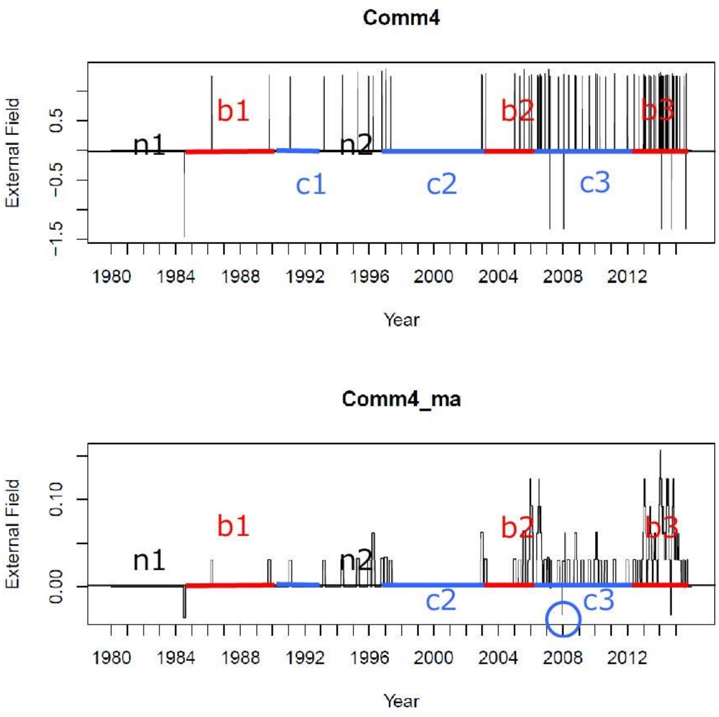

Fig. 12 Exogenous shock acting on community C_4

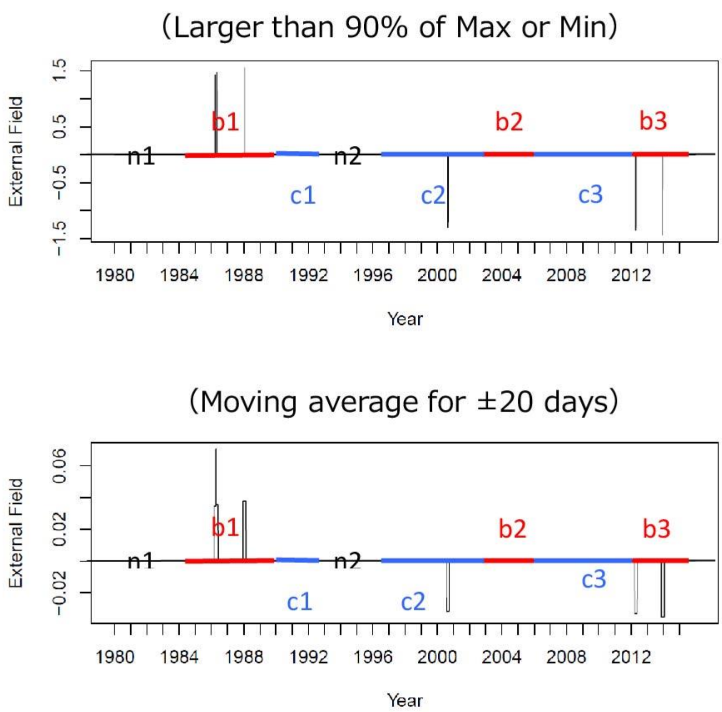

Fig. 13 Exogenous shock acting on community C_5

The major modes of exogenous shocks acting on communities C_{11} and C_{15} are shown in figs. 14 and 15, and the results are quite similar for both the communities. We have negative shocks from the asset bubble crisis (c1), the financial crisis in Japan (c2), and the US subprime loan crisis (c3). Direct degradation of real economy is evident. However, the effect on other communities is minor.

