The Effect of Managerial Overconfidence on Banking Systemic Risk

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ABSTRACT

Our researcSh aims to examine the relationship between managerial overconfidence and its implication to the banking systemic risk. From behavioral finance perspective, overconfidence managers are more likely to overestimate the future return of the investment project or undertake risky project thus increase their contribution of systemic risk. In this research we use conditional value at risk (CoVaR) approach to measure systemic and to measure managerial overconfidence we use investment based proxy derived from the deviation of expected investment. Using data of Indonesian banks from 2004 – 2014, we found that bank with managerial overconfidence have statistically significant positive influence to the systemic risk compared to non-overconfidence managerial banks.

Keywords: *Overconfidence managers, CoVaR, Systemic Risk*

1. INTRODUCTION

U.S financial crisis in 2007 - 2009 known as the worst financial crisis since Great Depression in 1930 and become global consider global by many economist as the most serious financial crisis. US financial crisis triggered by the failure of one of the biggest investment bank in US, Lehman Brother. The failure lead shock to financial institution across the globe, when a bank experience shock its distress could spill over to other bank and threaten to contaminate the whole financial system. This is what regulator refers to as systemic risk (Ma at al., 2018). Differs from other risk faced by financial institution, systemic risk is much more known for its effect rather than its caused (Guerra et al. 2016). Systemic risk as the effect of interconnection of many factor that make difficulties in describing systemic risk clearly.

Qin and Zhou's (2014) describe the determinants of systemic risk contribution depend on the financial structure of whether a country has a bank-based or market-based financial system. The impact of non-traditional banking activities contributes to systemic risk when the market (non-bank) is more important for the economy. The contribution of systemic risk is generally greater for banks in market-based systems. Supported by previous research from López - Espinosa et al., (2013) which suggests that combining investment bank activities with the presence of foreign markets can worsen financial stability as well as unstable funding are the main factors driving systemic risk, and Sedunoy (2016) which documents activities off balance sheet by banks increases the contribution of systemic risk.

As research related to systemic risk continues to grow, another perspective from behavioral finance possibly allow important new understanding to the nature of systemic risk. The concept of overconfidence in this study is defined as the tendency of individuals to overestimate their abilities and chances of success. Managerial overconfidence estimates excessive returns to projects undertaken by the company and

estimates excessive profits followed by high optimism about cash flow or ignoring the possibility of loss to the company (Heaton, 2002). Ma (2015) investigate how banks invest before and during crisis and shows that banks with overconfidence managers experience a 20% growth in real estate loans and 15% decline stock return during crisis period. In line with Ho et al (2016) defined that banks with managerial overconfidence tend to lower lending standards and raise the level of leverage which caused bank more fragile to shocks. In this case the financial crisis is caused by the bias behavior of banks which loosen lending standards, excessive risks taking and heating the economy (Akerlof & Shiller, 2009). Related to company's investment decision, Schrand and Zechman (2011) proofs that managerial overconfidence reflect from the faster growth of asset values than sales which concluded that company managers make excessive investments. Overconfidence managers tend to overinvest in mega projects which reflect in huge capital expenditures compared to non-overconfidence managers (Ben-David et al., 2010).

This research aims to examine the relationship of managerial overconfidence to the systemic risk in bank level. We measure overconfidence from investment-based proxy and used market based measures of systemic risk the conditional Value-at-Risk (CoVaR) by Adrian and Brunermeier to see the contribution of each bank to the banking systemic risk.

2. METHODS

2.1 Managerial Overconfidence Measurement

We use annual financial statement data of publicly Indonesia bank from 2004 to 2018, our measurement perform on 16 public commercial banks. To measures managerial overconfidence we use investment-based proxy following Duellman et al. (2015). The overconfidence proxy measure is defined using the residual from the regression of investment on lagged sales growth and classified a bank as overconfidence equal as one if the residual of the regression is in the top quartile and zero otherwise. The regression as follow :

$$Investment_{i,t} = \beta_0 + \beta_1\, Sales\, Growth_{i,t} + \varepsilon_{i,t}$$

Company with overconfidence CEO are more likely to have greater capital expenditure (Ben-David et al, 2013) and invest more in capital project (Malmendier and Tate, 2005) thus we add dummy variable equal to one if bank's capital expenditure deflated by total asset are greater than the median on banking industry. Also we add loan loss provision as control variable related to managerial overconfidence. Since the main investment project of a bank is lending money, so it is manager's job to inspect the past event and forecast loan loss provision based on present and expected future changes in non-performing loan (Beatty et al. 2011). Overconfidence managers expect better profitability and the future prospect for loan recovery. Thus, overconfidence manager exaggerate bank's loan performance and miscalculate the loan losses and then perceive lower loan provision (Chen, 2013).

