Economic Journal of Emerging Markets, 9(2) October 2017, 150-158

EJEM
Econ. J. Emerg. Mark.

Economic Journal of Emerging Markets

Available at http://journal.uii.ac.id/index.php/jep

Systemic risk, bank's capital buffer, and leverage

Buddi Wibowo

Department of Management, Economic and Business Faculty, Universitas Indonesia, Jakarta, Indonesia
E-mail: buddi.wibowo@ui.ac.id

Article Info

Article history:
Received : 2 February 2017
Accepted : 14 August 2017
Published : 1 October 2017

Keywords:
systemic risk, bank competition, distance-to-default, capital buffer, leverage

JEL Classification:
G21, G31, G33

DOI:
10.20885/ejem.vol9.iss2.art4

Abstract

This paper measures individual bank's impact on banking systemic risk and examines the effect of individual bank's capital buffer and leverage to bank's systemic risk impact in Indonesia during 2010-2014. Using Merton's distance-to-default to measure systemic risk, the study shows a significant negative relationship between bank's capital buffer and systemic risk. High capital buffer tends to lowering bank's impact on systemic risk. Bank's leverage level also influences its contribution to systemic risk, even though the impact is much lower compared to that of capital buffer impact.

Abstrak

Makalah ini mengukur dampak sistemik dari setiap bank serta menguji pengaruh *capital buffer and leverage bank* terhadap risiko sistemik perbankan di Indonesia untuk periode 2010-2014. Dengan metode Merton's *distance-to-default* sebagai pengukuran risiko sistemik, hasil riset menunjukan tingkat *capital buffer bank* secara signifikan berpengaruh negatif terhadap risiko sistemik perbankan Indonesia. Semakin tinggi *capital buffer* sebuah bank, semakin rendah dampak sistemik bank tersebut. Tingkat leverage bank memiliki pengaruh yang signifikan juga terhadap dampak sistemik sebuah bank, walau pengaruhnya jauh di bawah *capital buffer*.

Introduction

World financial crisis reveales a new problem, namely systemic risk, in which failure of a bank is correlated with many banks in a banking system. World financial crisis revealed a new problem, namely systemic risk, in which failure of a bank is correlated with other banks in a banking syst. Bank failures occur simultaneously in very short period of time, and their effect spread to other financial institution. Bank failure not only threatens banking system but also overall financial system. The fragility of the banking system due to the increasing probability of an individual bank failures threatens financial system and the economy as a whole. The stability of the banking system is no longer affected by the absolute risk of an individual bank, but rather how serious contribution of an individual bank into a failure of the banking system as a whole (Anginer, Demirguc-Kunt, & Zhu, 2014). This phenomenon directs a new orientation in update macro-prudential regulation and banking supervisions. Deposit insurance premium in almost all countries in the world today, according to Basel Committee on Banking Supervision (2012a, 2012b) has been associated with systemic impact of a bank or usually called as risk-based deposit insurance premium.

Some researchers has built some definitions of a bank's systemic impact and its measurement method. (Anginer et al., 2014) define systemic impact of a bank as correlation of bank default risk which is measured by the R^2 of the regression equation between the change of a bank default risk and the change of all banks' default risk. The high correlation of all banks' risk taking behavior increase probability of simultaneous bank failures. Adrian & Brunnermeier (2016) proposed CoVAR or Correlated VaR as a measure of a bank's systemic impact. CoVaR measures how much changes Value at Risk (VaR) of banking system as a whole is affected by a bank's VaR changes. Acemoglu, Ozdaglar, & Tahbaz-Salehi (2015)define systemic risk as the financial contagion that can be measured through inter-bank network structure so that the banks interconnections creates a propagation effect of a counterparty risk suffered by an individual bank. Elliott, Golub, & Jackson (2014)construct a model to measure banks systemic risk in the existence of cross shares ownership among banks and other financial institutions. They suggest the potential loss of all banks and financial institutions that hold shares in a bankrupt bank which trigger a chain reaction in the banking system and spread to whole financial system. Georg (2013) and Battiston, Delli Gatti, Gallegati, Greenwald, & Stiglitz (2012) observed the impact of interbank networks to the propagation of macroeconomic shocks which influence the health of banks that can lead to a collapse of the banking system. Shin (2009) highlights securitization of bank loans that causes extended effect of bank failures to holders of the loan securitization. Gai, Halande, & Kapadia (2011) studied the networking model of inter-bank loans with unsecured claims and using numerical simulations, they showed that more complex and more concentrated financial network create more fragile banking system.

