Measuring Systemic Risk on Indonesia's Banking System

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Abstract

Inter-connectedness is one important aspect in measuring the degree of systemic risk arising in the banking system. In this paper, this aspect besides the degree of commonality and volatility are measured using Principal Component Analysis (PCA), dynamic Granger causality tests and a Markov regime switching model. These measures can be used as leading indicators to detect pressures in the financial system, in particular the banking system. There is evidence that the inter-connectedness level together with degree of commonality and volatility among banks escalate substantially during the financial distress. It implies that less systemically important banks could become more important in the financial system during the abnormal times. Therefore, the list of systemically important banks as regulated in the Law on Prevention and Mitigation of Financial System Crisis (UU PPKSK) should be updated more frequently during the period of financial distress.

JEL codes : C32, C38, G21

Keywords : Inter-connectedness, systemic risk, Principal Component Analysis, Granger causality, regime switching

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Abstraksi

Interkoneksi merupakan salah satu aspek penting dalam mengukur tingkat risiko sistemik yang muncul dalam sistem perbankan. Tulisan ini bertujuan menganalisis hal ini, termasuk tingkat kesamaan dan volatilitasnya yang terjadi, dengan menggunakan metode Analisis Komponen Utama, tes hubungan kausalitas Granger secara dinamis, dan model perubahan rezim. Ukuran-ukuran ini dapat menjadi indikator untuk mendeteksi tekanan pada sistem keuangan, khususnya sistem perbankan. Hasil analisis menunjukkan bahwa tingkat interkoneksi, tingkat kesamaan, dan volatilitas perbankan mengalami peningkatan yang signifikan ketika pasar keuangan dalam kondisi tertekan. Hal ini berarti bahwa bank-bank yang sebelumnya tidak termasuk kategori bank berdampak sistemik bisa menjadi memiliki dampak sistemik pada periode sistem keuangan mengalami tekanan. Oleh karena itu, daftar bank-bank yang berdampak sistemik sebagaimana diatur dalam UU PPKSK perlu untuk diperbaharui secara lebih rutin selama periode pasar keuangan dalam tekanan.

Kode JEL : C32, C38, G21

Kata kunci : Interkoneksi, risiko sistemik, Analisis Komponen Utama, kausalitas Granger, perubahan rezim

1. Introduction

Initiated by depreciating Baht Thailand, banking crisis coupled with currency crisis during financial crisis 1997 had hurt the East Asian economies harshly. Some findings reveal that damage stemming from this crisis accounts for 30 per cent of GDP for South Korea and Thailand and 20 per cent of GDP for Malaysia and Indonesia in terms of the cost of bank recapitalization (Goldstein, Kaminsky, & Reinhart, 2000). For Indonesia itself, not only is the cost for resolving banking crisis costly, but it also prolongs up to five years with total general public loss amount of 40 per cent of GDP (McLeod, 2004). Following this crisis, many has developed an early warning model with the purpose of predicting the next crisis.

After a decade of the Asian financial crisis, the world is shocked with the collapse of a number of financial institutions in the US which is categorized as 'too big to fail' and then it spreads throughout the global economies becoming global financial crisis and countries affiliating to the US economy suffer. Indonesia experienced the same pressure during the global financial crisis 2008 – 2009, particularly in currency and banking system which ended up with a bail-out for Bank of Century. Both experiences of the Asian financial crisis 1997 – 1998 and global financial crisis 2008 – 2009 have underscored an important lesson of which once a financial institution fails, it can easily spread to the other financial institutions becoming a negative sentiment or even triggering another collapse of a financial institution, regardless prolonging debate of the decision of the bail-out for Bank of Century in Indonesia. As a consequence, it is imperative to assess systemic risks of a financial institution seeing its ability to spread quickly to other financial institutions within the financial system which may eventually damage the whole economy.

After the global financial crisis 2008 – 2009 or known as subprime mortgage crisis, many studies have been performed investigating the systemic risks of a financial institution (Billio, Getmansky, Lo, & Pelizzon, 2010). Instances of these studies are a study by the Bank of England examining funding liquidity risk using a network model to evaluate probability of a bank default (Aikman et al., 2009) and a study of measuring systemic risk of twelve major banks in the U.S. using ex-ante probabilities of bank default and correlations of forecasted asset returns (Huang, Zhou, & Zhu, 2009). However, most of those studies focus on advanced economies, in particular the U.S. economy. An emerging economy like Indonesia may pose different risks as its financial institutions have different characteristics compared with financial institutions in the advanced countries.

Having passed in March 2016, the Law on Prevention and Mitigation of Financial System Crisis (UU PPKSK) is a pivotal role for the Indonesia's financial system focusing on banking system as banks dominate the Indonesia's financial sector. One of the key features of the law is establishment of list of banks categorized as systemically important based on their interconnectivity, capacity and complexity, which is predetermined evaluated every six months (Syaifullah et al., 2016). Nevertheless, this arrangement could possibly carry a risk as interconnectedness among financial institutions, in particular banks, are likely to escalate during financial distress implying that less systemically important banks could become more important in the financial system during the abnormal times.

