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Usman Arief
Faculty of Economics and Business, Universitas Gadjah Mada, Indonesia, usman.arief@ugm.ac.id

Zäafri Ananto Husodo
Faculty of Economics and Business, Universitas Indonesia, z.husodo@gmail.com

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Systemically Important Banks in Indonesia: Findings From Multivariate GARCH Conditional Value at Risk

Usman Arief[1]* and Zäafri Ananto Husodo[2]
[1]Faculty of Economics and Business, Universitas Gadjah Mada, Indonesia
[2]Faculty of Economics and Business, Universitas Indonesia, Indonesia

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We investigate the systemically important banks in the Indonesian financial system using Multivariate GARCH Conditional Value at Risk (CoVaR). The systemic risk measurement, ΔCoVaR, defined as the change from CoVaR in its benchmark state as a one-standard-deviation event to its CoVaR under financial distress. We estimate the systemic risk contribution using 21 commercial banks from January 2007 to December 2018. Our study reveals that the top five ranking systemic banks are dominated by state-owned banks, and its ranking is consistently the same in the period before, during, and after the global financial crisis. Finally, we empirically find that systemic risk in Indonesia is strongly affected by external factors rather than bank characteristics. Based on this finding, we suggest that the government should maintain the regulation of external effect rather than the domestic effect.

Keywords: *Systemic Risk, GARCH, Spillover, Crisis, Banks*

JEL Classification: G12, G17, G21, G28, G32

Introduction

Systemically important banks are the main concern of the central bank in order to maintain overall stability in the financial system. These banks have been identified to have a systemic risk as the failure of these banks would have a significant costs to the financial system and the economy as a whole. Systemic risk has its moment when the recent financial turmoil hit the world starting in the summer of 2007 could infect the entire US financial and global banking system. While the banking system became generally affected by the crisis, bank wealth differed substantially in terms of market valuations and on the scale of government intervention received.

The global financial crisis shows us that the accumulation of deteriorating global economic and financial conditions that undermined the bank system in both developed and emerging markets has alerted the public to the fragility of the financial system and the importance of systemic risk. Hence, it is very fundamental to understand the nature and the measurement of systemic risk to keep financial stability. Research from Nier, Yang, Yorulmazer, & Alentorn, (2008) argued that the nature of systemic risk arises through four primary mechanism: 1) direct bilateral exposures between banks; 2) correlated exposure of banks due to conventional source of risk; 3) feedback effect from fire sales assets by distressed institutions; 4) Contagion and spillover.

* Corresponding author's email: usman.arief@ugm.ac.id

Understanding the nature of systemic risk can serve as a benefit to the government and scholars. The structure of a banking sector and network among banks determine the degree of concentrated systems as prone to systemic risk. Bisias, Flood, Lo, and Valavanis (2012) provide a survey of 31 quantitative systemic risk measurement in the economic and finance literature. These measurements indicate that 31 definitions of systemic risk do not converge. However, the various definitions refer to one keyword as mentioned by Bandt and Hartmann (2000) which defines systemic risk as a risk of financial instability which widespread and impairs the functioning of the financial system to the point where economic growth and welfare would suffer significantly.

The definitions of systemic risk as we mentioned above regarding the widespread risk or spillover from the failure of the system to financial institutions or vice versa serve as a motivation for this study to measure the systemic risk using spillover mechanism (see (Acharya, Pedersen, & Richardson, 2016). However, recent studies from Adrian & Brunnermeier (2016) introduce systemic risk measurement from a spillover point of view: Conditional Value-at-Risk (CoVaR). They define CoVaRi,j as the VaR of institution *i* conditional on institution *j* being in financial distress. By conditioning on another institution's financial distress, Girardi & Ergün (2013) aim to go beyond idiosyncratic risk and to capture the possible risk spillovers among financial institutions, combining the idea of a multivariate GARCH approach and CoVaR. They modify the definition of CoVaR proposed by earlier that the distress event condition on institution *j* is *at most* at its VaR, as opposed to being *exactly* at its VaR. The results from multivariate GARCH CoVaR has proven to be more precise than the original CoVaR. Finally, we define the systemic risk as to the shortfall contribution of financial institution *i* to the financial system, ΔCoVaR.