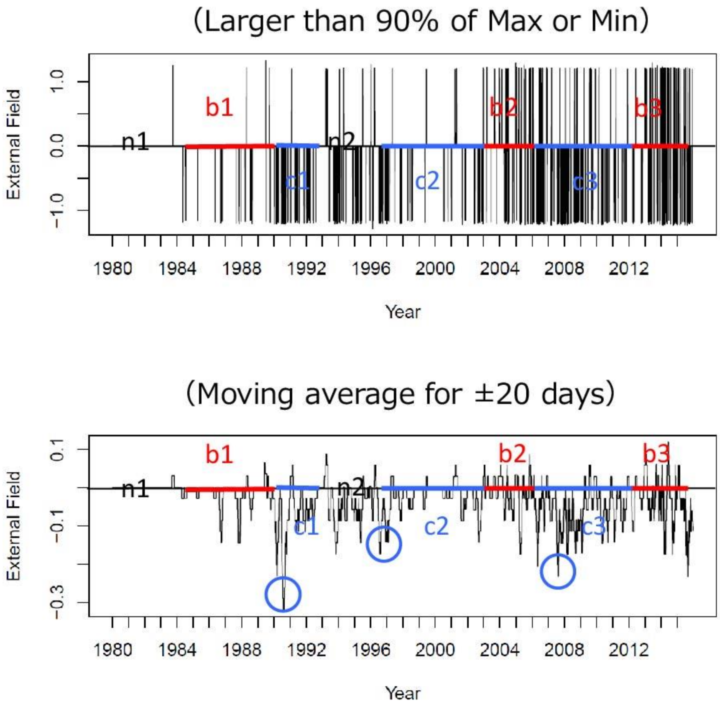

Fig. 14 Exogenous shock acting on community C_{11}

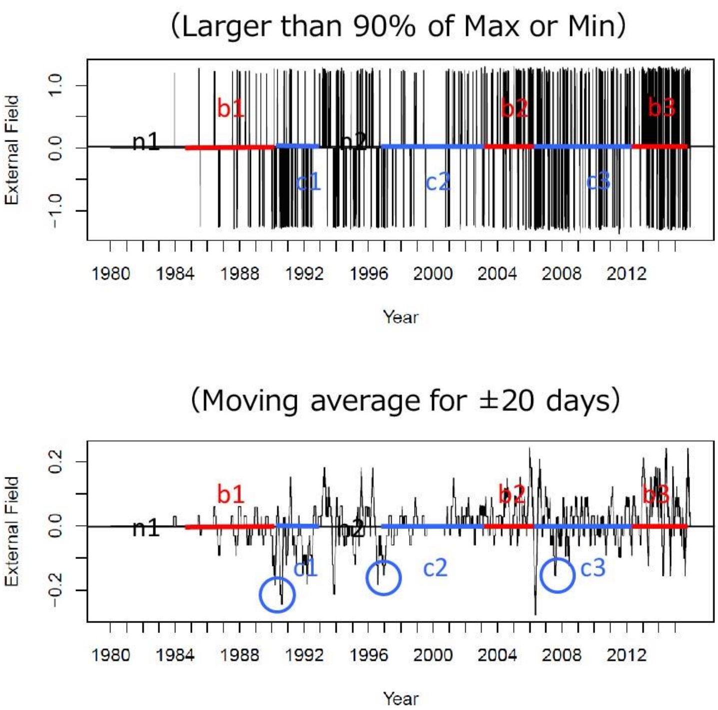

Fig. 15 Exogenous shock acting on community C_{15}

The major mode of exogenous shock acting on community C_{23} is shown in Fig. 16. For community C_{23}, no large negative shock was obtained at the beginnings of T_{c1} (1989) and T_{c2} (1997). We note that $M\sim-1$ is observed for these communities at the beginnings of T_{c1} (1989) and T_{c2} (1997). This is interpreted as evidence of the channels of distress propagation from the financial sector to real economy through the supply chain network in Japan from 1980 to 2015. Note that we show a negative shock from the US subprime loan crisis (c3) although the shock is not significant.