The rest of this paper is organized as follows. Section 2 describes literature reviews on measuring systemic risks of financial institutions, while Section 3 explains both the methodology and the data used. Section 4 then discusses the findings and results and finally Section 5 concludes.

2. Literature Review

A number of studies has been conducted to describe and measure systemic risk of the financial institutions. One important concept of systemic risk is that a systemic event may affect a number of financial institutions transmitting failures from one institution to another, so that a measure of systemic risk should be able to identify the risk of systemic institutions, which are so large and interconnected exposing negative spillover effects on others (Brunnermeier & Oehmke, 2013; Hartmann, Straetmans, & Vries, 2005). It is also imperative to map out relationships or inter-linkages among financial institutions in order to be able to identify systemic risk as well as financial fragility (Allen & Gale, 2007). Thus, to measure the systemic risk on the Indonesia's financial institutions, this paper focuses from those points of view. Since the Indonesia's financial institutions are dominated by banks, in terms of assets, this paper concentrates to measure systemic risk on Indonesian banks.

Theoretical framework lying beneath analyses in this paper refers to relationships among the Indonesian banks which may spread either through fundamental shocks or negative externalities, as well as network effects or escalating volatility (Allen & Gale, 2007; Anandarajan, Lee, & Anandarajan, 2001; Brunnermeier, 2008; Daníelsson & Peñaranda, 2011; Diamond & Rajan, 2009; Shin, 2012). Such relationship or interconnectivity is one of the important features of systemic risks described in the Law on Prevention and Mitigation of Financial System Crisis (UU PPKSK).

Billio et al. (2010) divides empirical literatures of systemic risks into three groups. The first group deliberates studies on bank contagion, while the second gives attention to crises of banks, booms of lending and aggregate fluctuations. The last group focuses on spillover effects, contagion of financial institutions and joint crashes in financial markets. In studying the bank contagion, the first group bases on the autocorrelation of the number of bank returns and bank defaults as well as bank exposures among others meaning that a bank default may make other banks insolvent (de Bandt & Hartmann, 2000). Other studies categorized in this group use correlations of bank asset portfolios and default probabilities (Lehar, 2005), besides bank trading risk similarities (Wong, 2008) and bank failures with maximum likelihood estimation of cumulative negative abnormal returns (Bartram, Brown, & Hund, 2007) as measures of systemic risks.

The second group of the studies concentrates on ratios of bank capital and its liabilities such that macro fundamentals can have noteworthy predictive power in order to detect systemic risks in the banking sector (Gonzalez-Hermosillo, Pazarbasioglu, & Billings, 1997; Hardy & Pazarbaşioğlu, 1999). Other studies in this group use indexes of credit derivatives prices (Bhansali, Gingrich, & Longstaff, 2008) and inter-linkages between macroeconomic conditions and financial markets together with their intermediaries (De Nicolo & Lucchetta, 2009) as measures of systemic risks among the financial institutions.

The third group of the studies brings together spillover effects, contagion of financial institutions and joint crashes in financial markets as measures of systemic risks. This group uses such as correlations resulted from Granger causality tests between exchange rates and interest rates before and after the Asian crisis (Kaminsky, Lizondo, & Reinhart, 1998) and simple correlations to measure volatility changes during the Asian crisis (Forbes & Rigobon, 2001). They find similar results finding that there were many causal correlations detected during the crisis.

In order to measure the systemic risks, this paper follows Billio et al. (2010) who measure the degree of connectivity among the U.S. financial institutions. Due to the complexity of the financial system in the U.S., they define the system incorporating banks, brokers, hedge funds and insurance companies. Rather than following them in dividing into four types of financial institutions, this paper stresses on just banks since the Indonesia's financial sector is dominated by banks in terms of assets. Adopting Billio et al. (2010) methods, this paper uses principal component analyses, regime switching models and dynamic granger causality tests as measures of systemic risk on the Indonesia's banking system.

3. Methodology and Data

3.1. Principal Component Analysis (PCA)

Principal component analysis (PCA) can detect empirically increased commonality among the asset returns, for instance banking asset returns. This method models variance structure of a set of variables using linear combinations of the variables by decomposing the covariance matrices, so that it can measure the degree of commonality among the variables (Barber & Copper, 2012; Billio, Caporin, Pelizzon, & Sartore, 2012). For instance, asset returns are driven by a linear K-factor model, the first K principal components explain most of the time-series variation in returns.

$$R_{jt} = \alpha_j + \delta_1 F_{1t} + \cdots + \delta_k F_{kt} + \varepsilon_{jt} \quad (1)$$

Where $E\left[\varepsilon_{jt}\varepsilon_{j't}\right] = 0$ for any $j \neq j'$, so the covariance matrix $\sum$ of the vector of returns $R_t \equiv [R_{1t} \dots R_{jt}]'$ can be expressed as

$$Var[R_t] \equiv \Sigma \quad = Q\theta Q', \theta = \begin{bmatrix} \vartheta_1 & 0 & . & . & 0 \\ 0 & \vartheta_2 & & & 0 \\ . & & . & & . \\ . & & & . & . \\ 0 & . & . & 0 & \vartheta_N \end{bmatrix} \quad (2)$$

Where θ contains eigenvalues of Σ along its diagonal and Q is the matrix of subsequent eigenvectors. The unit length linear combination of the original variables with maximum variance is expressed by the first principal component, while subsequent principal components maximize variance among unit length linear combinations which are orthogonal to the former components (Johnson & Wichern, 2002).

