THE EFFECT OF CREDIT AND LIQUIDITY RISK AGAINST SYSTEMIC RISK IN FOUR ASEAN BANKS

Rinda Siaga Pangestuti
Management Department of '45' Islamic University
Email: rindasiaga@ymail.com

ARTICLE INFO
Article History:
Received 22 May 2018
Revised 15 June 2018
Accepted 15 July 2018

JEL Classification:
E51, G21

Keywords:
Systemic Risk,
Credit Risk, and
Liquidity Risk

Abstract

This study examines the effect of credit risk and liquidity risk on the potential increases in systemic risk of the banking sector in four ASEAN banks. Two systemic risk measurements, namely dCoVaR and MES, are used in order to evaluate the effect of credit risk and liquidity risk on systemic risk of individual bank (dCoVaR) and systemic risk when the market is in distress (MES). The result from the regressions shows that credit risk and liquidity risk significantly affect systemic risk at the market distress. Meanwhile, credit risk and liquidity risk do not affect systemic risk of individual bank. The crisis affects systemic risk is showed by two regressions which are conducted in four ASEAN banks. The result is interesting because when the regression is conducted for all the countries, there is a positive and significant effect of crisis on systemic risk in four ASEAN banks, but when it is conducted for each country (as an additional analysis), not all the countries are affected by the crisis.

INTRODUCTION

Bank is an institution that is vulnerable to the financial and macroeconomic condition due to its function as the fund collector and distributor in the financial system (Hadad *et al*., 2003). Therefore, the bank default will affect the financial system that can lead into domino and systemic effect (Acharya, 2010; Patro *et al*., 2013). Lo (2008) mentioned that systemic risk could not be eliminated, where systemic events would give the negative effect to the financial market and economy (Patro *et al*., 2013), and also would cause bank closures by the monetary authority (Arena, 2008). If the financial institutions experience the default altogether, systemic risk will appear as the impact of this situation (Rodrigues-Moreno *et al*., 2010).

Empirically, systemic risk can be measured by delta Conditional Value at Risk (dCoVaR) (Girardi and Ergun, 2013), Marginal Expected Shortfall (MES) (Acharya *et al*., 2010), Component Expected Shortfall (CES) (Banulescu and Dumitrescu, 2012), and Systemic RISK Measure (SRISK) (Acharya *et al*., 2012). Girardi and Ergun (2013) explained dCoVaR as the difference percentage of CoVaR when the bank is in distress to the one when it is not. Acharya et. al. (2010) explained that MES corresponds to the bank expected equity loss when market falls below a certain threshold, 5%. Banulescu and Dumitrescu (2012) explained that the CES quantifies each bank contribution to the overall risk adding the capital weight into the analysis. Acharya *et al*. (2012) explained that SRISK measured the expected capital shortfall of an institution conditional on a crisis, using the size and leverage.

Pierret (2015) had found the weakness of SRISK was the assumption of Book Value (BV) of the debt that was not changed for about six months even more in the crisis period, in this case, the result of the measurement would be useful just in short-term forecast. Banulescu and Dumitrescu (2012) mentioned that CES was developed from MES (Acharya *et al*., 2010) by adding the capital weight into the analysis but it still used the same main data source, i.e. market return. Banulescu and Dumitrescu (2012) claimed that CES was a hybrid measured to catch *Too Big Too Fail* (TBTF) and *Too Interconnected Too Fail* (TITF), where by using MES (Acharya, 2010), Lestari (2015) found the same result. Lopez-Espinosa *et al*. (2012) found that dCoVaR was useful to catch contagion and balance sheet deleveraging in the banking system. Meanwhile, MES can be used to measure the bank resilience to the systemic risk in the moderate level (Idier *et al*., 2013; Weiβ *et al*., 2014). Yun and Moon (2014) used dCoVaR and MES and found that the result of the measurements were almost the same in term of cross-section dimension. This research uses dCoVaR (Girardi and Ergun 2013) and MES (Acharya, 2010) to measure systemic risk based on two methods approached.

The purpose of this research is to discuss the effect of credit risk and liquidity risk against systemic risk in the developing countries banking sector in four ASEAN banks (Indonesia, Malaysia, the Philippines, and Thailand). Developing countries are vulnerable to the crisis that happens in the developed countries (Goldstein and Xie, 2009). Bank becomes the main financial source of private business sector in Asia countries so the bank stability in this area becomes an important issue (Adams, 2008). Moreover, the integration of ASEAN banks due to the ASEAN Economic Community in 2020 will increase the competition level (Matousek, 2015). The main contribution of this research lies on the usage of two systemic risk measurements associated with the credit risk and liquidity risk in four ASEAN banks.