We investigate the systemic risk in emerging countries, particularly in Indonesia. This country has a unique characteristic compared to other countries in Southeast Asian since the country heavily depends on the banking system. The proportion of the total fund from Indonesia's banking system to GPD was 42 % in 2017 and is projected to reach 60% in 2020. The study from Law & Singh (2014) reveals that too much dependency on the banking sector will have a potential malfunction in the financial system in which directly harm economic growth. Secondly, we examine the time-series relation between ΔCoVaR and institution characteristics such as; value at risk each institution, size, and beta (see (Lorenc, Zhang, & Zhang, 2020), and (Anna & Veraart, 2020). Given the issue of "too big too fail" and various proposals regarding the policy-makers scrutiny that institutions bearing the idiosyncratic factors to drive the systemic risk. The relation between the size, value at risk, and beta is crucial to understand the most significant factors to determine the systemic risk in Indonesian banking system. Furthermore, we control the regression model using specific factors such as time dummy before and during the crisis, the United States stock index, S&P 500 stock index, and international interbank interest rates, SIBOR 1 month. Hence, this study will look to answer these following questions:

1. How the systemically important banks in Indonesia using CoVaR measurement?
2. What factors determine the systemic risk in Indonesian banking system?

The contribution of this study for financial stability is threefold. Firstly, we provide the estimation of systemic risk that is more sensitive to the changes in regime-switching period and sufficiently reliable for day-to-day use. Secondly, our study can be considered as the early warnings signal to assess systemic events since CoVaR can be estimated using a high-frequency basis and can be updated anytime. Lastly, this study can improve the supervisory approach to monitor the highest systemically bank that potentially harm the financial system in Indonesia.

According to the empirical results, we find that the VaR of each institution has a positive and significant effect on systemic risk at the 99% level. Also, our results suggest that systemic risk in Indonesia can be positively and significantly explained at the 99% level by the external factors included in the study, namely the United States stock index (S&P 500), and

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SIBOR 1-month. This finding implies the driver of systemic risk in Indonesia comes from both the internal as well as the external factors. Our results are consistent with the findings from Reboredo & Ugolini (2015) who argued that the determinants of systemic risk are common and specific factors from both external and internal countries. The remainder of the paper is organized as follows: Section 2 formally defines CoVaR and presents the estimation procedure. Section 3 describes the methodology and data. Section 4 provides the findings. Section 5 concludes the study.

Literature Review

The Concept of Systemic Event

To understand the definition of systemic risk in a financial system, first of all, we need to understand the concept of a systemic event. Bandt and Harmant (2000) described a systemic event into two perspectives. First of all, the narrow sense where the emergence of "bad news" in a financial institution that causes sequential effects on one or several financial institutions causing the failure of the financial system. In this case, although the financial system is fundamentally solvent, the idiosyncratic shock from one institution has a contagion effect on other institutions so that the failure will spread and affects the financial system as a whole. Second, the broad sense concept of systemic events is the failure of large numbers of institutions or markets at the same time due to the severe and widespread effect of *systematic* shocks.

Based on these two terms (narrow and broad sense), then systemic risk can be defined into two key elements: namely shocks and widespread mechanism. The first key element is the shock which can be idiosyncratic or systematic. Following the financial theory, idiosyncratic shock initially only affects one particular financial institution. For example, the failure of a single regional bank due to internal fraud can affect a national financial system in the whole country. Secondly, a systematic shock is the type of shock that can affect the whole financial system or economy such as a stock market crash can be a systematic shock on most financial institutions despite the different exposure for each financial institution.

The second key element of systemic risk is the spillover mechanism from one institution to another, and ultimately it affects the financial system. The spread of the shock in the financial system can be channelled through physical exposure or the information effects (including potential losses). Based on this perspective, we should evaluate further on the various widespread mechanisms of the network in banking and financial markets. From the concept of adjustment equilibrium, the process of "shock transmission" does not always serve as an adverse event as it makes the condition of the financial system returns to the equilibrium point, called as the self-establishing adjustment. However, in systemic conditions, the risk of shock transmission is destabilizing and leads to a default of crashes between real and financial variables. For example, the global financial crisis (GFC) in 2008 may trigger a wave of failures of banks, and this can deeply harm the financial system as a whole in the United States.

The arrival of internal shocks within countries and the subsequent propagation is uncertain. For example, the strong systemic events such as a crisis have low probability events, which might lead as an insignificant concern to the the government. However, this might be a significant problem when the financial structures are strongly interconnected globally. The severe systemic events from other countries will have a destabilizing effect to the internal financial system. Therefore, this argument undermines the reason why the government should consider both internal and external factors.