3.2. Markov Regime Switching Model

Following Billio et al. (2010), the next measure of systemic risk can be captured through sudden regime-changes in the volatilities of the expected returns of financial institutions, which is in this case they are banks. This regime-switching model is proposed because in general the linear models are not able to capture regime shifts or discrete changes which commonly happens during financial distresses. Examples of regime shifts are Mexican crisis 1994-1995, Asian crisis 1997-1998 and global financial crisis 2008-2009 (Billio et al., 2010).

The regime switching model proposed in this paper is a simple two-state model for the banks in order to get a measure of systemic risk. Such two-state model is empirically able to gauge the possibility of a regime switching from a normal to a distressed financial regime (Bekaert & Harvey, 1995; Duong & Swanson, 2011; Guidolin, 2011a, 2011b). The composite index return is characterized by volatility in each of the two states of the Markov chain $Z_{i,t}$, which is estimated for both low and high volatility states. This paper follows the convention that $Z_{i,t} = 0$ is defined as the low-volatility regime and $Z_{i,t} = 1$ is defined as the high-volatility regime. The regime switching process can be expressed as follows:

$$R_{i,t} = \mu_i(Z_{i,t}) + \sigma_i(Z_{i,t})u_{i,t} \quad (3)$$

In which $R_{i,t}$ is the returns of index i in period t, σ_i is the volatility of index i, $u_{i,t}$ is independently and identically distributed over time, and $Z_{i,t}$ is the two state Markov chain with transition probability matrix $P_{z,i}$ for index i. The first order Markov assumption requires that the probability of being in a regime depends on the previous state, so that

$$P(S_t = j|S_{t-1} = i) = p_{ij}(t) \quad (4)$$

Or in a transition matrix equation (4) can be written as:

$$p(t) = \begin{bmatrix} p_{11}(t) & \dots & p_{1M}(t) \\ . & \dots & . \\ p_{M1}(t) & \dots & p_{MM}(t) \end{bmatrix} \tag{5}$$

Where the ij –th element reflects the probability of transitioning from regime i in period $t-1$ to regime j in period t. An alternative measure of systemic risk is constructed by taking average of probabilities of being in the high-volatility states of different groups of banks, including banks book four, banks book three as well as banks book two, so that:

$$S_{p,t} = \frac{1}{m}\sum_{i=1}^{m} Prob(Z_{i,t} = 1|R_{i,t}) \tag{6}$$

Where $S_{p,t}$ is simply average of all probabilities of high volatility regime among all banks. Evidence of interdependence between banks is present when there is a noteworthy increase in the average probability $S_{p,t}$.

3.3. Dynamic Granger Causality

The third measure of systemic risk used in this paper is Granger causality which is performed dynamically rolling-over 36 months. Not only is the degree of interconnectedness important, but also the direction of the relationship is also essential. Classical Granger causality can help predict such direction (Billio et al., 2010). The linear inter-relationships can be represented with the following model:

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \epsilon_t \tag{7}$$

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \mu_t \tag{8}$$

Where a_j, b_j, c_j, d_j are the estimated coefficients, m is the maximum lag considered, while ϵ_t and μ_t are two uncorrelated errors following white noise processes.

Causality denotes that Y causes X when b_j is significantly different from zero and X causes Y when c_j is significantly different from zero. If both hypotheses are true, it implies that there is a two-way or feedback relationship between the series. The number of maximum lags selection is based on Bayesian Information Criterion. The results of the causality tests are based on F-test with null hypotheses that b_j or c_j are equal to zero.

3.4. Data

The data used for the estimation is a monthly data for banking stock indices incorporating 32 banks with sample period of February 1992 – March 2016. All data is obtained from the Bloomberg. Banks returns are then constructed as monthly percentage changes. Composite index of all banks returns are formed weighted based on their market capitalizations in the stock market.

Subsamples are also created to test performances of different groups of banks within varied subsample periods. The groups of banks are categorized based on their size of core capital. According to the Regulation of the Financial Services Authority No. 6/POJK.03/2016, banks are categorized into four groups, i.e. banks book 1 with core capital less than 1 trillion rupiahs, banks book 2 with core capital greater than 1 trillion but less than 5 trillion rupiahs, banks book 3 with core capital greater than 5 trillion but less than 30 trillion rupiahs, and banks book 4 with core capital at least 30 trillion rupiahs. However, data for banks book 1 is unavailable on Bloomberg, so that this paper only covers banks book 2 to 4.

Unit roots tests of the raw data and constructed variables are performed using Augmented Dickey Fuller (ADF) and Phillips Perron tests in Eviews version 8. The results show that all raw data are integrated processes of order one (I (1)) at 1 per cent significance level. After constructions, all are I (0) or stationary.

