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Identifying Systemically Important Banks in Indonesia: CoVaR Approach

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Abstract: The Global Financial Crisis of 2008 had a significant impact on banks' bailout decisions due to its high cost of Rp. 6.76 trillion (USD 499.5 million). That shifted the focus from analyzing bank size to a broader notion of systemic risk. Therefore, this research aims to systemically identify important banks in Indonesia using Conditional Value-at-Risk (CoVaR) approach. We conduct the following three steps measurement for population-based on all commercial banks data. Firstly, this study uses Merton Model to gauge the probability of default of commercial banks. Secondly, this study quantifies the value at risk of each bank, including its contribution to the whole banking systemic risk. Finally, this study measures financial linkage among banks and the individual bank value at risk contribution, conditional on other banks being in financial distress, i.e., at its Value at Risk (ΔCoVaR $_{A|B}$). A threshold of 20% ΔCoVaR (A|B) was used to determine 12 out of 119 Indonesian commercial banks that are systemically important and the size ability to affect CoVaR positively. The novelty of the research is to integrate Probability of Default derived from the Merton Model into the CoVaR Model developed by Adrian & Brunnermeier.

Keywords: systemic risk, probability of default, CoVaR, financial linkage.

识别印度尼西亚的系统重要性银行：有条件的风险价值 方法

摘要：2008年的全球金融危机对银行的救助决策产生了重大影响，因为它的印尼盾成本很高。6.76万亿美元（4.995亿美元）。这将重点从分析银行规模转移到了更广泛的系统性风险概念。因此，本研究旨在使用条件风险价值方法系统地识别印度尼西亚的重要银行。我们基于所有商业银行数据对人口进行以下三步测量。首先，本研究使用默顿模型来衡量商业银行的违约概率。其次，本研究量化了每家银行的风险价值，包括其对整个银行系统性风险的贡献。最后，本研究衡量银行之间的金融联系和单个银行的风险价值贡献，条件是其他银行处于财务困境中，即其风险价值（Δ有条件的风险价值$_{A|B}$）。20%Δ条件风险价值(A|B)的阈值用于确定119家印度尼西亚商业银行中的12家具有系统重要性以及对条件风险价值产生积极影响的规模能力。该研究的新颖之处在于将源自默顿模型的违约概率整合到阿德里安和布鲁纳迈尔 开发的 有条件的风险价值 模型中。

关键词：系统性风险、违约概率、有条件的风险价值、金融联系。

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1. Introduction

According to [1], the 2008 Global Financial Crisis (GFC) raised concerns regarding systemic risk. Adrian & Brunnermeier [2] stated that studies on the economy and finance after the GFC have been flooded with many quantitative measurements associated with systemic risks, such as the conditional Value-at-Risk (CoVaR) approach. CoVaR uses quantile regression to estimate the tail loss of financial market returns, conditioned on a given financial institution reaching its VaR level. Adrian & Brunnermeier [2] stated that tail events tend to spill across banks during financial crises, usually preceded by a phase in which risk builds up.

The Century Bank bailout case was one of the biggest problems faced by Indonesia during the 2008 global financial crisis. That is because, at that time, its decision involved a "fantastic" value of Rp. 6.76 trillion (USD 499.5 million), which shifted the assumption of a wider systemic risk threat. Prior to the Global Financial Crisis (GFC), the Asia Financial Crisis (AFC) had significantly and negatively affected Indonesian banks in high fiscal costs from 1997-1998 at approximately Rp 600 trillion (USD 44.3 billion), which is almost equivalent to half of Indonesia's current GDP. The cost is also very high compared to the 43% loss of the country’s economic growth potential in the five years immediately after the 1997 crisis [3].

According to the Indonesian Financial Services Authority [4], the financial sector in Indonesia in June 2020 as a whole was still dominated by the banking sector, even though during this period, there have been significant reforms in some financial sectors. Nevertheless, the level of diversification in the financial sector in Indonesia is still very low. The banking sector still plays a dominant role (79.7 percent of the entire financial sector) compared to other financial sectors such as finance companies, pension funds, mutual funds, insurance companies, which account for only 20.3 percent of the financial sector. Despite growth in the financial system as a whole, the relative shares of various types of institutions in the financial sector have hardly changed, and the basic structure of the financial sector in Indonesia remains more or less the same as in 2012. The challenge ahead is to balance the banking industry and the non-bank financial industry by strengthening the role of the non-bank financial institution sector and the capital market.

The 1997-1998 financial crisis provided numerous valuable experiences, which promoted the Indonesian government to make various efforts to build a more resilient financial system. Furthermore, on March 17, 2016, the government, along with the House of Representatives, ratified Law Number 9 of 2016 concerning the Prevention and Resolution of Financial System Crisis [5] to anticipate the possibility of a repeat of the financial crisis in Indonesia.

Based on two main considerations, the law is specifically designed to prevent and mitigate systemically important banking problems. The first is to prevent the collapse of the payment system for the effective functioning of banks, while the second is to manage public funds by protecting their main functions and services from the threat of failure that needs to be prioritized.

Systemically important banks are indicated by the size of their assets, capital, liabilities, extensive network, or complexity of transactions in banking services. That is in addition to its relationship with other financial sectors, which leads to operational failure. According to [6], it is important to realize that bank failures harm the economy.

Giglio et al. [7] reported that systemic risk measurement must be significantly linked to macroeconomic policy and regulatory decisions. Accordingly, this type of research needs to provide useful input to public policy. Therefore, the research aimed to identify how smaller banks were “trapped” into going along with calling Bank Century a systemically important financial institution when it had initially been called a “potentially” important one. This research supports regulatory decisions to oversee systemically important banks in line with [7].