Conditional Value at Risk (CoVaR) Adrian and Brunnermeier

According to Adrian & Brunnermeier (2016), $CoVaR_i$ is defined by the VaR of the whole financial sector conditional on institution *i* being in a particular state. The systemic risk measure is ΔCoVaR in which the difference between CoVaR conditional on the distress of an institution and the CoVaR conditional on the median state of the institution. ΔCoVaR is a statistical tail-dependency measure, and measure the contribution of a financial institution to the whole financial system when the condition at its VaR.

Suppose that the return from the institution *ri* and the significance level is *q*, $VaR^i_{q,t}$ is defined as the *q*-quantile of the return distribution in equation (1). (Adrian & Brunnermeier, 2016) or AB proposed that CoVaR is implicitly defined by the *q*-quantile of the conditional distribution (see equation 2) where VaR_j is the value at risk of financial system, *j*.

$$Pr(R^i_t \leq Var^i_{q,t}) = q \tag{1}$$

$$Pr\ (R_{it} \leq CoVaR_{i\ q,t} = VaR_{j\ q,t}) = q \tag{2}$$

In order to make a time-varying estimation of VaRj and CoVaRi, AB runs a *q*-quantile regression of R_j on a set of (lagged) state variables. Once the regression has run, they obtain $VaR_j = \alpha + \beta M_t$ and the estimation of CoVaR_i will be:

$$CoVaR_i = c + dVaR_j + eM_{t-1} \tag{3}$$

Where M is a vector of state variables, and the risk contribution from a financial institution to the financial system at median state or $\Delta CoVaR_i = CoVaR_i - CoVaR_{i50,t}$. The equation (3) describes that CoVaR_i is the product function of state variable *M*. The correlation between financial system *j* and individual financial institution *i* is time-varying, the parameter of quantile regression is the same. Hence, the potential problem will arise when estimating CoVaR for a long horizon since the dynamic relationship between an individual and state variables will not be captured. To solve the problem, (Girardi & Ergün, 2013) proposed the CoVaR estimation using the Multivariate GARCH model to capture the dynamic relation overtime.

Research Methodology

Multivariate GARCH CoVaR Estimation

In this section, we will describe the Multivariate GARCH (M-GARCH) CoVaR estimation process and prior to the process, the author did preliminary measures such as stationarity test. We use the three stages of estimation from Girardi & Ergün (2013). The first step is estimating the marginal model for each institution *i*. Following Reboredo & Ugolini (2015), the marginal model of financial institutions is the function between the conditional mean of individual bank returns and the common as well as the specific factors. Where the common factors, X_{1t}, include interbank interest rates, interbank loan rates, and dummy variable crisis. The specific factors,X_{1t}, are the stock market index return (Rm, t) and volatility index, VIX. Volatility Index is a real-time market index that represents the 30-day forward-looking volatility. The index is derived from the price inputs of the S&P index options. This study uses the VIX because it provides a measure of market risk and investors' sentiment. Typically, research analysts and portfolio managers look to VIX as the benchmark before deciding to invest or not. Thus, combining with those factors, the marginal model for individual banks is specified as:

$$R^i_t = \mu_t + \beta_1 R^i_{t-1} + \gamma X_{1t} + \lambda X_{2t} + \theta\varepsilon_{t-1} + \varepsilon_t \tag{4}$$

To seize the asymmetric volatility, we estimate equation (4) using GJR-GARCH (1,1) from Glosten, Jagannathan, and Runkle (1993). Where σ^{2i}_t is the conditional variance for institution *i,* and I_t, a dummy variable.

$$\sigma^2_{it} = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \beta_1\sigma^2_{t-1} + \gamma\varepsilon^2_{t-1}I_{t-1}$$
$$I_t = \begin{cases} 1, & if\ \varepsilon_t < 0 \\ 0, & Otherwise \end{cases} \tag{5}$$

The second step, we estimate the multivariate process using Dynamic Conditional Correlation (DCC) from (Engle, 2012). Let there a two returns R*j* is the return of value weighted financial institutions and R*i* whose joint dynamics equation (R_j= Rsys, R_i);

$$R_t = \mu_t + \varepsilon_t$$

$$E_t = \Sigma^{1/2}_t z_t$$

Where Σ_t is the metrics conditional covariance of the disturbance term εt and μt is the