4. Empirical Results and Analysis

This section discusses estimated measures of systemic risks as described in Section 3 using historical data of monthly return of banking stock indexes, consisting of four different measures. Subsection 4.1 reports estimated results of PCA in a number of different subsamples with various periods, while Subsection 4.2 reports the results of estimates using Markov Regime Switching Model. Subsection 4.3 and 4.4 subsequently discuss results of dynamic granger causality tests in graph and network diagram.

4.1. Principal Component Analysis (PCA)

As the central point of a systemic risk is commonality among a number of financial institutions, this first measure captures the commonality through the PCA analysis which is able to extract the main components driving variations among the institutions. As banks dominate the Indonesia's financial sector in terms of assets, this paper focuses on the banking sector. Table 1 presents the first principal components in different subsamples and different time periods to capture behavior of different groups of banks in different periods of time.

To test behavior of different groups of banks and also due to data availability, the sample is divided into 5 subsamples, including group of six banks which has longer available data since 1994, group of 15 banks with data since 2004, and finally 3 groups of banks classified based on their assets. Banks with assets more than 30 trillion rupiahs are grouped in Book 4 (sample of 10 banks), while banks with assets between 5 and 30 trillion rupiahs are grouped in Book 3 (sample of 6 banks), and banks with assets between 1 and 5 trillion rupiahs are put in Book 2 (sample of 6 banks).

The sample period for estimation is divided into 8 groups based on periods of financial crises or period of financial distress. According to literatures, Indonesia has experienced several periods of financial distress, such as during the Asian financial crisis in 1997-1998 and during global financial crisis of 2008-2009. Ending quantitative easing program by the US in 2013 as well as Chinese yuan devaluation and uncertainty of the Fed's plan to hike interest rate in 2015 are also some instances of events which has already put Indonesia's financial sector under pressure. Therefore, the sample period in these estimates are grouped into several different times.

Table 1 Principal component analysis (1st principal component) of the monthly return of banking stock indexes

Sample	Description	1994-1996	1997-1999	2000-2002	2004-2006	2007-2009	2010-2012	2013-2015	2013-2016
6 banks	PC 1	2.37	**4.84**	2.29	2.60	2.44	2.18	**2.19**	1.74
	Proportion	0.39	**0.81**	0.38	0.43	0.41	0.36	**0.37**	0.29
15 banks	PC 1	-	-	-	6.47	5.67	5.60	**5.89**	5.39
	Proportion	-	-	-	0.43	0.38	0.37	**0.39**	0.36
BUKU 4 (4 banks)	PC 1	-	-	-	4.44	**5.42**	3.70	**4.72**	4.37
	Proportion	-	-	-	0.44	**0.54**	0.37	**0.47**	0.44
BUKU 3 (12 banks)	PC 1	-	-	-	1.84	**2.86**	2.47	1.72	1.67
	Proportion	-	-	-	0.31	**0.48**	0.41	0.29	0.28
BUKU 2 (6 banks)	PC 1	-	-	-	-	-	-	2.95	2.44
	Proportion	-	-	-	-	-	-	0.49	0.41

Source: Author's calculation

The results in Table 1 show that during the periods of financial distress, degree of commonality as reflected in the eigenvalues of the first principal component as well as their proportions scales up, for example in 1997-1999. Proportion of 0.81 in 1997-1999 was much higher compared with the proportion during 1994-1996 and 2000-2002, the periods before and after the Asian financial crisis.

However, a slight different results come up for sample period of 2007-2009. Not all groups of banks experienced increase of the degree of commonality during the period. Estimates with group sample of 6 banks and 15 banks show that those banks even experienced lower degree of commonality as reflected by lower eigenvalues of the first principal component, but estimates with group sample of banks book 4 and banks book 3 show the other way around with evidence of significant increase of the degree of commonality among the banks. It may indicate that the banks are segmented or in other words, a book-4-bank is likely willing to lend to or borrow from other banks book 4 only and a book-3-bank prefers doing business with other alike banks with the same type only, especially during the financial distress.

Estimates with sample period of 2013-2015 also reveals an interesting feature with evidence of no increase in degree of commonality in banks book 3 during the period. It may reveal the fact that more open a financial institution in capital market, more sensitive they are to external shocks. Aside from the external shocks, the higher commonality implying growing pressures on groups of 6 banks, 15 banks and banks book 4 may also be influenced by domestic shocks, such as interest rate cap announced by the Financial Services Authority. The intervention from the regulator seems seriously hit banks book 4. In addition, the estimates using more recent sample period (2013-March 2016) signal that pressures on banking sector have cooled down.