Some researchers such as Fiordelisi & Marques-Ibanez (2013) use bank's financial report data as a measure of bank default risk. Bank stability is measured from the stability of bank profitability in a given period of time and is known as the bank's Z-score. Measuring bank default risk based on accounting data has its own problems, namely the availability of accounting data, depends on the release of the financial statements and bank's accounting method make significant difference between book value and market value. These limitations prohibit accurate estimation of bank's systemic risk at specific time period.

Recent researches like Anginer et al. (2014) and Sundaresan (2013) show that measurement of bank default risk which is the most powerful and widely accepted among academics and practitioners is Merton (1974). Merton model can estimate the probability of bank default on a daily basis by using market value of bank equity in the stock market. Accommodating investors' valuation in capital markets, the probability of default generated by Merton models can reflect the actual condition of the bank, subject to assumption that capital markets are efficient. However, this is an advantage of Merton model but also its weakness. Merton model can only be used to estimate the risk of a bank which its shares are traded on the stock exchanges.

Merton model uses market value of the company's assets which reflects company's prospects and business value in the future. The market value of the assets changes over time depending on external and internal situation of the company so we may assume it moves like a random walk. The next pillar of the Merton model is that the market value of equity and debt can be modeled as a contingent claims on company's assets. Corporate debt can be considered as a contractual option to sell (put option) on the company's assets with a strike price amounting to the principal amount of debt (face value of debt). The put option is due exactly upon the maturity of the debt. On the other hand, company's equity can be modeled as a call option.

If the market value of asset (V_t) is higher than face value of debt at maturity date (F) then the creditors will receive the entire principal of debt. If the market value of the assets is lower than face value of debt, (F_t<V_t), the company is in a state of default in Merton definition, so the company is unable to pay the principal of debt. The creditors or bond holders will receive market value of company's assets (V_t) and suffered a loss, (F_t-V_t). However, if the bond holder holds a put option contract with a specification that has been described above, at the time of default, bond holders can still get the principal debt fully by exercising of the put option contracts at a strike price of debt principal. Portfolio risky bond combines with a put option can be a risk free portfolio. Price of the put option contract will be high if the probability of company default is high. So, probability of bankruptcy is reflected on the probability of the put option will be exercised. In terms of derivatives contracts, the probability of a put option contract is in-the money (Anginer et al., 2014). The more likely the bank failure, put option contract will be at the higher value (in-the money). Following Merton (1974), value of corporate debt can be modeled as a put option, while the corporate equity value can be modeled as a call option.

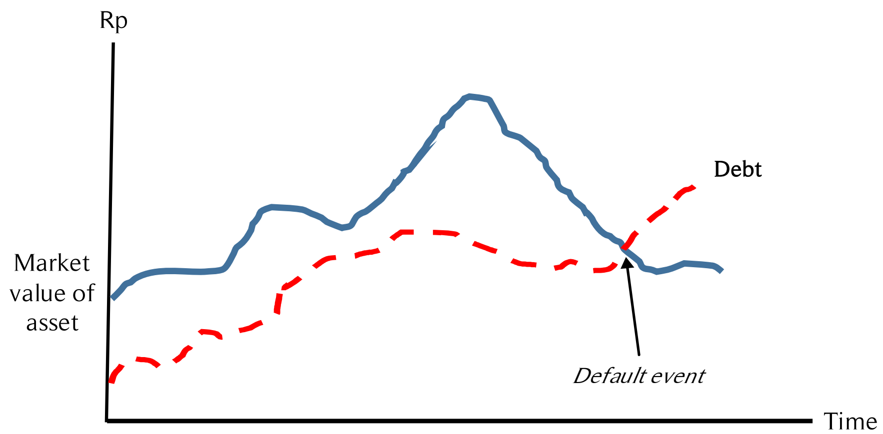

Figure 1. Default event

The estimation method of asset market value has been a focus of research implementing Merton model in the presence of variable in which the data are not available in the market (unobserved variable). Stock market value is approximated by its market value of equity that can be seen on the company's stock price traded on the stock exchange. Method of estimation of the market value of a company's assets and the volatility is becoming one of the topics of research of its own and is still growing in the context of the implementation of this model of Merton (Afik, Arad, & Galil, 2016).