LITERATURE REVIEW

Systemic Risk

Patro *et al*. (2013) assumed systemic risk as likelihood from previous systemic events or financial system failures caused by systemic events that have negatively impacted financial markets and the economy. Separately, Lo (2008) explained that systemic risk is different from systemic failure. Systemic failure can occur or is not based on the strength of the event that triggers an increased risk, while systemic risk cannot be eliminated.

The Factors Drivng Systemic Risk

Credit Risk and Liquidity Risk

Ahmad and Ariff (2007) examined credit risks in developing countries during the crisis and they found that Indonesia, Malaysia and Thailand had 49%, 19%, and 48% of bad loans, respectively, which was calculated from the ratio of non-performing loans to total loans. Credit risk can be served as a proxy for bank risk taking behavior considering the high credit ratio indicates aggressive behavior of banks which is an indication of bank risk-taking behavior (Hannan and Rhoades, 1987). On the other side, Adrian and Brunnermeier (2011) found that maturity mismatch in the commercial banks will lead on systemic risk. Maturity mismatch is the difference of asset maturity and bank liability that make a bank vulnerable to the higher risk (Ruprecht *et al*., 2013).

Competition and Bank Size

Soedarmono *et al*. (2013) found that competition and bank size caused systemic risk. It happened because in the high competition level, small and big banks compete to each other in order to exist in the market (Hakenes and Schnabel, 2011). The higher competition level is the higher risk is taken by the bank (Cubillas and Gonzales, 2014). Besides competition, systemic risk can be affected by bank size. Jonghe *et al*. (2015) claimed that combination of size and scope will give double effect on systemic risk. It leads to the Too-Big-Too-Fail (TBTF) issues where the bigger th bank size is the bigger chance it has systemic risk (Lestari, 2015).

GDP and Inflation

Weiß *et al*. (2014) measured systemic risk in terms of systemic event trigger factors during financial crisis period. The main results were regulatory characteristics, GDP, and inflation dominantly affected systemic risk globally.

RESEARCH METHODOLOGY

Analysis Unit

Analysis unit in this research is the banks listed in four ASEAN countries (Indonesia, Malaysia, Philippines, and Thailand) during 2007-2013 periods. This research uses commercial banks regarding to its freedom in doing business mix and facing the limited boundaries between countries (Soedarmono *et al*., 2013). Banks without a complete data needed (stock prices and annual financial statements) for three consecutive years will be excluded from the sample (Ariss, 2010). After filtering the banks data, there are 34 banks listed in Indonesia and 11 banks are used, 10 banks in Malaysia and 8 banks are used, 14 banks in the Philippines and 11 are used, and 10 banks in Thailand and 9 banks are used. The data is taken from Datastream Thomson Reuters.

Methodology

This research used dCoVaR and MES as the model because dCoVaR can be used to indentify systemic risk based on individual bank so it can catch TBTF and TITF issues (Bisias *et al*., 2012). This research follows Girardi and Ergun (2013) to measure dCoVaR that is described as the difference between CoVaR when the bank is in the distress period and the CoVaR in the normal period. Meanwhile, MES (Acharya, 2010) defined as banks expected equity loss when the market falls below 5%.

Empirical Model

1. Delta Conditional Value at Risk (dCoVaR)

This research follows Ahmad and Ariff (2007) to count credit risk as bad loans percentage during three months or more to the total loans, Yun and Moon (2014) to count liquidity risk as the ratio of total loans to total deposit, and Girardi and Ergun (2013) to count individual bank systemic risk by using dCoVaR. Girardi and Ergun (2013) has described VaR bank *i* (*i ≡ s* is financial system) as *q-th quantile* from return bank distribution bank *i* that written by R_t^i:

$$\Pr\left(R_t^i \leq VaR_{q,t}^i\right) = q \quad (1)$$

Then, dCoVaR $^{i/j}{}_{q,t}$ is defined as *q-th quantile* from bank *i return* that is conditional to bank *j*. dCoVaR $^{i/j}{}_{q,t}$ can be described as VaR bank *i* that is conditional to market distress. Return bank *i* will be less than or equal to the VaR value when the market distress happens.

$$\Pr\left(R_t^i \leq dCoVaR_{q,t}^{\frac{i}{j}} \middle| R_t^j \leq VaR_{q,t}^j\right) = q \quad (2)$$