4.2. Markov Regime Switching Model

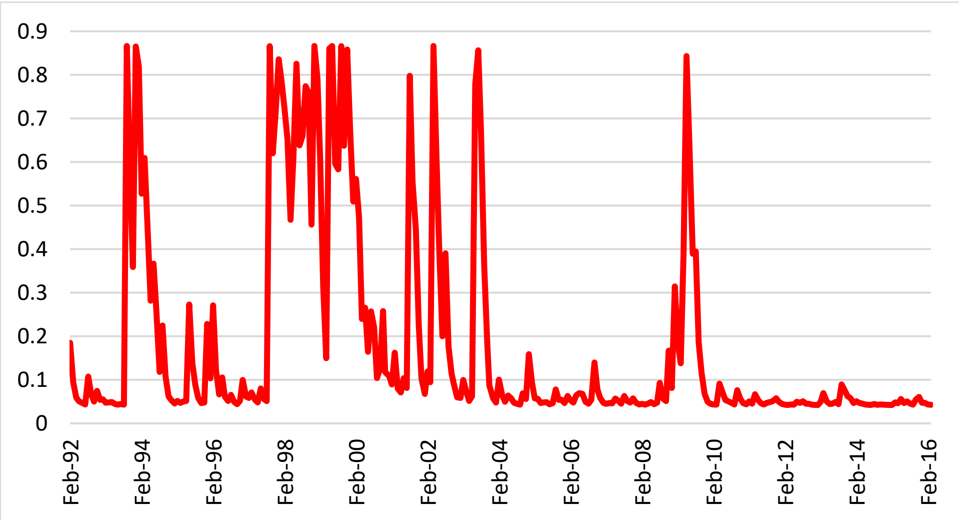
The second systemic risk measure is the estimate of the Markov regime switching model presented in Figure 1. The composite index return is characterized by volatility in each of the two states of the Markov chain $Z_{i,t}$, which is estimated for both low and high volatility states. This paper follows the convention that $Z_{i,t} = 0$ is defined as the low-volatility regime and $Z_{i,t} = 1$ is defined as the high-volatility regime.

The graph in Figure 1 shows the probability of being in the high-volatility state (Z=1) for the whole sample for the banking composite index return. Banks had been in a high-volatility state from the fourth quarter of 1993 to the first quarter of 1994 and subsiding thereafter until mid-1997. This later period is called period of the "calm before the storm" (Billio et al., 2010). During the Asian financial crisis since 1997 Indonesia's banks had been in the high-volatility state and descending by the end of 2003. It shows how severe Indonesia's banking system hit by the crisis and it takes a long time to recover. There were also sparks of growing probability of being in the high-volatility regime at the end of 2004 at which Indonesia had a problem on its mutual funds, but the probability was quite relatively low compared with during the financial crisis period. Another spark surfaced during and after 'mini crisis' in 2005-2006, but again the level was quite low.

The next dramatic increase of probability of being in a high-volatility regime was during the global financial crisis in 2008-2009 with the peak of just under 0.9 (90 per cent) on April 2009. Not surprisingly, the high-volatility states of banking index are also associated with crisis periods.

In 2013 when the Fed announced that they would end their quantitative easing program, a spike appeared. So was at the end of 2015 before the Fed started to tighten its monetary policy by rising its benchmark interest rate for the first time since the global financial crisis. However, the level of probability of being in high-volatility state was far below the probability level during either Asian financial crisis 1997-1998 or the global financial crisis 2008-2009.

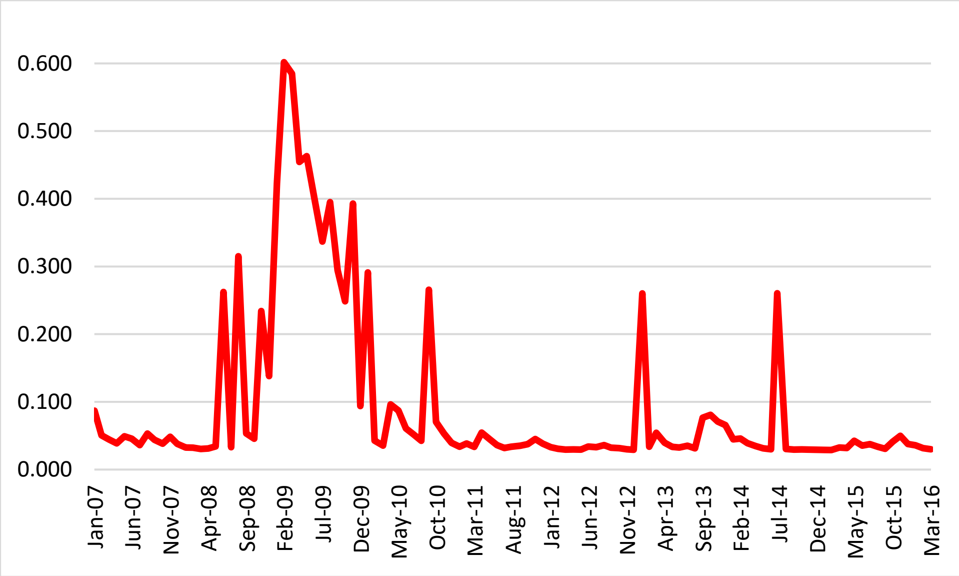
Figure 1 Probability of being in the high volatility regime for the monthly return of banking stock indexes, February 1992 – March 2016