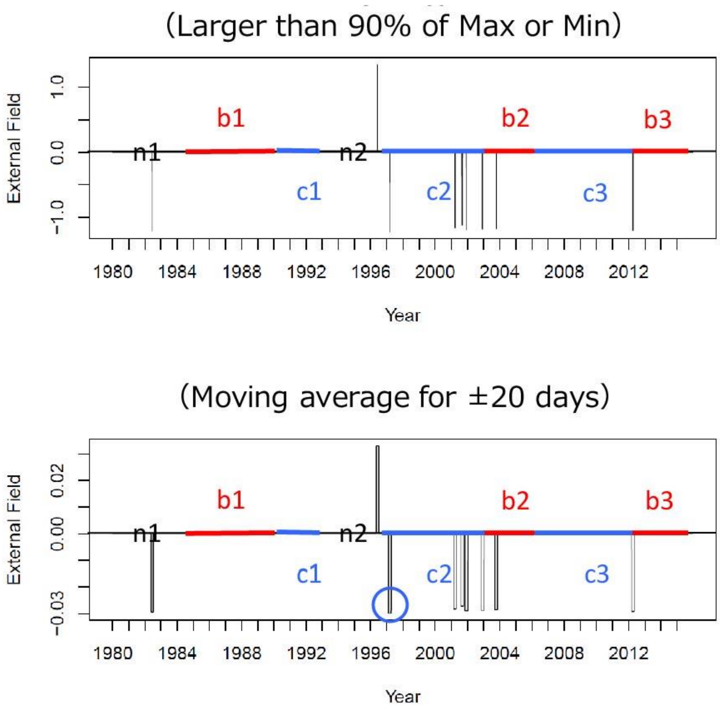

Fig. 16 Exogenous shock acting on community C_{23}

5.4 Causal Network

Relationships between exogenous shocks (acting on financial sector and communities C_4, C_5, C_{11}, C_{15}, and C_{23}) and macroeconomic variables (Monetary base, Call rate, Exchange rate, Money stock, Bank lending, Land price index, and Number of bankruptcies) were examined using Vector Auto Regression analysis (VAR) (1) in Eq. (9). Causal networks among these variables were constructed with directed links from explanatory variables to explained variables in the bubble and crisis periods. Obtained causal networks in b1, b2, b3, c1, c2, and c3 periods are shown in Figs. 17–22, respectively.