(2x1) vector conditional means. *{Dxx}t = {Σxx} t, {Dx,y}t = 0* for *x, y =s, j* is the diagonal matrix with the conditional variances which are modeled as GJR - GARCH (1,1).

$$\sigma_{x,t}^2 = \theta_0^x + \theta_1^x \varepsilon_{x,t-1}^2 + \theta_2^x \sigma_{x,t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}$$
$$\sigma_{y,t}^2 = \theta_0^x + \theta_1^x \varepsilon_{x,t-1}^2 + \theta_2^x \sigma_{y,t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}$$

Hence, the conditional covariance $\sigma_{xy,t}$ is

$$\sigma_{xy,t} = \rho_{xy,t} (\sigma_{x,t}^2 \sigma_{y,t}^2)^{1/2} \quad (6)$$

Let $C_t = D_t^{-1/2} \Sigma_t D_t^{-1/2} = \{\rho_{xy}\}_t$ be the (2x2) matrix of conditional correlations of ε_t, then the conditional correlation matrix as follows:

$$C_t = diag\ (Q_t) - 1/2\ x\ Q_t\ x\ diag\ (Q_t) - 1/2$$
$$Q_t = (1-\delta 1-\delta 2)\ Q + \delta 1\ (u_t - u'_{t-1}) + \delta 2\ Q_{t-1} \quad (7)$$

The final step we combine step 1 and step 2 to obtain CoVaR for individu institution *i* for time period *t*. Given the definition of $\text{CoVaR}_{i,t}$ follows:

$$Pr(R_t^j \le CoVaR_i \le VaR_i) = q$$
$$Pr(R_t^j \le CoVaR_i \le VaR_i) / Pr(R_i \le VaR_i) = q$$

We back to the definiton of VaR_i, $Pr\ (R_i \le VaR_i) = q$, so $Pr\ (R_t^s \le CoVaR_i,\ R_i \le VaR_i) = q^2$

When we let x,y = s, h given the VaRi for estimation in step 1, we can solve the following double integral for CoVaR

$$\int_{-\infty}^{CoVaR_i} \int_{-\infty}^{VaR} Pdf(x,y) dy dx = q^2 \quad (8)$$

The calculation of CoVaR_i follows the three step procedure above,but we use benchmark state instead of being less than its VaR_i which is $\mu_t - \sigma_t \le r_t \le \mu_t + \sigma_t$. Once we retrieve the marginal probability $Pr\ (\mu_t - \sigma_t \le r_t \le \mu_t + \sigma_t) = p_t$ for each institution *j,* CoVaR_i is defined by the following joint probability $Pr(R^i_t \le CoVaR_i,\ \mu_t - \sigma_t \le r_t \le \mu_t + \sigma_t) = p^i_t q$. The calculation of CoVaR_i is similar from solving the double integral.

$$\int_{-\infty}^{CoVaR_i} . \int_{\mu t - \sigma t}^{\mu t + \sigma t} Pdf(x,y) dy dx = p_t^i q \quad (9)$$

We solve the problem of double integral by combining the simple expression for *VaR* if losses are distributed, we can solve the problem of CoVaR_i as follow:

$$CoVaR_i = \theta^{-1}(q\%) \sigma_t^{sys} (1-(\rho_t^i)^2)^{1/2} + \theta^{-1}(q\%) \rho_t^i \sigma_t^{sys} \quad (10)$$

because $\theta^{-1}(50\%)=0$, and under Gaussian Framework we also solve the problem of *ΔCoVaR* which is pinned down by three determinants measurement; the correlation, the volatility of financial system, and the Gaussian quantile.

$$\Delta CoVaR_i = \theta^{-1}(q\%)\ \rho^i \sigma_t^{sys} \quad (11)$$

The Data

In this study, we employ monthly stock transaction data from *Thomson Reuters database* and *datastream*. Our sample period is from January 2007 to December 2018. We use this sample window as the main goal of the study is to investigate the financial heating in Indonesia during and recovery period from the global financial crisis in 2008. Wang (2014) argues that the financial turbulence in the US started in 2007 during the summer session (August 2007) and ended on April 2, 2009 when the G20 summit was held in London and the global economy was on the turn from this point. The range of periods are very useful to identify systemic risk and which institutions were in the worst condition during this period in Indonesia. According to this time window, we find 21 banks that are consistently listed during the period.