Source: Author's calculation

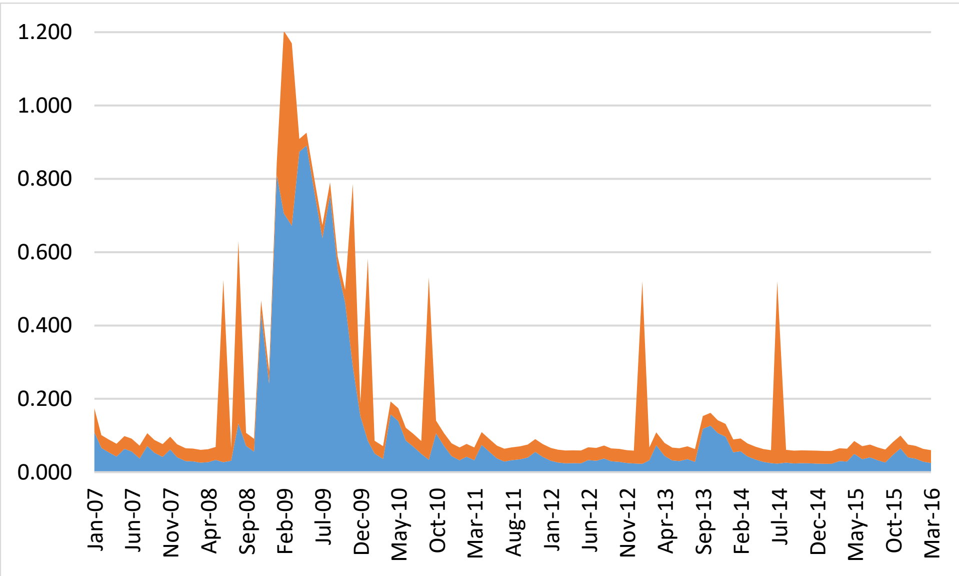
An alternative measure of systemic risk is constructed by taking average of probabilities of being in the high-volatility states of different groups of banks, including banks BUKU 4, banks BUKU 3 as well as banks BUKU 2. However, due to data availability, this alternative measure only covers banks BUKU 4 and BUKU 3 with subsample January 2007 – March 2016. In addition, the probability of each banks BUKU 4 and BUKU 3 being in the high volatility regime for the monthly return of banking stock indexes are also plotted to look at their contributions. As expected, banks BUKU 4 have greater contributions to the overall probability of being in the high volatility regime during financial distress (see Figure 2 and 3).

Figure 2 Average probability of being in the high volatility regime for the monthly return of banking stock indexes of banks BUKU 4 and BUKU 3, January 2007 – March 2016



Source: Author's calculation

Figure 3 Contribution of banks BUKU 4 (blue area) and BUKU 3 (orange area) to the probability of being in the high volatility regime for the monthly return of banking stock indexes, January 2007 – March 2016 (stacked area chart)



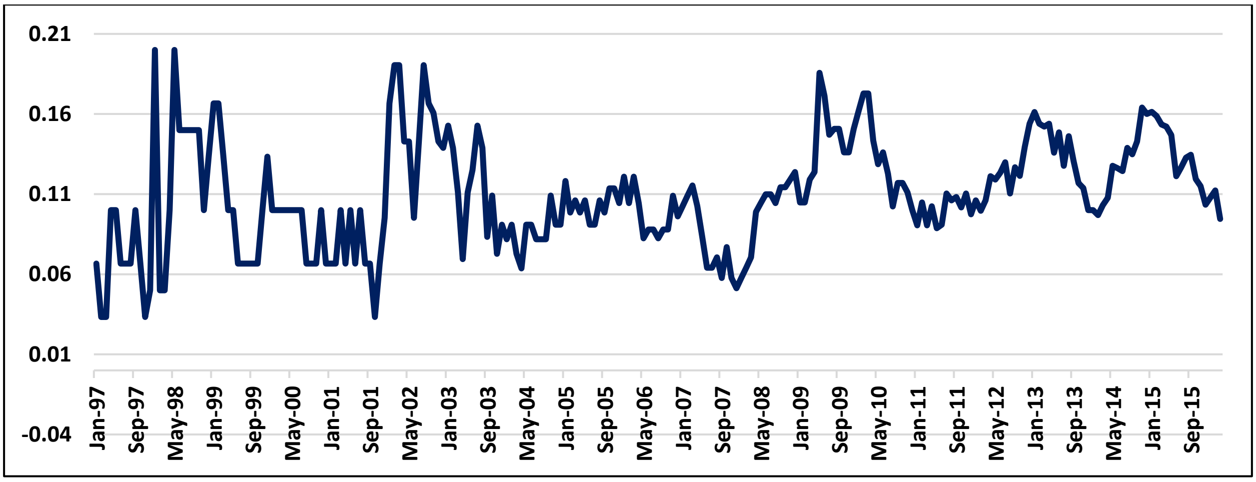
Source: Author's calculation

4.3. Dynamic Granger Causality

The third measure of banking systemic risk is resulted from linear Granger causality test which is dynamically performed among 36-monthly returns of banks with sample period from January 1997 to March 2016. Based on causal interconnectedness, this systemic risk measure may capture both contagion effects between banks as well as exposures among them to a common factor, such as the Indonesian equity market.