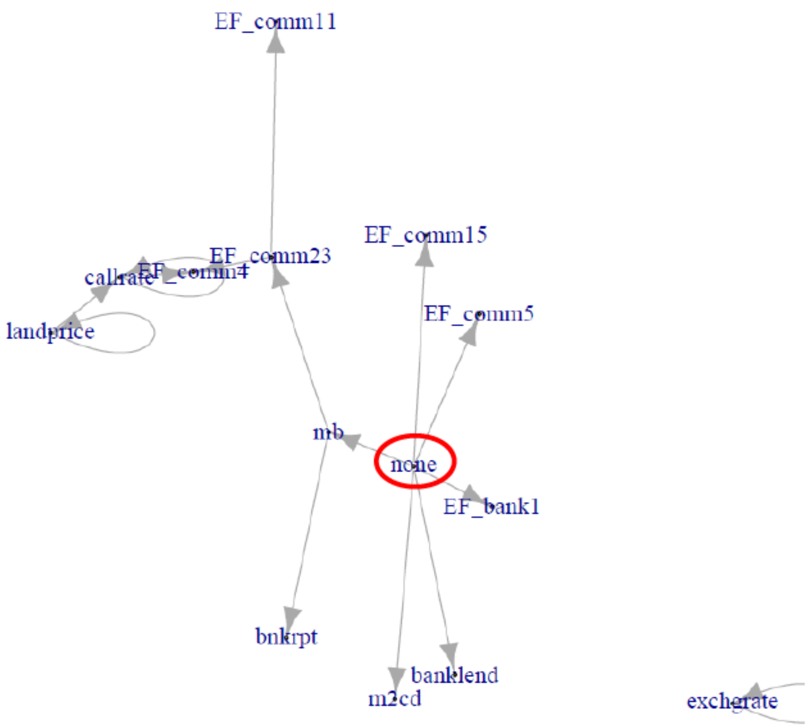

Fig. 17 Causal Network in b1 period

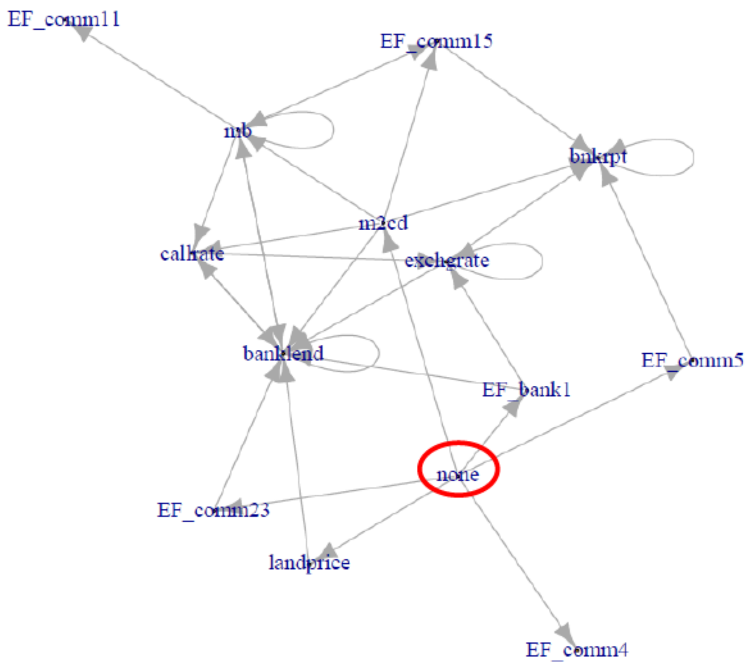

Fig. 18 Causal Network in b2 period

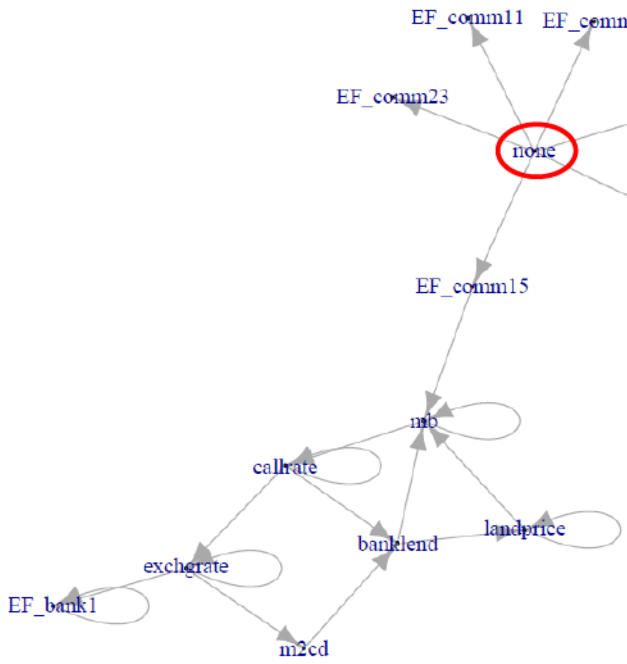

Fig. 19 Causal Network in b3 period

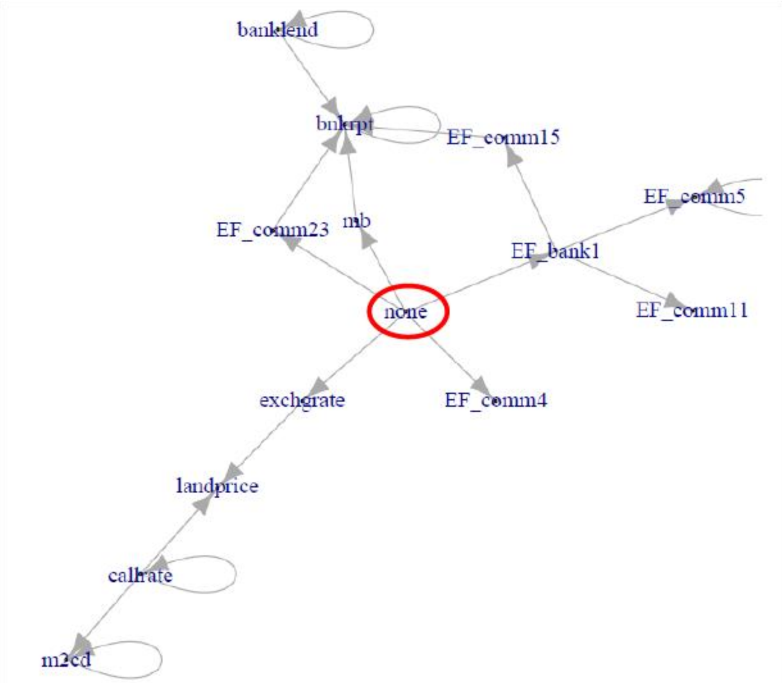

Fig. 20 Causal Network in c1 period

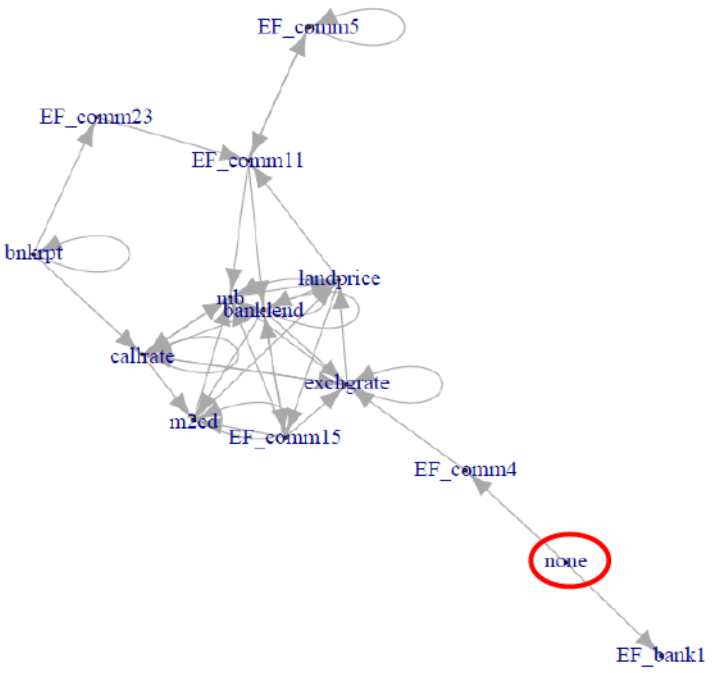

Fig. 21 Causal Network in c2 period

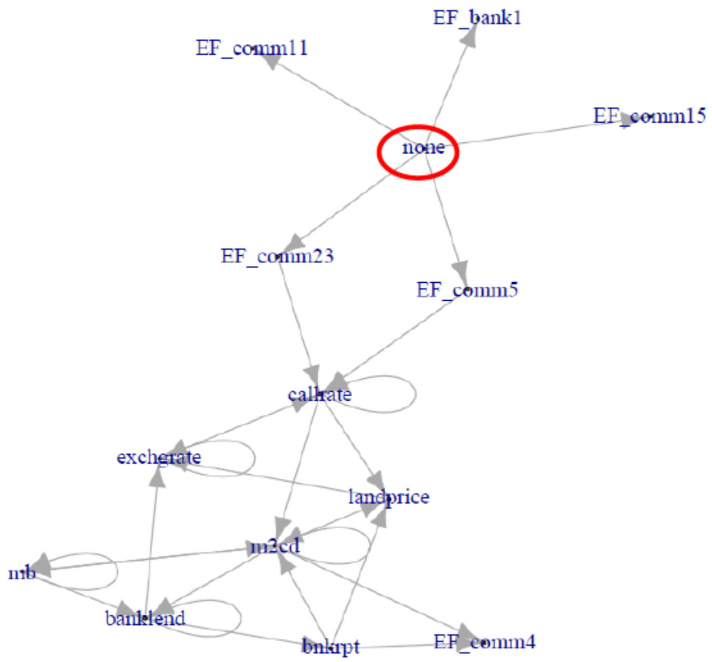

Fig. 22 Causal Network in c3 period

Shortest path length, in-degree, and out-degree were estimated for the causal networks in the bubble and crisis periods. These quantities were used to characterize change in the causal relationship from the bubble period to the crisis period. If the path length is small, node x_i is considered the relatively leading node. Conversely, if the path length is large, node x_i is considered the relatively lagging node.

Shortest path in bubble periods is shown in Fig. 23. During bubble periods, exogenous shocks, Monetary base “mb,” and Money stock “m2cd” are leading. Note that the behavior during the b3 period is different from that during other periods. The shortest path length in economic crisis periods is shown in Fig. 24. During crisis periods, longer path lengths are a general tendency. Exogenous shocks acting on communities 5 and 15 are lagging. The difference of shortest path length caused by a bubble burst is shown in Fig. 25. With a bubble burst, exogenous shocks acting on communities 5 and 15, Monetary base “mb,” Money stock “m2cd,” Bank lending “banklend,” and Number of bankruptcies “bnkrpt” became lagging, and Exchange rate “exchgrate” become leading.