2.2 Systemic Risk Measurement

To measure systemic risk, this research use CoVaR (conditional value at risk) approach by Adrian & Brunermeier (2016) which asses the Value-at-Risk (VaR) of the financial system conditional on some other institutions being in distress, to estimate the severity of the systemic risk and defined ΔCoVaR as the contribution of an individual institution to systemic risk, which is the difference between CoVaR conditional on the loss of an institution in crisis and that in a normal situation. Following Adrian & Brunermeier (2016), we obtain CoVaR by employing quantile regression to observe the relationship between regresor variable and dependent variable on tail condition. Quantile regression performs in two regression, first from individual asset return of bank i as dependent

variable and state variable M as independent variable, and second from asset return of banking system as dependent variable and state variable M as independent variable. State variable in this research following Adrian and Brunermeier (2016) lag period of return index stock and BI rate.

We obtain return asset (R_t^i) from market value of total equity (MCap) times with ratio of total asset divided by book value of equity (Lev). Asset return (R_t^{system}) of banking system is the average asset return of all existing bank in our sample The equation of two quantile regression as follow :

$$R_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i$$
$$R_t^{system} = \alpha^{system|i}$$
$$+ \gamma^{system|i} M_{t-1} + \beta^{system|i} R_t^i + \varepsilon_t^{system}$$

After applying two quantile regression, we get the coefisien of α β γ to determine the value of VaR and CoVaR with following equation:

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1}$$
$$CoVaR_t^i(q) = \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{system|i} VaR_t^i + \hat{\gamma}_q^{system|i} M_{t-1}$$

Finally we can calculate the contribution of each to the banking systemic risk with ΔCoVaR by following the equation:

$$\Delta CoVaR_t^i(q) = CoVaR_t^i(q) - CoVaR_t^i(50\%)$$
$$= \beta^{system}(VaR_t^i(q) - VaR_t^i(50\%))$$

2.3 The Relationship Between Managerial Overconfidence and Systemic Risk

Main focus of this research aims to investigate whether managerial overconfidence influence a bank's contribution to systemic risk by empoying data panel regression equation below:

$$SysRisk_{i,t} = \alpha_0 + \alpha_1 Overconfidence_{i,t} \times Crisis08 + \beta Bank_{i,t} + \vartheta_i + \varepsilon_{i,t}$$

Where $SysRisk_{i,t}$ is systemic risk for bank i in each year, $Overconfidence_{i,t}$ is dummy variable that equals one if bank i as overconfidence bank at time t and zero otherwise, $\beta Bank_{i,t}$ is bank specific character, and $\varepsilon_{i,t}$ error term. Also we add dummy variable of Crisis08 that equals one if the year is 2008 and zero otherwise to examine whether bank with overconfidence manager contribute more to the systemic risk.

3. RESULTS AND DISCUSSION

The result from employing several methods from our previous explanation, lets begin with all the statistical descriptive of variable from this research as follow:

Table 1. Statistic descriptive for all variables

Variable	Mean	Median	Max	Min	Std. Dev
OC	0.313	-	1	-	0.464
OI	0.563	1	1	-	0.496
Specific Bank Characteristic					
SIZE	24.876	25.0279	27.887	21.1504	1.60371
LEV	9.433861	9.161905	21.0201	1.72844	3.06378
MM	-0.02095	0.044753	0.19226	-0.95252	0.23883
ROA	1.517801	1.685	4.51	-5.87	1.28005
LLP	0.01059	0.00911	0.11919	-0.48692	0.03588

From the table above, we provide a summary of the variable used in this research, the sample contain of public bank in Indonesia over 2004 to 2018. OI of Duellman et al. (2015) is equal one for overconfidence bank derived from standard deviation of residual from total investment lagges sales growth. OC of Ben – Davis et al. (2013) is equal one if the banks have larger capital expenditure than other banks. SIZE is log of Total Asset. LEV is the leverage ratio which equals a ratio of the book value of debt to the market value of equity. MM as maturity mismatch is a ratio of the difference between cash holdings and short-term debt to total assets. ROA as return on asset is a ratio of net income to total asset. LLP as loan loss provision.