Results and Discussions

In this section, we will provide the findings from our estimation results. Table 2 provides the summary statistics for $\Delta CoVaR_{99,t}$ for each institution from 2005 to 2018. Recall that ΔCoVaR measures the change in the value at risk of the financial system associated with stress at institution *i.* We report the mean, median, maximum, minimum, and standard deviation for the 21 commercial banks in Indonesia. The highest mean of ΔCoVaR estimation is from Bank Mandiri and Bank BCA (BBCA) at 15.55% and 14.34% respectively. This finding

Table 1. Sample Banks

Code	Name of bank	Date of IPO
AGRO	Bank Rakyat Indonesia Agroniaga Tbk	08/08/2003
BABP	PT Bank MNC Internasional Tbk.	15/07/2002
BBCA	Bank Central Asia Tbk	31/05/2000
BBNI	Bank Negara Indonesia Tbk	25/11/1996
BBNP	Bank Nusantara Parahyangan Tbk	10/01/2001
BBRI	PT Bank Rakyat Indonesia (Persero) Tbk	10/11/2003
BCIC	PT Bank JTrust Indonesia Tbk.	25/06/1997
BDMN	Bank Danamon Indonesia Tbk	06/12/1989
BEKS	PT Bank Pembangunan Daerah Banten Tbk.	13/07/2001
BKSW	PT Bank QNB Indonesia Tbk	21/11/2002
BMRI	Bank Mandiri (Persero) Tbk	14/07/2003
BNGA	PT Bank CIMB Niaga Tbk	29/11/1989
BNII	PT Bank Maybank Indonesia Tbk	21/11/1989
BNLI	Bank Permata Tbk	15/01/1990
BSWD	Bank of India Indonesia Tbk	01/05/2002
BVIC	Bank Victoria International Tbk	30/06/1999
INPC	Bank Artha Graha Internasional Tbk	29/08/1990
MAYA	Bank Mayapada Internasional Tbk	29/08/1997
MEGA	Bank Mega Tbk	17/04/2000
NISP	PT Bank OCBC NISP Tbk	20/10/1994
PNBN	Bank Pan Indonesia Tbk	29/12/1982

Notes: We exclude banks which are not listed from January 2007 to December 2018

Table 2. Full Sample Estimation of $\Delta CoVaR_{99,t}$

	Mean	Median	Maximum	Minimum	Std. Dev.
Briagro	5.56%	4.73%	26.58%	1.57%	3.43%
Mnc	4.05%	3.46%	16.15%	2.53%	1.94%
Bbca	14.34%	12.26%	57.65%	8.80%	6.81%
Bbni	13.88%	11.72%	62.30%	8.25%	7.09%
Bbnp	-0.08%	-0.07%	-0.04%	-0.33%	0.05%
Bbri	15.34%	12.97%	65.65%	9.35%	7.64%
Bcic	8.64%	8.22%	31.18%	2.86%	3.67%
Bdmn	12.81%	10.76%	57.85%	7.15%	6.82%
Beks	3.27%	2.40%	30.70%	-2.58%	3.23%
Bksw	4.88%	3.98%	35.26%	-4.72%	4.17%
Mandiri	15.55%	13.38%	67.45%	8.05%	7.95%
Bnga	11.90%	10.00%	60.29%	4.78%	6.69%
Bnii	9.01%	7.69%	35.94%	5.62%	4.31%
Bnli	9.78%	8.08%	58.70%	3.94%	6.01%
Bswd	3.45%	2.97%	12.44%	1.98%	1.56%
Bvic	7.34%	6.32%	40.78%	2.55%	4.13%
Inpc	6.99%	6.31%	29.98%	0.85%	3.89%
Maya	3.12%	2.52%	18.36%	1.08%	2.01%
Mega	3.48%	2.97%	14.13%	1.20%	1.82%
Nisp	6.65%	5.70%	30.46%	2.98%	3.35%
Pnbn	10.51%	9.05%	51.26%	5.45%	5.55%

Notes: the table reports summary statistics for ΔCoVaRi99t for 99 percent risk measure for all banks in the Indonesian's Banking system. ΔCoVaRi99 is obtained using M-GARCH estimation process to measure the contribution of distress from individual banking i to the banking system.