Tabel 1. Debt holder pay off

		Default	
	Not default	Without option hedging	With option hedging
	$V \geq F$	$V < F$	$V < F$
Debt holder pay off	F	V	F

Some experts argue that bank's capital buffer contributes big and important parts in banking systemic risk (Acemoglu et al., 2015). Capital buffer considers risk weighted asset, not only book value of asset. Capital buffer measures more accurately bank stability than bank's asset value. Capital buffer reflects bank capacity to absorb risk independently. With enough amount of capital, bank can survive amid correlated defaults in banking system and have better resiliency in monetary crisis.

Some expert also argue that bank leverage led to greater impact to systemic risk (Campbell, Hilscher, & Szilagyi, 2008; Elliott et al., 2014). Even bank's debt does not correlate with other banks, high leverage put bank in risky position that threaten bank stability. Bank with high leverage is more susceptible to macroeconomic variable fluctuations. If susceptible banks are highly interconnected than a failure in one bank will be followed by many defaults of bank.

This study examines the effect of bank's capital buffer and leverage on banking systemic risks based on Indonesia public banks data. By observing the condition of banks in developing countries like Indonesia banking industry which consists of a lot of banks with various characteristics, the study can sharpen and extend the results of previous research in terms of the measurement of systemic risk and the factors that influence it. By using Merton's distance-to-default as the measurement of systemic risk, this study gives a scientific measure of Indonesia banks' impact on systemic risk and gives a solid foundation for regulator to classify the systemic important financial institution, understanding important factors influencing the systemic risk and develop regulatory setting to maintain banking system stability.

Research Method

Data

The study examines Indonesia banking data between 2010 and 2014. The selection of this period is to avoid the influence of the global economic crisis in 2008. The data was obtained from Thomson Reuters Data stream data for the stock market data, while monthly banks' financial statements were obtained from Indonesian Banking Directory Bank Indonesia. The criteria in determining the sample are as follows: (1) Indonesia commercial banks operated in Indonesia and its financial report for 2010-2014 is available; (2) The banks had IPO at the latest in 2008; (3) Bank was never delisted from the Indonesia Stock Exchange during the period 2008-2014; (4) Bank's shares were actively traded in the period 2008-2014; (5) Bank's shares were never under sanction of suspension. Referring to the above criteria, the number of samples that can be collected from public commercial banks listed on the Indonesia Stock Exchange are 24 banks.

Model

To empirically test the significance and the pattern of the relationship between the level of banking competition with systemic risks, this study uses a research model as follows:

$$risk_{i,t}=\alpha+\beta_1\, Capital\ Buffer_{i,t-1}+\beta_2\, Leverage_{i,t-1}+\varepsilon_{i,t} \qquad (1)$$

where the dependent variable is banking systemic risk which is measured by using *Merton's distance-to-default.* The independent variables are bank's capital buffer and leverage.

Systemic risk measurement

To measure individual bank's default risk, the study uses contingent claim framework following(Merton, 1974). Merton Model puts value of bank's equity as a call option on the bank's assets. Bank's default probability equals the probability of that bank call option became "in the money", ie when the market value of bank assets is lower than total liabilities. Many researchers measures the probability of default by using the distance to default which is the difference between the values of the company's assets with its face value of debt. Merton's Distance to Default has proven to be a better predictor of default than accounting data based-models (Sundaresan, 2013; Campbell et al., 2008; Bharath & Shumway, 2008).

Compared to accounting data based-risk model such as Z-score, Merton's distance to default which is based on market data has several advantages. Firstly, the distance to default can be calculated with high frequency and in shorter interval period so it can estimate default risk at a particular point of time. Audited financial statements are available on annual basis or for the unaudited is monthly basis. Stock market information are available on a daily basis. Secondly, information's in the stock market usually are forward-looking so that the distance to default can reflect market perceptions on condition of the bank in the future.