The result of systemic risk measurement stated below, first we calculate VaR(q%) which defines as the maximum loss of Bank i at the q%–confidence level. But a single institution's risk measure does not automatically define its connection to overall systemic risk

Table 2. Statistic descriptive for Value at Risk (5%)

| No	Thicker	Mean	Median	Max	Min	Std. Dev
1	INPC	-0.2189	-0.2202	-0.1293	-0.2889	0.0201
2	BBCA	-0.1008	-0.1000	0.0225	-0.2957	0.0415
3	BNGA	-0.1929	-0.1859	-0.0195	-0.5245	0.0742
4	BDMN	-0.1553	-0.1462	0.0454	-0.5411	0.0914
5	BMRI	-0.1149	-0.1079	0.1188	-0.5830	0.0861
6	MAYA	-0.2290	-0.2309	0.0029	-0.3784	0.0473
7	MEGA	0.1695	0.1710	0.2673	0.0488	0.0237
8	BBNI	-0.1690	-0.1645	0.0365	-0.5796	0.0741
9	PNBN	-0.2033	-0.2008	0.0028	-0.5679	0.0688
10	BNLI	-0.1213	-0.1207	0.0534	-0.4905	0.0613
11	BKSW	-0.1661	-0.1635	0.0662	-0.5188	0.0722
12	BBRI	-0.1535	-0.1513	0.0470	-0.5810	0.0772
13	BVIC	-0.1480	-0.1473	0.0070	-0.3875	0.0481
14	NISP	-0.1747	-0.1737	-0.0490	-0.4253	0.0415
15	BABP	-0.2363	-0.2360	-0.0850	-0.4560	0.0427
16	BNII	-0.1516	-0.1492	0.0400	-0.3819	0.0489
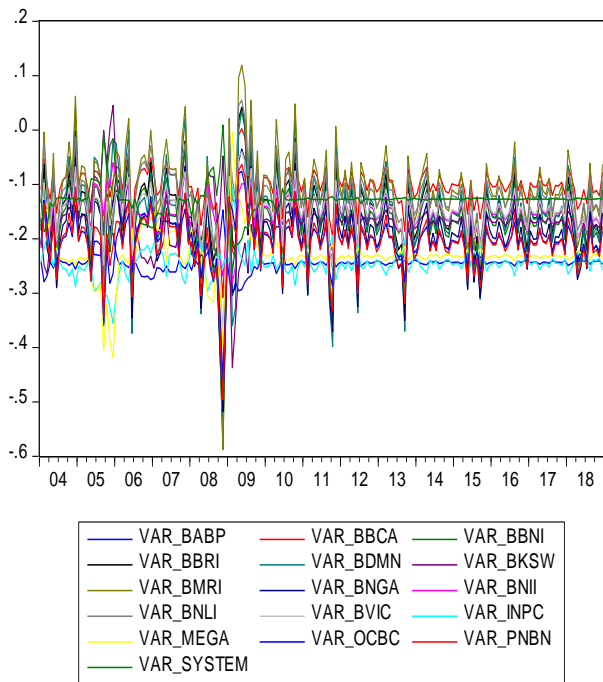
Figure 1. Graph of Banking Value at Risk

The result of Value at Risk at 5% quantile shows that Bank Artha Graha (INPC) and Bank MNC (BABP) has the highest average of VaR5%. INPC's VaR5% has the lowest average value of -21.9%, while BABP's of -23.6%. From the category of big 5 banks, Bank CIMB Niaga has the highesr average VaR of -19.39%. And from figure 1 above value at risk for all bank in our sampel drop due to subprime mortgage crisis although some research stated tha Indonesian bank were not significantly affected (Wibowo, 2017). After calculate the VaR5% of the bank, we could measure the contribution of each bank to the banking systemic risk and the result as follow :