Upward trends in Figure 2 present increasing interconnectedness among banks and propagating shocks from one bank to another. The interconnectedness peaked during Asian financial crisis 1997-1998, 2001-2002 and during global financial crisis 2008-2009. There were also evidences of soaring interconnectedness during the US taper tantrum in 2013 and during the financial distress in 2015, i.e. when the Fed was going to raise its benchmark interest rate for the first time after seven years of low-nearly zero interest rate. There was also an intensifying interconnectedness among the banks during 'mini crisis' 2005-2006. These findings are consistent with the previous findings using two different measures in Section 4.1 and 4.2.

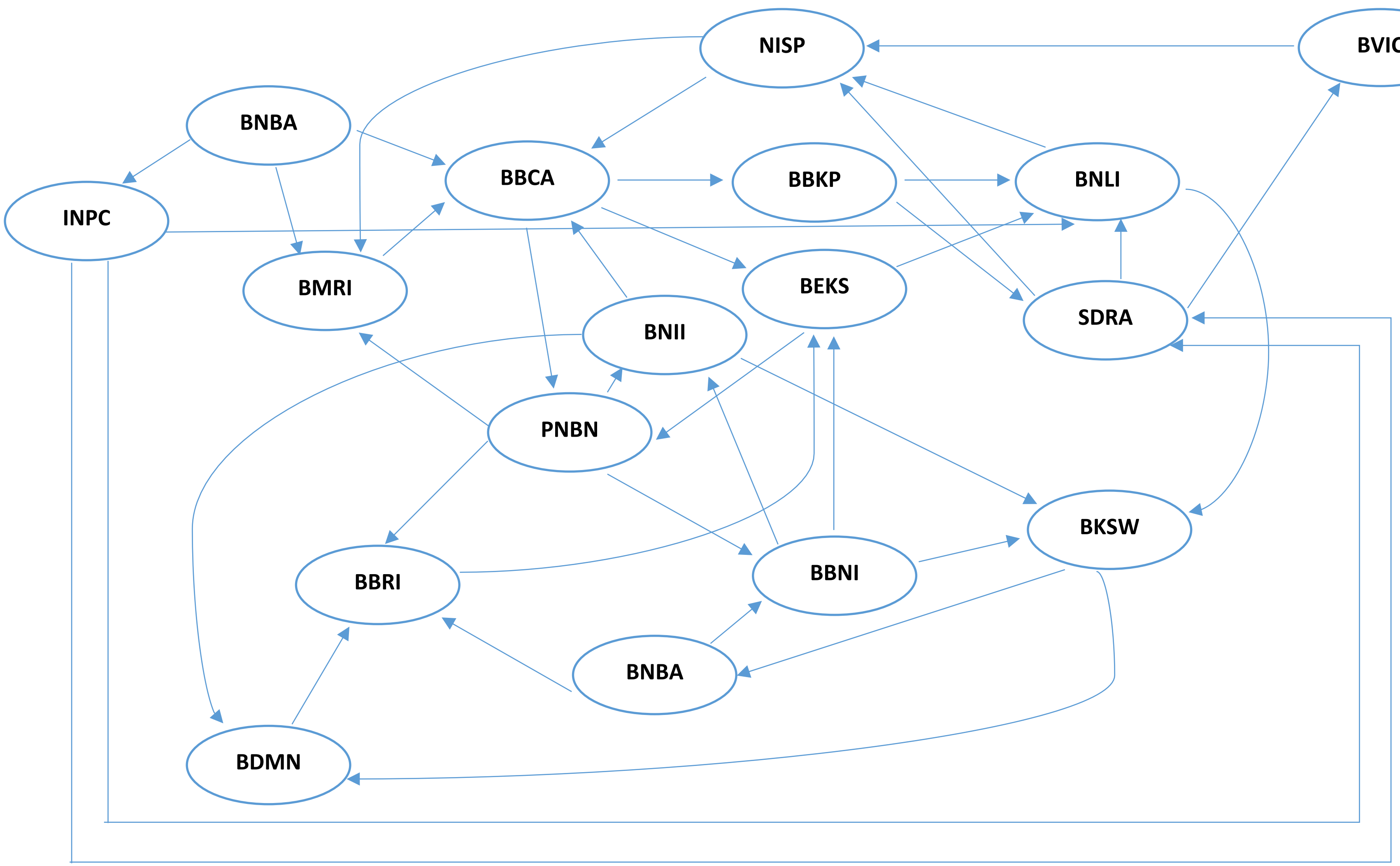
Figure 4 Dynamic linear granger causality relationships (at 10% level of statistical significance) among the 36-monthly-return of banking stock indexes, January 1997 – March 2016