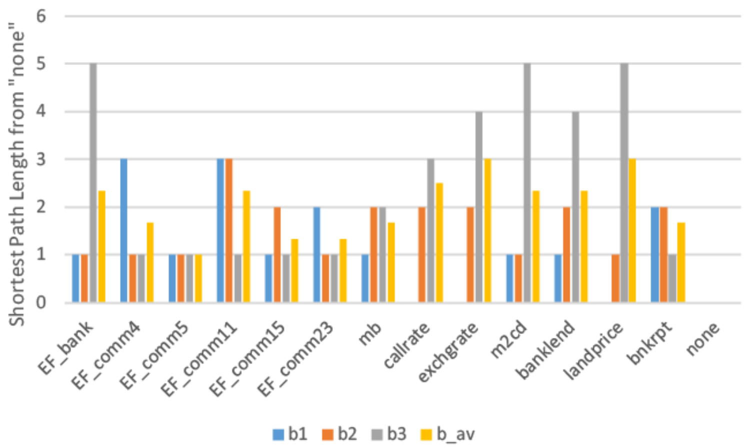

Fig. 23 Shortest Path in Bubble Periods

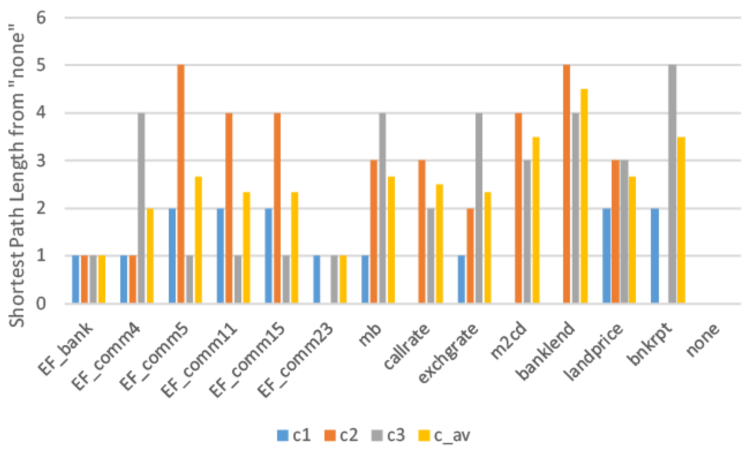

Fig. 24 Shortest Path Length in Economic Crisis Periods

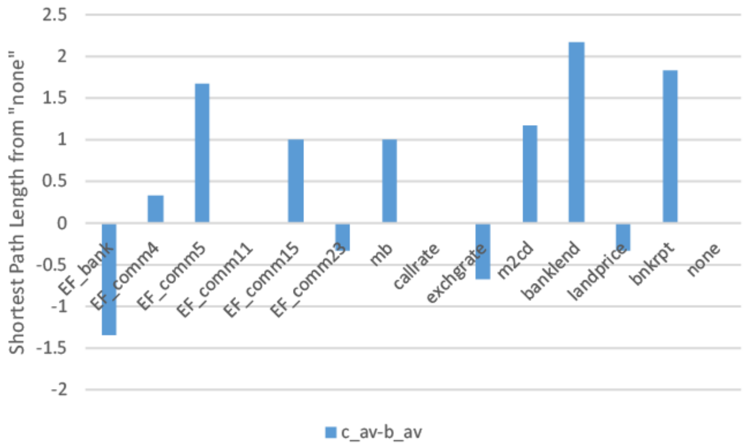

Fig. 25 Difference of Shortest Path Length

In-degree of a node corresponds to the number of explanatory variables of the node. In-degree in bubble periods is shown in Fig. 26. During bubble periods, exogenous shocks and Money stock “m2cd,” and Residential land price “landprice” have small in-degree effects. The behavior of these variables is difficult to be explained by the small number of explanatory variables due to small value of determination coefficient. In-degree in economic crisis periods is shown in Fig. 27. During economic crisis periods, in-degree increases for most variables and therefore the variables are explained better. This corresponds to the fact that correlations among most variables increase because these variables behave similarly. The difference of in-degree caused by bubble burst is shown in Fig. 28. With a bubble burst, call rate “callrate,” Exchange rate “exchgrate,” Money stock “m2cd,” and Residential land price “landprice” have larger in-degree. In contrast, Bank lending “banklend” has smaller in-degree effects.