means that if these two banks fail, then their failure will contribute 30% to the failure of the banking system in Indonesia. Also, the maximum value of ΔCoVaR from State-Owned Enterprises (SOE) banks, namely Bank Mandiri, BNI Bank (BBNI), BRI Bank (BBRI) is more than 60%. This finding implies that in the most severe conditions, these state-owned banks

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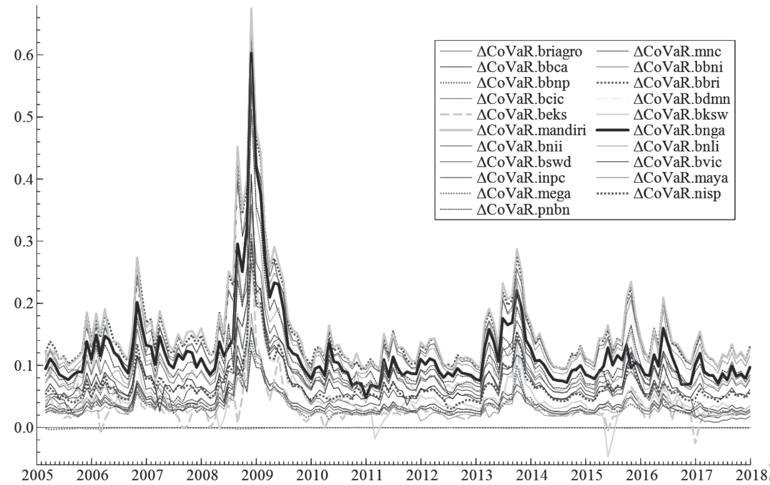
Figure 1. Conceptual Framework



Note: The figure shows the time series of monthly $\Delta CoVaR_{99,t}$ from 2005 to 2018 for a sample of 21 commercial banks in Indonesia.

Table 3. Systemically Bank Ranking Based on ΔCoVaR Estimation

Bank	Size	Before Crisis (2005-2007)	During Crisis (2007-2010)	After Crisis (2010-2012)	Recovery (2012-2018)
BBRI	Big	1	2	2	2
BMRI	Big	2	1	1	1
BBCA	Big	3	3	3	3
BBNI	Big	4	4	4	4
BDMN	Big	5	5	5	5
BNGA	Big	6	6	6	6
PNBN	Medium	7	7	8	8
BNLI	Medium	8	8	9	9
BNII	Big	9	9	10	10
BVIC	Small	10	12	12	11
NISP	Medium	11	13	13	12
BCIC	Medium	12	10	7	7
INPC	Medium	13	11	11	13
BKSW	Small	14	15	15	15
BRIAGRO	Small	15	14	14	14
MNC	Small	16	16	16	16
BSWD	Small	17	19	18	18
MEGA	Medium	18	18	17	17
MAYA	Medium	19	20	20	20
BEKS	Small	20	17	19	19
BBNP	Small	21	21	21	21

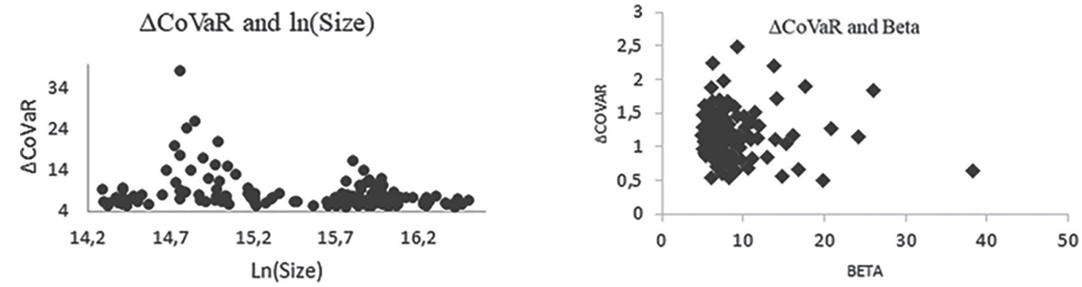
Notes: The table the bank ranking for four periods from $\Delta CoVaR_{99,t}$ estimation.

would have the most significant contribution to the collapse of the banking system in Indonesia. As a consequence, government regulations are needed to monitor these banks to avoid high-risk activities that can increase the probability of failure in the Indonesian banking system.