Next, to count the percentage of dCoVaR, market VaR that is conditional to the bencmark bank *j* deducted from market VaR that is conditional to distress. The percentage of dCoVaR is counted as:

$$dCoVaR_{q,t}^{s/j} = \frac{100x(CoVaR_{q,t}^{\frac{s}{j}} - CoVaR_{q,t}^{\frac{s}{bi}})}{CoVaR_{q,t}^{s/bi}} \quad (3)$$

Conditional benchmark bank *j* b^i can be defined as standard deviation from mean event:

$(\mu_t^j - \sigma_t^j) \leq R_t^j \leq (\mu_t^j + \sigma_t^j)$ (4)

where,

b^i : Event when return bank *j* between μ–σ and μ+σ, i.e. (μ–σ)≤R≤(μ+σ)

μ_t^j: Conditional mean bank *j*
σ_t^j: Standard deviation bank *j*

2. Marginal Expected Shortfall (MES)

This research follows Acharya (2010) to count MES that is described as expected equity loss when the market falls below 5%.

$$MES_i^{5\%} = -E\left\{\frac{w_1^i - 1}{w_0^i}\middle| I_{5\%}\right\} \quad (5)$$

$$MES_i^{5\%} = -E$$

where,

$\frac{w_1^i}{w_0^i}$: $Return\ Bank$

$I_{5\%}$: $Market\ return\ worst\ days$

Panel Regression Model

1. Delta Conditional Value at Risk (dCoVaR)

The first regression is done by using panel data to regress credit risk and liquidity risk against systemic risk of individual bank (dCoVaR) based on this model:

$$dCoVaR_{i,t}=\alpha_0+\alpha_1 NPL_{i,t}+\alpha_2 LDR_{i,t}+\alpha_3 Size_{i,t}+\alpha_4 GDP_t+\alpha_5 Com_{i,t}+\alpha_6 Inf_t+\alpha_7 Ind_t+\alpha_8 Mal_t+\alpha_9 Thai_t+\alpha_{10} Cris_t+e_{i,t} \quad (6)$$

where,
$dCoVaR_{i,t}$: dCoVaR bank i at t year
$LDR_{i,t}$: Liquidity risk bank i at t year
$NPL_{i,t}$: Credit risk bank i at t year
$Size_{i,t}$: Size bank i at t year
GDP_t: GDP at t year
$Comp_{i,t}$: Competition bank i at t year
Inf_{it}: Inflation at t year
Ind_t: Country dummy at t year; Indonesia=1, others=0
$Cris_t$: Crisis dummy at t year; crisis (2007-2009) = 1, others (2010-2013) = 0
$e_{i,t}$: Residual of the result

2. Marginal Expected Shortfall (MES)

The second regression is done by using panel data to regress credit risk and liquidity risk against systemic risk when the market is in distress based on this model:

$$MES_{i,t}=\alpha_0+\alpha_1 NPL_{i,t}+\alpha_2 LDR_{i,t}+\alpha_3 Size_{i,t}+\alpha_4 GDP_t+\alpha_5 Comp_{i,t}+\alpha_5 Inf_t+\alpha_6 Ind_t+\alpha_7 Mal_t+\alpha_8 Thai_t+e_{i,t} \quad (7)$$

where,
$MES_{i,t}$: MES bank i at t year
$LDR_{i,t}$: Liquidity risk bank i at t year
$NPL_{i,t}$: Credit risk bank i at t year
$size_{i,t}$: Size bank i at t year
GDP_t: GDP at t year
$Comp_{i,t}$: Competition bank i at t year
Inf_{it}: Inflation at t year
Ind_t: Country dummy at t year; Indonesia=1, others=0
$e_{i,t}$: Residual of the result

RESULT AND DISCUSSION

Table 1. Shows the statistic description of the data

Variabel	Mean (%)	Median (%)	Max (%)	Min (%)
dCoVaR	63.82	59.87	229.9	2.201
MES	2.837	3.023	7.264	0.061
NPL	3.934	3.132	17.46	0.331
LDR	94.04	95.18	211.2	31.44
Size	712.9	720.5	824.4	575.9
Com.	37.34	37.18	95.15	13.94
GDP	494.3	487.3	535.2	465.1
Infl.	2.672	1.288	1.151	-1.109

Source: Self proceed

Based on the dCoVaR calculation in Table 1., bank gives contribution to systemic risk for about 63% on the average. Meanwhile, based on the MES calculation, each bank gives almost 3% (on the average) contribution to systemic risk. Generally, based on the data after dCoVaR is counted, it can be concluded that big banks in Indonesia, Philippine, and Thailand give more contribution to systemic risk. This finding is in agreement with another research finding by Jonghe *et al*. (2015) that the big bank contribution to systemic risk is bigger than small banks. On the other hand, from the output of dCoVaR, it is also known an interesting finding that small banks in Malaysia give more contribution to systemic risk than big banks. Zebua (2010) explains that small banks will be able to give a bigger effect to systemic risk as the bank runs issue, especially in the crisis period.