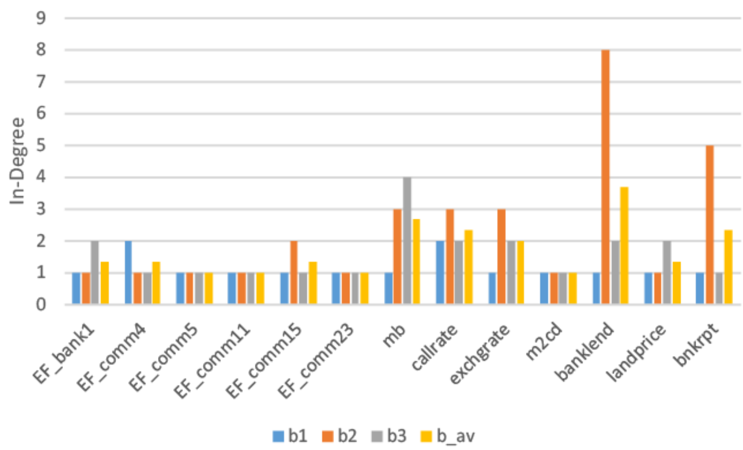

Fig. 26 In-Degree in Bubble Periods

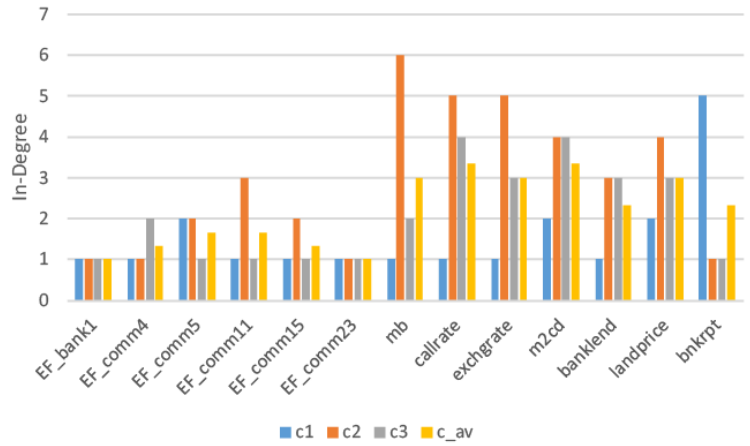

Fig. 27 In-Degree in Economic Crisis Periods

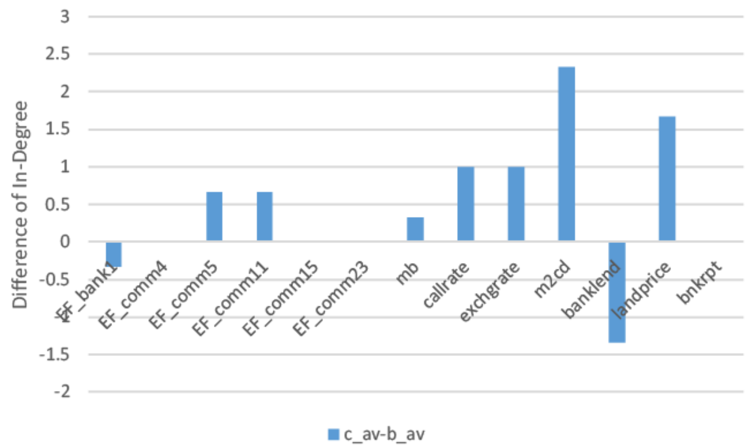

Fig. 28 Difference of In-Degree

Out-degree of a node corresponds to the number of explained variables of the node, and out-degree in bubble periods is shown in Fig. 29. During bubble periods, out-degree of exogenous shocks and Number of bankruptcies “bnkrpt” are small. These (explanatory) variables do not affect the behavior of other (explained) variables due to small value of determination coefficient. Out-degree in economic crisis periods is shown in Fig. 30. During economic crisis periods, out-degree increases for most variables and therefore the variables explain other variables better. This corresponds to the fact that correlations among most variables increase because these variables behave similarly. Difference of out-degree caused by a bubble burst is shown in Fig. 31. With a bubble burst, out-degree of exogenous shocks except for financial sector, call rate “callrate,” Money stock “m2cd,” Bank lending “banklend,” and Number of bankruptcies “bnkrpt” increase. However, out-degree of Monetary base “mb” and Residential land price “landprice” decrease.