Figure 1 shows the value of ΔCoVaR for all banks over time. Before the crisis period (2005 - 2007), overall ΔCoVaR was less than 30% with the least number was 5% for bank BBNP. During the crisis period, ΔCoVaR for all banks reaches a peak with the highest value of more than 60% for Bank Mandiri. From 2010 to 2013 was a stable period in which the overall ΔCoVaR reached the lowest point at about less than 30%.

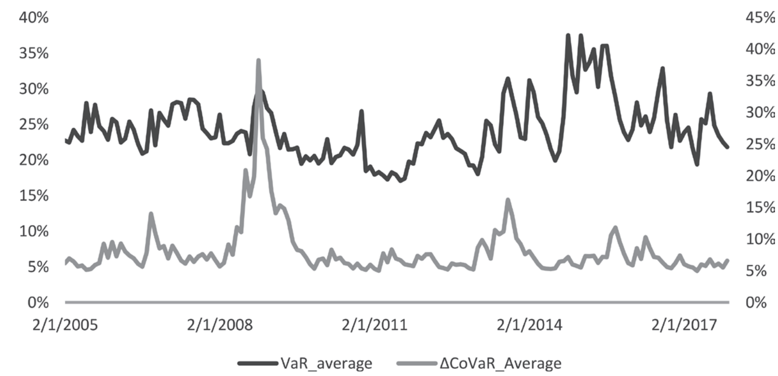
We consider that the ranking of systemically important banks based on ΔCoVaR will be different dynamically depend on the changing of macroeconomic cycles. Table 3 explains the systemic bank ranking based on ΔCoVaR for the four periods before the crisis, during the crisis, after the crisis, and recovery. In general, the top five rankings for the five big banks in In-

Figure 2. Cross-section relation between financial institutions characteristics and contribution to systemic risk



Note: The figure reports the cross-section plots of contribution to systemic risk (measured by average ΔCoVaR), and institution size (measured by market capitalization), and Institution's beta.

Figure 3. Conceptual Framework



Note: The figure reports time-series plot of average ΔCoVaR and VaR for all banks. ΔCoVaR series are plotted on the left axis and VaR series on the right axis.

donesia, namely BBRI, BMRI, BBCA, BBNI, and BDMN, are always the same, even though in the period before the crisis BBRI was on the first ranking while on the rest of the period BMRI was consistently on to be the top ranking. Interestingly, there are two medium-sized banks ranked in the top 10, namely PNBN and BNLI.

Given the concept of " too big to fail" and various proposals about the regulatory scrutiny that these banks should get, it should be on the researchers' interest of to investigate the relation between the size of banks and their contribution to systemic risk. The left side of igure 2 shows the link between the bank's size (measured by total market capitalization) and the bank's ΔCoVaR. The scatter plot displays the weak relation between to measures, particularly for those big and medium-sized banks. However, it seems on the right side of figure 2, the relation between beta and ΔCoVaR has a somewhat negative correlation.

On the other hand, figure 3 reports a relationship between two measurements which are the time series of average ΔCoVaR and VaR. Although there seems to be a stronger relationship in time-series compared to the cross-section, we need to identify the exact relationship using regression. To confirm the relation between ΔCoVaR and bank's characteristics, we employ panel regression analysis. We regress ΔCoVaR for each bank as the dependent variable and the explanatory variables such as VaR, ln(size), institutions beta, time dummy before and after the crisis, and external control variables namely the United States Market Index (Standard and Poor 500) and SIBOR 1 month.

Table 4 shows the estimation results of ΔCoVaR and the explanatory variables. The effect of VaR on ΔCoVaR is positive and significant at 95% and the coefficient estimate is 0.311. The results confirm the dynamic plots in figure 3 in which VaR banks have a positive impact on systemic risk. The effect of log(size) on ΔCoVaR is negative and statistically significant at 90% level. The weak relationship between

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Table 4. Determinants of Systemic Risk in the Indonesian's Banking System

Dependent variable	ΔCoVaR
Constant	0.641*
	(1.893)
VaR	0.311**
	2.042
Beta	-0.003
	(-0.375)
Size	-0.040*
	(-1.786)
D1	0.011
	(-0.782)
D2	0.009
	(1.289)
SIBOR one month	2.029***
	(4.752)
S&P 500	0.174 ***
	(2.313)

Note: t-statistics reported in parentheses are based on the Newey-west standard errors to rectivy serial correlation and heteroscedasticity problems. * Significance at the 10% level, ** Significant at the 5% level, *** Significance at the 1% level.