The Effect of Credit Risk and Liquidity Risk against Systemic Risk of Individual Bank

The purpose of this regression is to know the effect of credit risk and liquidity risk against systemic risk of individual bank in four ASEAN banks. The regression is done to answer the first question of this research.

Table 2. The Effect of Credit Risk and Liquidity Risk against Systemic Risk in Four ASEAN Banks

dCoVaR	C	T-Stat	Prob.
C	2.642	4.230	0.000***
NPL	0.041	0.215	0.829
LDR	0.012	1.025	0.306
Size	0.013	1.18	0.238
Com.	0.037	1.37	0.171
GDP	-0.508	-4.029	0.001***
Infl.	0.367	1.072	0.284
Ind.	0.296	4.074	0.001***
Mal.	0.005	0.227	0.820
Thai.	0.082	0.023	0.004**
Crisis	0.054	3.144	0.002***
Adj. R^2	50%		

*** Significant level 1% ** Significant level 5%; *Significant level 10%
Source: Self proceed

Based on the Table 2., it is known that credit risk and liquidity risk do not affect systemic risk of individual bank. However, it is known that crisis gives a positive significant effect to systemic risk at the 1% significant level. It is interesting because when the regression is done for each country (for additional analysis), only Indonesian banks showing that crisis affects systemic risk. It means that if the banks in four ASEAN banks are integrated in a single market area, the systemic risk will increase due to the crisis condition. Weiß *et al*. (2014) also found the same result that crisis gives an effect to systemic risk.

Furthermore, it is also found that Indonesia and Thailand give contribution to systemic risk in four ASEAN banks but GDP gives a negative significant effect to systemic risk. It means that if the GDP decreases, systemic risk will increase. If the goods production decreases, the business profit will also decrease. It may affect the credit payment to the bank as the company usually borrows money from the bank. Adams (2008) found that bank was the main source of fund of the private business sector in Asia. That is the reason why the bank stability becomes an important issue.

The Effect of Credit Risk and Liquidity Risk against Bank Systemic Risk at the Market Distress

The second regression is done between credit risk and liquidity risk against systemic risk at the market distress. It is in order to know the effect of credit risk and liquidity risk against systemic risk especially under the market distress condition.

Table 3. The Effect of Credit Risk and Liquidity Risk Against Systemic Risk at the Market Distress in ASEAN-4 Banks

MES	C	T-Stat	Prob.
C	0.094	2.352	0.019
NPL	0.050	2.385	0.018**
LDR	0.007	2.424	0.016**
Size	0.020	13.14	0.000***
Com.	0.005	1.535	0.125
GDP	-0.043	-5.558	0.000***
Infl.	-0.093	-2.250	0.025**
Ind.	0.035	7.331	0.000***
Mal.	-0.037	-15.41	0.000***
Thai.	0.003	1.074	0.284
Adj.R^2	62%		

*** Significant level 1%; ** Significant level 5%;
*Significant level 10%
Source: Self proceed

At the market distress, it is known that credit risk and liquidity risk affect systemic risk under 5% significant levels. It means that, if the crisis happens in four ASEAN banks, credit risk and liquidity risk will give a positive significant effect to the systemic risk. The result of this regression is interesting as when the regression for each country is done (for additional analysis), it is found that systemic risk in Malaysian banks are not affected by the credit risk and liquidity risk. It means that if the four ASEAN banks are integrated in a single market area, both credit risk and liquidity risk will affect systemic risk under the market distress.

Moreover, it can be seen from the table that banks in Indonesia affect systemic risk in four ASEAN banks, while banks in Thailand does not show the same thing. Malaysian banks affect systemic risk in four ASEAN banks with negative correlation. It can be explained by looking at the result of MES calculation. Based on the calculation, banks in Malaysia show the lowest contribution (on the average) to the systemic risk compared with the other three countries. This is reasonable since Malaysia was less affected by the 2008 crisis and the Malaysian banks show a relatively good performance over the sample period. It can be seen from the credit ratio which is about 3.2% and the liquidity ratio which is about 95% over the sample period.

CONCLUSION

After all, the main result from this research is the greater possibility of systemic risk when banks of four ASEAN countries are incorporated in a single market area. Both of the regressions show that crisis gives a significant effect to the systemic risk. However, during the market distress condition, credit risk and liquidity risk give a significant effect against systemic risk.

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