Merton's distance-to-default was calculated through the method that has been widely used also in previous studies (Anginer et al., 2014; Sundaresan, 2013). This method was proposed by Merton (1974) where the value of the bank's equity markets can be modeled as a call option on the bank asset:

$$V_E = V_A e^{-dT} N(d_1) - Xe^{-rT} N(d_2) + (1 - e^{-dT}) V_A \quad (2)$$

$$d_1 = \frac{\log\left(\frac{V_A}{X}\right) + \left(r - d + \frac{S_A^2}{2}\right)T}{S_A\sqrt{T}};\ d_2 = d_1 - S_A\sqrt{T} \quad (3)$$

Equation (2) is the Black-Scholes-Merton formula for call option value estimation. V_A is the market value of the bank's assets, $V_E$is the market value of the bank's equity. X is the Face Value of bank debt maturing at time T and linearly interpolated for each point daily over a period using the average position beginning of the month and the end of the month. This method needs to be done in order to obtain a smooth process of asset value and avoid spikes (jumps) on the result implied default probability. The same method performed by Anginer et al. (2014) and Anginer, D., & Demirguc-Kunt (2011).r is the risk-free interest rate, and d is the percentage of the dividend to the market value of bank assets. S_A is the volatility of the bank's assets. Because the market value of bank assets and the volatility of bank asset (V_A dan S_A) are unobservable variables, both estimated by Newton iteration through equations 2 and 4 as follows Anginer et al. (2014):

$$S_E = \frac{V_A e^{-dT} N(d_1) S_A}{V_E} \quad (4)$$

S_E is the standard deviation of daily bank's stock returns rolling over one year. T is equal to 1 year. r is the Government Securities yield with one year maturity. With two variables that can be calculated from the stock market which are market value of the bank's equity and its volatility ($V_E$andS_E) and face value of debt (X) which are obtained from bank's financial statements, we can solve the problem of estimating two unobservable variables, V_A and S_A, simultaneously by using Newton's method into equation (3) and (4). The initial value entered in Newton iteration process: $V_A = V_E + X$ and $S_A = S_E V_E/(V_E + X)$. The iteration process is done by using a program optimization *Solver* in *Microsoft Excel*. In calculating volatility of bank asset (S_A), $S_E$and $V_E/(V_E + X)$ were winsorized at 5% percentile and 95% in order to reduce the influence of outliers.

After we managed to estimate the market value of bank assets and volatilities ($V_A$and S_A), then we can calculate the amount of Merton's distance-to-default through the following equation 5:

$$dd = \frac{\log\left(\frac{V_A}{X}\right) + \left(m - r + \frac{S_A^2}{2}\right)T}{S_A\sqrt{T}} \quad (5)$$

dd is the distance to default, m is the equity risk premium. We assume the equity risk premium at 6% following Anginer et al. (2014) and Campbell et al. (2008). r is the yield of Indonesia government bond with

1 year maturity. Probability of *default* (PD) is a normal transformation of bank's *distance to default,* $PD = F(-dd)$, where F is a cumulative standard normal distribution. Each bank's *distance-to-default* was calculated on monthly basis.

Using the estimation of individual banks' default risk through equation (5), we can measure a bank's systemic risk contribution to the banking system. Bank's contribution to systemic risk is default probability of banking system collapses because of simultaneous bank defaults triggered by default of an individual bank. This study uses the definition of systemic risk proposed by Anginer et al.(2014). Contribution to systemic risk is measured by correlation of a bank's risk-taking behavior with majority banks risk-taking behavior. Correlation of banks' risk taking behavior was measured by R-squared of the regression equation between changes the default risk of a bank and the average changes all existing banks' default risk.

To measure the impact or contribution of a bank to the banking systemic risk, we use a procedure proposed by Anginer et al. (2014) and Karolyi, Lee, & Van Dijk (2012) which use the R^2 obtained from equation (6) with the following formula:

$$\Delta dd_{i,t} = \alpha_{i,j} + \beta_{i,t}\frac{1}{n}\sum_{k=1,k\neq i}^{n}\Delta dd_{k,t} + \varepsilon_{i,t} \quad (6)$$

To estimate the equation 6 and obtain R-squared for each bank, we need to be measure previously the magnitude of Δdd_i which is monthly bank i's default risk changes and average change of all banks' default risk of all banks, excludes bank *i*, $\{\frac{1}{n}\sum_{k=1,k\neq i}^{n}\Delta dd_{k,j}\}$.

High R^2 of equation (6) for an individual bank shows this bank has been exposed to same sources of credit risk suffered by most of banks. High R squared shows banks interdependence and interconnection. Interconnected banks create amplified bank risk exposures that comes from a given risk factors. Similar risk among most banks in a country led to vulnerable banking sector. Default probability of banks becomes higher and occur simultaneously, triggered by only an increase of one or several risk factors and macroeconomic variables changes.