ΔCoVaR and size justify the result in table 3 and figure 2 that the size of banks does not have a major role in determining the systemic risk. Finally, we find the effect of each bank'beta does not have an impact on systemic risk in Indonesia, suggesting that market sensitivity does not affect contributing to systemic risk.

One interesting finding is that the effect of external factors is positive and significant at 99% level. The US market index has a strong impact on systemic risk in Indonesia with the coefficient estimation is 2.029. The results suggest that the systemic risk in Indonesia strongly depends on market conditions in the US. In line with the previous result, the effect from SIBOR 1-month has a positive and significant with the coefficient 0.174. Therefore, the external factors have a strong contribution to systemic risk in Indonesia.

Overall, the findings from Table 4 are different from previous studies such as Acharya et al. (2010) and Adrian and Brunnermeier (2016) that size and beta are not important in explaining systemic risk contribution. We argue that previous papers using developed countries such as the United States where the institution characteristics have a strong contribution to determine the systemic risk. Another reason, the driver of systemic risk for the emerging market can come from the developed countries since they have the possibility to spillover to emerging countries when in severe conditions. Our findings are consistent with the findings of an earlier study conducted by (Buch, Krause, & Tonzer, 2019) that argue the external factors have a major role in contributing to a systemic risk. The results are relevant for macroprudential policy discussions since they give informative results regarding to the degree of systemic risk, the relevance of bank characteristics, and argues that externalities are important for the surveillance of systemic risk. If banks' characteristics do not have a significant contribution to systemic risk, the regulation should not overlook the contagion from externalities factors. Under this condition, the regulator can tighten the regulatory "international effect" rather than the national effect.

Conclusion

The recent global financial crisis has raised the public and regulators awareness of systemically important banks. Banks that are considered systemically important banks have the potential to harm the financial system and the economy as a whole. Bisias et al. (2012) conducted a systemic risk survey, and they found that there are 31 systemic risk measurements. It implies that there are various systemic risk definitions following these measurements. However, we consider that the various definitions refer to one keyword as mentioned by Bandt (2000) which defines systemic risk as a risk of financial instability which is widespread and impairs the functioning of the financial system to the point where economic growth and welfare suffer materially.

The systemic risk can be defined into two key elements, namely shocks and widespread mechanism. The first key element is the shock which can be idiosyncratic or systematic. Following the financial theory, idiosyncratic shock initially affects only the health of one financial institution. The systematic shock is the type of shock which can affect the whole financial system or economy. For example, a stock market crash can be a systematic shock on most financial institutions despite the different exposure for each financial institution. The second key element of systemic risk is the spillover mechanism from one institution to another institution and the financial system. The spread of shock in the financial system can be through environmental exposure or information effects (including potential losses).

From the spillover point of view, we investigate systemic risk in the Indonesian Financial System using the modification of Conditional Value at Risk (CoVaR) proposed by Girardi and Ergun (2013) since the original CoVaR from Adrian and Brunnermeier (2016) could not capture the dynamic effect when estimating for the long horizon. We employ CoVaR estimation using the Multivariate GARCH model to capture the dynamic relation over time and robust for the long horizon. Finally, we define ΔCoVaR as the systemic risk contribution of an institution under financial distress.

Our systemic risk measurement, ΔCoVaR, shows that the top five systemically essential banks in Indonesia are dominated by state-owned banks, including Bank Mandiri, Bank BRI, and Bank BNI. During the crisis period, these banks had the highest contribution to the systemic risk of more than 60% compared to other banks. Furthermore, we find that the ranking of the top five banks with the most significant contribution to the systemic risk is relatively stable in the period before, during, after, and the recovery period from the crisis.

We also examine the relationship between bank characteristics and systemic risk contribution. We empirically find that individual bank characteristics have a weak relation to systemic risk. In contrast, we find that the external factors have a robust relation to systemic risk in the Indonesian banking system. Finally, these findings have important implications for regulators; the government should not overlook the contagion effect from externalities factors. Under this condition, the regulator can tighten the regulatory "international effect" rather than a national effect to enhance the surveillance and to maintain systemic risk in Indonesia.

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