Table 3. Statistic descriptive for DCOVAR

No	Thicker	Mean	Median	Max	Min	Std. Dev
1	INPC	-0.0332	-0.0335	-0.0173	-0.0416	0.0030
2	BBCA	-0.0503	-0.0508	-0.0196	-0.0818	0.0082
3	BNGA	-0.1814	-0.1814	-0.1697	-0.1909	0.0022
4	BDMN	-0.0341	-0.0336	0.0213	-0.1237	0.0174
5	BMRI	-0.0740	-0.0738	-0.0599	-0.0975	0.0044
6	MAYA	-0.0054	-0.0054	0.0125	-0.0168	0.0032
7	MEGA	-0.0328	-0.0328	-0.0271	-0.0381	0.0013
8	BBNI	-0.0302	-0.0302	-0.0208	-0.0346	0.0016
9	PNBN	-0.0130	-0.0131	-0.0054	-0.0227	0.0018
10	BNLI	-0.0615	-0.0613	-0.0500	-0.0776	0.0028
11	BKSW	-0.0142	-0.0141	-0.0072	-0.0245	0.0021
12	BBRI	-0.0792	-0.0796	-0.0572	-0.0942	0.0048
13	BVIC	-0.0191	-0.0190	-0.0164	-0.0236	0.0009
14	NISP	-0.0509	-0.0509	-0.0318	-0.0892	0.0063
15	BABP	-0.0145	-0.0146	-0.0034	-0.0278	0.0025
16	BNII	-0.1815	-0.1817	-0.1649	-0.1940	0.0038

The result of ΔCoVaR does not in line with the value of VaR5%, INPC and BABP which have the higest VaR5% by average only contribute 3.32% and 1.45% to the systemic risk, referring

the table above, Maybank (BNII) have the highest average value and volatility of ΔCoVaR, followed by BNGA as the second highest average value and volatility of ΔCoVaR. Mostly major banks contribute more to the systemic risk. BNGA contribute 18.14% to the banking systemic risk, followed by Bank Rakyat Indonesia (BBRI) 7.92% and Bank Mandiri account for 7,4%.

Our final step is to evaluate the relationship between managerial overconfidence and its implication to the systemic risk by employing data panel corrected standards error (PCSE) regression to treat the heteroscedastic and contemporanously correlated across panel from our research.

The table shows that our two proxy of overconfidence are statically significant and have positive influential thus implies that bank with overconfidence managers contribute more to the systemic risk. In line with the prediction from behavioral finance theory that the contribution to the systemic risk will be greater for institutions with overconfident managers, since they underestimate and willing to take more risk than non – overconfidence manager (Ben-David et al. 2013).

Table 4. managerial overconfidence to systemic risk measurement

Variable	Coefficient	Std. Error	P-Stat
OI	0.021260	0.0005752	0.000
OC	0.038470	0.0011907	0.000
CRISIS	0.005779	0.00403	0.152
LLP	- 0.25472	0.0165522	0.000
SIZE	-0.01529	0.0004674	0.000
LEV	-0.002844	0.0002167	0.000
MM	-0.0344901	0.0019227	0.000
ROA	-0.0110973	0.0004072	0.000
Adjusted R Square		0.3914	
Prob (F-Statistic)		0.0000	

Some prior research from De Jonghe (2010) and Adrian and Brunnermeier (2016) shows that bank's size increase systemic risk however Lopez-Espinosa (2012) show weak relationship that either size or leverage contributes to systemic risk, referring to the table above our proxy of bank's size have negative influence to the systemic risk which implies that bank's size decreases systemic risk. We add dummy variable crisis in our model which equals for year of 2008 and zero otherwise to check the managerial overconfidence affect the contribution on systemic risk during financial crisis, however our result is not statistically significant, indicate that overconfidence manager perform the same way in and out of a crisis (Lee et al. 2019).

The effect of ROA on systemic risk based on this research is negatively significant, thus we support the finding from Lee et al (2019) that ROA decrease systemic risk since bank with high performance generate more return and usually are less risky than other firms. LLP shows negatively significant which implies LLP decrease systemic risk. Our finding supported by Chen (2013) related to overconfident managers who believe that future prospect of better loan recovery so they recognize lower loan provision that would lead to future expected decrease in loan portfolio quality thus affect bank risk's taking behavior.

4. CONCLUSIONS

Witness from global crisis in 2008, the impact of systemic risk jeopardized the whole financial system, also the loss due to systemic risk quite high. It is important to regulator to anticipate the event and the source of systemic risk. Hence from this study examine the relationship between managerial overconfidence and systemic risk that we may conclude that overconfidence managers increase systemic risk which reflect from investment decision whether overconfidence manager tends overestimate thieve future income and to undertake risky project thus affect their level of risk taking. However, the risk taking behavior towards managerial overconfidence during the crisis period from our result shows statistically not significant thus conclude that

overconfidence managers perform the same way in and out crisis period.

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