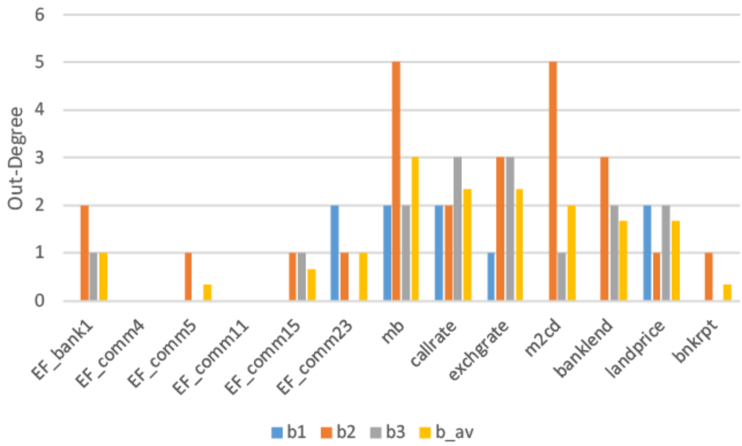

Fig. 29 Out-Degree in Bubble Periods

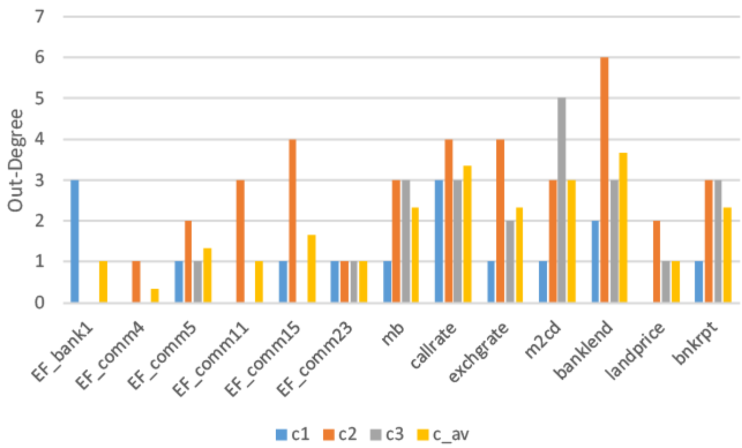

Fig. 30 Out-Degree in Economic Crisis Periods

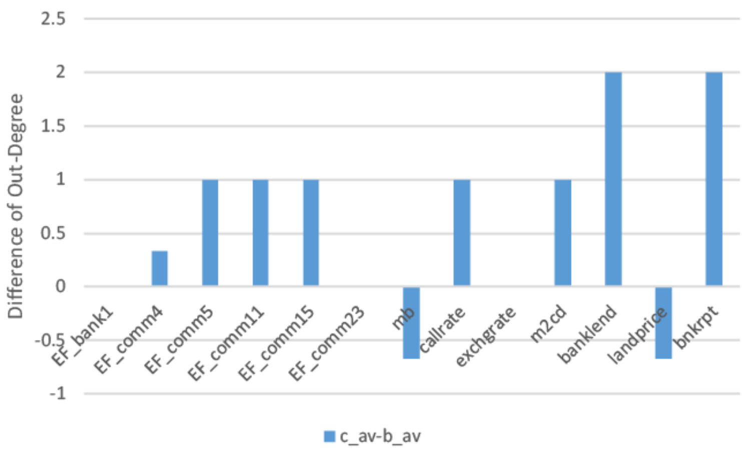

Fig. 31 Difference of Out-Degree

6 Conclusion

We studied channels of distress propagation from the financial sector to real economy through the supply chain network in Japan from 1980 to 2015 using a spin network model and discussed good indicators for macroprudential policy. Estimation of exogenous shocks acting on communities of real economy in the supply chain network provided evidence of the channels of distress propagation from the financial sector to real economy through the supply chain network. Causal networks between exogenous shocks and macroeconomic variables clarified the characteristics of the lead–lag relationship between exogenous shocks and macroeconomic variables at the bubble burst.

In summary, monitoring the temporal change of exogenous shocks and causal relationships among exogenous shocks and macroeconomic variables will provide good indicators for macroprudential policy. Causal relationships are summarized as follows: (1) Exogenous shocks acting on C_5 and C_{15}, Monetary base, Money stock, Bank lending, and Number of bankruptcies caused delay, and Exchange rate caused leading at the bubble burst. (2) Call rate, Exchange rate, Money stock, and Land price index obtained larger in-degree, and Bank lending obtained smaller in-degree at the bubble burst. (3) Exogenous shocks for other than financial sectors, Call rate, Exchange rate, Money stock, Bank lending, and Number of bankruptcies obtained larger out-degree, and Monetary base, and Monetary base and Residential land price obtained smaller out-degree at the bubble burst.

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