Capital buffer is a measure of bank's capital strength in reducing the emergence of risks that could threaten stability of the bank. In accordance with Basel II, the ratio of the minimum capital requirement is 8% of risk-weighted assets (RWA). In a simple formula required capital adequacy ratio requirement is:

$$\mathrm{CAR} = \frac{\mathrm{Capital}}{\mathrm{RWA}} \quad (7)$$

where

CAR : Capital Adequacy Ratio
RWA : Risk-Weighted Asset

Capital buffer is a difference between bank's CAR and minimum required CAR (8%).
Capital buffer is calculated through following formula:

$$\mathrm{BUF} = \mathrm{K_{it}} - \mathrm{K_{it}^{r}} \quad (8)$$

where
BUF is capital buffer
$\mathrm{K_{i,t}}$ is bank i' CAR at period t
$\mathrm{K_{i,t}^{R}}$ is minimum required CAR set by regulator

Results and Discussion

Table 2 shows descriptive statistics of Indonesia public banks' distance-to-default. Magnitude of distance-to-default show individual bank's default risk. Narrow Indonesia banks' distance to default implies a high default probability. Narrow distance to default allegedly caused by relatively high volatility of bank assets. Bank stock price volatility in Indonesia stock market leads to high volatility bank assets.

Table2. Merton's distance-to-default 2010-2014

Bank	Mean	Median	Maximum	Minimum	Std. Dev.
Mandiri	-0.26550	-0.78127	2.15257	-1.90994	1.00453
BRI	-1.97662	-0.83494	0.18288	-30.30402	4.97842
BCA	0.18761	0.14216	2.96519	-1.26701	1.01809
BNI	-0.59922	0.04803	2.35721	-7.01960	2.02590
CIMB Niaga	-0.20849	-0.06602	3.06178	-4.57107	1.33889
Danamon	0.11768	0.22401	2.10353	-1.40621	0.86430
Permata	-0.83190	-0.38788	1.77467	-10.25261	2.00762
Pan	-0.04508	0.13633	1.91540	-3.78859	1.05148
Maybank	0.15439	0.33714	2.53253	-5.23370	1.34103
OCBC NISP	-0.12065	0.06235	1.63702	-3.38739	1.06391
Bukopin	-7.27824	-1.45716	7.78307	-24.73769	8.99475
BTPN	0.83703	0.76429	2.20834	-0.95299	0.66313
Mega	-3.22387	0.26498	2.67928	-22.13659	7.66688
Mayapada	0.03009	0.29093	15.02577	-10.41570	3.64849
Artha Graha	-3.48065	-2.05645	2.59464	-20.02456	3.86885
Victoria	-3.03195	-1.68596	1.64831	-16.27373	3.68698
QNB	1.20061	0.57844	4.65111	-0.92105	1.47912
Woori Saudara	0.18493	0.32030	1.02123	-2.57728	0.56714
Windu Kentjana	-0.54411	-0.22933	2.31324	-7.99442	1.35901
MNC Internasional	0.44923	-0.75952	98.90828	-9.31776	13.34060
Capital Indonesia	-0.65742	-0.49278	5.10445	-5.95892	1.65660
Pundi Indonesia	-0.36497	-0.04029	1.67396	-5.66805	1.32404
BRI Agroniaga	-0.06663	0.07408	2.27241	-3.32697	0.85511
Bumi Arta	-2.73896	-1.36807	1.79368	-14.11766	3.28313