Source: Author's calculation

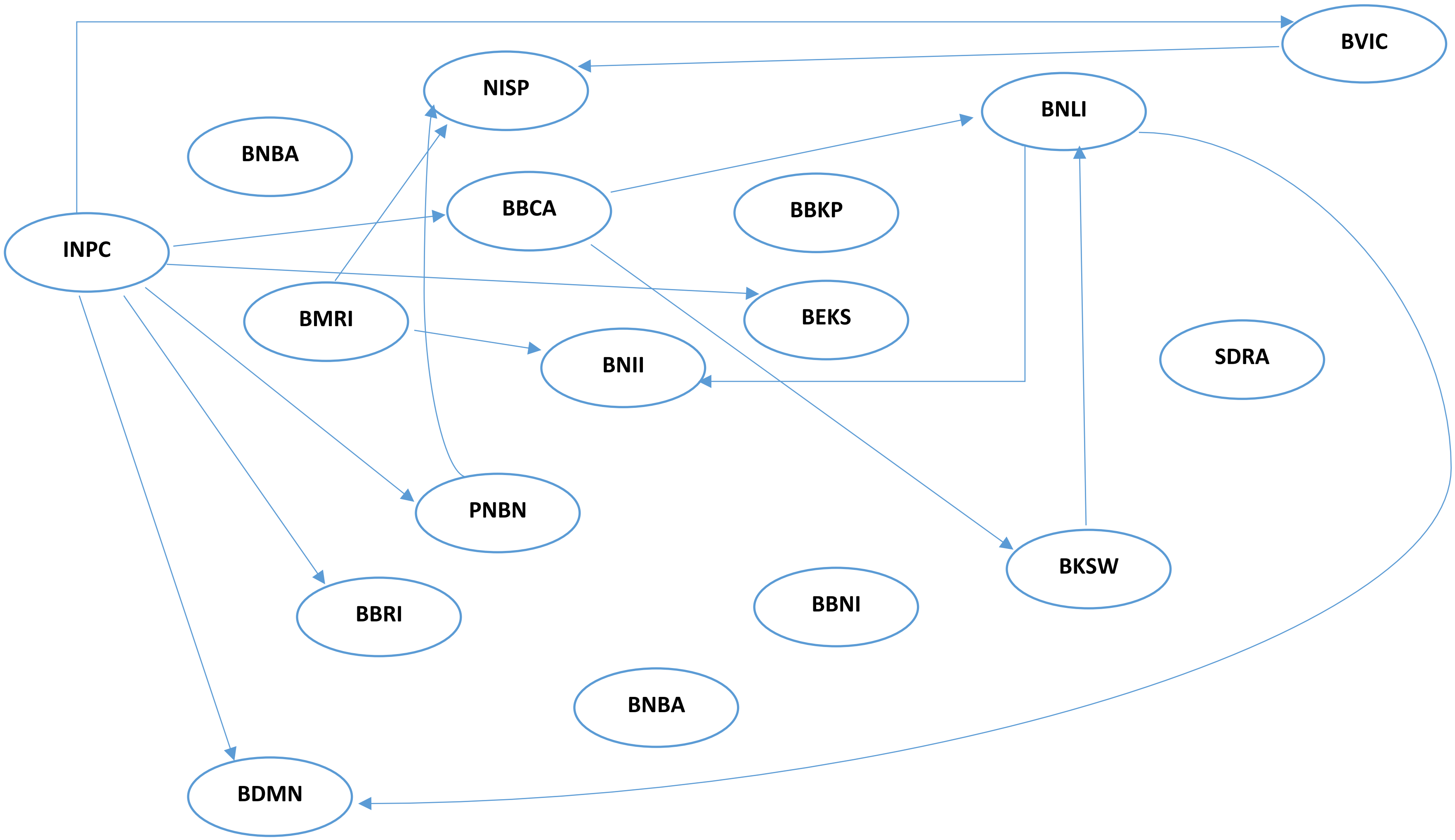
Analyzing more deeply by looking at the level of individual banks, the results imply the same conclusions. During the financial distress, the interconnectedness among banks rises dramatically (see Figure 5 and 6). This dynamic Granger causality tests can also actually be used to rank banks which are categorized as systemically important banks. Banks with more connections can be considered as more systemically important banks from the interconnectedness point of view. Another important finding from Figure 5 and 6 is that banks which might not be systemically important during normal times, may pose higher degree of systemic risk during period of financial distress.

Figure 5 Pairwise Granger causality tests, significant at 10 per cent level, sample: May 2007 – April 2010



Source: Author's calculation

Figure 6 Pairwise Granger causality tests, significant at 10 per cent level, sample: January 2004 – December 2006



Source: Author's calculation

5. Conclusion and Policy Recommendation

Inter-connectedness is one important aspect in measuring the degree of systemic risk arising in the banking system. It can be used as a leading indicator to detect growing pressures in the financial system, in particular the banking system. There is evidence that the inter-connectedness level together with degree of commonality and volatility among banks escalate substantially during the financial distress. It implies that less systemically important banks could become more important in the financial system during the abnormal times. Therefore, the evaluation period of six months in setting up list of systemically important banks as regulated in the UU PPKSK could possibly carry a risk during the period of financial distress. During the abnormal times, the list should be updated more frequently, for instance in a monthly basis.

In addition, there are still some drawbacks in this paper. One drawback is the linearity assumption used in estimating the dynamic Granger causality tests as well as in estimating the Markov regime switching model. The relationships among banks may not be linear. Therefore, estimating nonlinear Granger causality tests and also nonlinear regime switching model can be a worth extension of this paper in the future. Autoregressive lags may also be possible to be incorporated in the regime switching model.

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