Table 3. Bank's contribution to systemic risk

Nama Bank	Mean	Median	Maximum	Minimum	Std. Dev.
Mandiri	0.45943	0.54298	0.73998	0.22143	0.22189
BRI	0.40785	0.55075	0.71272	0.02192	0.29188
BCA	0.69742	0.76503	0.83725	0.44538	0.15389
BNI	0.69111	0.82814	0.87208	0.08623	0.33950
CIMBNiaga	0.65988	0.81783	0.92228	0.02813	0.36928
Danamon	0.58727	0.69910	0.93770	0.23427	0.33244
Permata	0.64382	0.71225	0.95145	0.22419	0.29105
Panin	0.71192	0.80253	0.94070	0.16746	0.31244
Maybank	0.67305	0.85261	0.97289	0.01115	0.40426
OCBC	0.67724	0.71500	0.90786	0.31064	0.23045
Bukopin	0.30795	0.18986	0.86664	0.05738	0.31996
BTPN	0.62335	0.62400	0.95609	0.33043	0.25734
Mega	0.46202	0.23965	0.86685	0.19544	0.34493
Mayapada	0.46835	0.32824	0.85007	0.09734	0.34680
Artha Graha	0.54747	0.66366	0.80437	0.19696	0.27394
Victoria	0.64554	0.79497	0.93321	0.05997	0.36435
QNB	0.25750	0.13536	0.76614	0.00941	0.29615
Woori Saudara	0.67496	0.70325	0.94268	0.37856	0.22439
Windu Kentjana	0.60892	0.73683	0.94763	0.01253	0.35842
MNC Internasional	0.60896	0.79443	0.95742	0.06357	0.37763
Capital Indonesia	0.61727	0.69375	0.96371	0.02385	0.37315
Pundi Indonesia	0.66809	0.80494	0.89459	0.24497	0.27377
BRI Agroniaga	0.67390	0.75812	0.83682	0.28847	0.22015
Bumi Arta	0.54233	0.70011	0.96655	0.00155	0.43635

Based on Merton's distance-to-default, individual bank's contribution to banking systemic can be calculated. Impact of individual bank to banking system vulnerability is measured by estimating effect of changes in individual bank's distance-to-default to changes of banking systemic risk. We get estimation of an individual bank's contribution to banking systemic by estimating equations 6 and obtain the R-squared for each bank. The magnitude of the systemic impact of any bank can be seen in Table 3.

Table 3 shows majority of Indonesia banks have high R-squared, greater than 50%. This findings suggests that there are high similarity in banks' risk-taking behavior of Indonesian banking system. High R-squared indicates strong interconnection and interdependent among Indonesia banks. Correlation of bank default risk is relatively high, that it is potential to trigger a banking system collapse because of default cascades.

Table 4 shows average Indonesia banks' capital buffer and leverage. On average, Indonesia public bank has enough capital buffer to anticipate unexpected macroeconomic and monetary shock. Some small banks has high capital buffer which because they are in early phase after they sell their share to public and had not fully channeled loans. Indonesia banks' leverage also almost at same level, they still rely on conventional source of funding like bank deposits.

Table 4. Average capital buffer and leverage

Nama Bank	Capital Buffer	Leverage
Mandiri	0.07142	0.2354
BRI	0.08194	0.1732
BCA	0.07074	0.0536
BNI	0.08894	0.1163
CIMBNiaga	0.06384	0.0514
Danamon	0.09642	0.1622
Permata	0.07016	0.0833
Panin	0.09588	0.0995
Maybank	0.05292	0.0698
OCBC NISP	0.08040	0.0727
Bukopin	0.05812	0.1213
BTPN	0.14352	0.0935
Mega	0.07184	0.0951
Mayapada	0.06104	0.0832
Artha Graha	0.06714	0.0841
Victoria	0.08894	0.0524
QNB	0.15492	0.0449
Woori Saudara	0.08508	0.0888
Windu Kentjana	0.06926	0.0751
MNCInternasional	0.06153	0.0770
Capital Indonesia	0.13086	0.0705
Pundi Indonesia	0.09386	0.0920
BRI Agroniaga	0.08906	0.0515
Bumi Arta	0.11242	0.0883

To test empirical significance relationship between banking systemic risk and bank loan, we estimated the equation 1. Bank's systemic risk was transformed using the procedure proposed by Anginer et al. (2014) and Karolyi et al. (2012). The procedure transforms logistic R squared obtained from equation 6 through following formula:

$$Bank's\ i\ Systemic\ Risk\ Effect = \log\left(Rsq_{i,j}/(1 - Rsq_{i,j})\right) \quad (10)$$

Karolyi et al. (2012) argue that R^2 logistic transformation is needed because R^2 value is between 0 and 1. The descriptive statistics of the variables included in the research model can be seen in Table 5.

Table 5. Descriptive statistics

Variable	Mean	Median	Maximum	Minimum	Std. Dev.
$Log(rsq_{i,j}/(1-rsq_{i,j}))$	0.14854	0.36716	1.55496	-2.80847	0.83906
Capital buffer	0.08584	0.08194	0.15492	0.05292	0.026005
Leverage	0.093129	0.0837	0.2354	0.0449	0.043837

Table 6. Relationship between systemic risk, capital buffer, and leverage

Variable	Coefficient	t stat
Capital buffer	-3,35	3.227***
Leverage	1,26	1.398*

R square: 0,781
Durbin-Watson stat: 2,12
F test : 48,974**
***Significant at 1% level of error
** Significant at 5 % level of error
* Significant at 10% level of error

Table 6 shows empirical test results. Capital buffer significantly affect systemic risk, and has large negative magnitude. High capital buffer induces low systemic risk. Bank which has big capital buffer is more stable and its contribution to banking systemic risk is low. Bank's leverage also affect bank's contribution to systemic risk but its magnitude lower than capital buffer. Capital buffer has more serious impact on systemic risk than bank's leverage does.

Conclusion

Indonesia public banks are highly interdependent and interconnected between individual bank's distance to default and all banks' distance of default in banking system. This finding shows that Indonesia banks have similar sources of risk and quite similar bank's risk taking behavior. Changes in individual bank may cause potential systemic impact. The linkage between banks' sources of risk and risk taking behavior are so high enough that indicate there is relatively high risk of the banking system to fail simultaneously or sequentially (default cascades) because of a bank failures.

Bank's capital buffer significantly affect bank's impact on systemic risk. More capital buffer make bank to be more stable and resilient from macroeconomic and monetary turbulence. Bank's leverage also significantly influenced bank's contribution to systemic risk but its impact far below the impact of capital buffer.

References

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review*, *105*(2), 564–608 . https://doi.org/10.1257/aer.20130456

Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *American Economic Review*, *106*(7), 1705–1744. https://doi.org/10.1257/aer.20120555

Afik, Z., Arad, O., & Galil, K. (2016). Using Merton model for default prediction: An empirical assessment of selected alternatives. *Journal of Empirical Finance*, *35*, 43–67. https://doi.org/10.1016/j.jempfin.2015.09.004

Anginer, D., & Demirguc-Kunt, A. (2011). *Has the global banking system become more fragile over time?* (No. 5849).

Anginer, D., Demirguc-Kunt, A., & Zhu, M. (2014). How does competition affect bank systemic risk? *Journal of Financial Intermediation*, *23*(1), 1–26. https://doi.org/10.1016/j.jfi.2013.11.001

Basel Committee on Banking Supervision. (2012a). *A framework for dealing with domestic systemically important banks*.

Basel Committee on Banking Supervision. (2012b). *Core principles for effective banking supervision*.

Battiston, S., Delli Gatti, D., Gallegati, M., Greenwald, B., & Stiglitz, J. (2012). Default cascades: When does risk diversification increase stability? *Journal of Financial Stability*, *8*(3), 138–149.

Bharath, S., & Shumway, T. (2008). Forecasting default with the Merton distance to default model. *Review Financial Studies*, *21*(3), 1339–1369.

Campbell, J., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *Journal of Finance*, *63*(6), 2899–2939.

Elliott, M., Golub, B., & Jackson, M. O. (2014). *Online appendix: Financial networks and contagion* (Vol. 104). https://doi.org/10.1257/aer.104.10.3115

Fiordelisi, F., & Marques-Ibanez, D. (2013). Is bank default risk systematic? *Journal of Banking and Finance*, *37*(6), 2000–2010.

Gai, P., Halande, A., & Kapadia, S. (2011). Complexity, concentration, and contagion. *Journal of Monetary Economics*, *58*(5), 453–470.

Georg, C. (2013). The effect of the interbank network structure on contagion and common shocks. *Journal of Banking and Finance*, *37*(7), 2216–2228.

Karolyi, G. A., Lee, K. H., & Van Dijk, M. A. (2012). Understanding commonality in liquidity around the world. *Journal of Financial Economics*, *105*(1), 82–112. https://doi.org/10.1016/j.jfineco.2011.12.008

Merton, R. (1974). On the pricing of corporate debt: The risk structure of interest rate. *Journal of Finance*, *29*(2), 449–470.

Shin, H. (2009). Securitisation and financial stability. *Economic Journal*, *119*(536), 309–332.

Sundaresan, S. (2013). A review of Mertons model of the firms capital structure with its wide applications. *Annual Review of Financial Economics*, *5*, 21–41.