The main novelty of this research is to integrate Probability of Default derived from the Merton Model [8] into the CoVaR Model developed by Adrian & Brunnermeier [2]. That is to identify SIB to align with the systemic risk definition by Bank for International Settlements (BIS). The definition is the risk that the failure of a participant to fulfill its contractual obligations may, in turn, cause other participants to default with a chain reaction leading to broader financial difficulties [9]. In calculating SIB determination, this research proposed the Probability of Default of each bank at a 20% threshold Δ CoVaR (A|B), by the sum of the products of each value of the random variable of % Δ CoVaR (A|B). This new approach aligns with the definition of systemic risk in the financial sector as the conditional probability of failure of a sufficiently large fraction of the total population of institutions in the financial system [10].

2. Literature Review

Generally, the systemic risk measures are divided into two groups, namely macro and micro, which focus on the institutional and aggregate systems [11]. The measurements included in the macro group are LIBOR Spread [11], Principal Component Analysis [12], and CDS Index and tranches [13].

Moreno & Pena [11] used LIBOR Spread (LS) to measure the distress on the interbank market. This method includes two indices, namely (1) LIBOR-OIS and (2) LIBOR-TBILL. LIBOR-OIS is used to measure liquidity and default risk, while LIBOR-TBILL is used to determine the effect of account liquidity, default risk, and flight to quality. Regarding its relationship to systemic risk, the higher the liquidity, the greater the flight ability to affect the quality. This measurement method cannot be applied in Indonesia, judging from the data requirement.

Adrian & Brunemeier [2] conducted research on the Conditional Value-at-Risk (CoVaR) where AB defines CoVaR $^{i\ |j}$ as VaR from institution i conditional to financial distress, while j described it as VaR institution. They also captured more than the idiosyncratic risks that a financial institution with CoVaR used to measure the possibility of risk spreading.

Adrian & Brunnermeier [2] proposed a set of "co-risk management" measures based on traditional management tools by estimating the CoVaRi of institution i's while considering the system as a value-at-risk (VaRs) conditioned with i (VaRi level). Based on CoVaR, the marginal contribution of institution i was calculated to determine the overall systemic risk and the difference between CoVaR and the unconditional entire system's VaR, denoted as ΔCoVaRi. A similar perspective was obtained in studies by Acharya et al. [14] and Brownlees et al. [15]. The third measure considered was at the micro group level, which consists of Adrian & Brunnermeier's [2] measure across all banks in the portfolio.

Moreover, Girardi & Ergun [16] attempted a comparison between CoVaR and MES using methods from [14, 15], which indicated a difference in the conditioning event and direction. According to them, when MES looks at institution returns, the financial system is distressed, and losses are incurred. CoVaR sees financial system yields when an institution is experiencing distress.

Furthermore, research conducted by Girardi & Ergun [16] generalized the CoVaR definition proposed by Adrian & Brunnermeier [2]. It assumes that the occurrence of financial distress refers to the condition whereby the institutional yield j equals its VaR ($R^j \leq VaR^j$), while the AB version is equivalent to ($R^j = VaR^j$). In addition, this change of assumptions also makes [16] capable of improving CoVaR's consistency concerning its parameter dependencies.

CoVaR is a derivative variant used to measure each institution's contribution to the system as a whole. Meanwhile, traditional measurement only focuses on individual institutions, increasing the systemic risk dimension. For example, institutions A and B have the same VaR value, with CoVaR of 0 and absolute, respectively. The two institutions seem to have the same level of risk with varying VaR values. However, B's risk contribution to the system is higher because it has a greater CoVaR level. Therefore, the regulator's ability to give the same treatment to the two institutions increases the systemic risk.

Giglio et al. [7] tested 19 systemic risk measurements in the United States, United Kingdom, and Europe. Tests were run with different periods at each location and tested on economic variables, namely production and income, labor, unemployment and hours of work (Employment, Unemployment, and Working Hours / EUH), Personal and Household consumption (PH), and Sell, Ordering, and Inventory (SOI).

Giglio et al. [7] then tested at the 20th percentile and median to assess the effect of systemic risk on macroeconomic shock. The results of testing the 19 measurement methods show that several measurements are better than CoVaR and CoVaR in showing the effect of systemic risk in the United States, United Kingdom, and Europe during the analysis period.

Chen et al. [17] conducted a study similar to [7]. They tested 12 systemic risk measures in China in the period 2003-2018. The study investigated the role of systemic risk in predicting macroeconomic shock. They tested 12 systemic risk measures at the 5th percentile for extreme downturn risk, then at the 20th percentile for moderate downturn risk, at the median, and the 80th percentile. The results showed that of the 12 systemic risk measurements, only 8 were significantly informative in the event of shock, where CoVaR was one of the 8 measurements.

Chen et al. [18] then conducted a study similar to their previous study in 2020. They predicted the full distribution of future economic growth dependent on systemic financial risk in four countries (United States, Japan, Korea, and China). They tested 12 systemic risk measures at the 5th percentile for extreme downturn risk, then at the 20th percentile for moderate downturn risk, at the median, and the 80th percentile. This study shows that CoVaR is the best systemic risk measurement in 4 countries in the "Institution to systemic risk" category. Chen et al. [18] stated that CoVaR could capture the negative spillover effect and is used to identify the "systemic importance" of each institution ("too big to fail").

This research uses the CoVaR measurement method and its derivative variant (ΔCoVaR) from [2] as the basis for developing systemic risk measurements. The approach is different from the MES method conducted by Acharya et al. [14] because it focuses more on the liquidity aspects of individual banks and the financial system during the crisis. MES is a good tool for projecting liquidity shortages likely to occur during a crisis without focusing on liquidity. The banking business practice is associated with several risks, such as various considerations related to the efficiency of supervision. In addition, systemic risk measures need to be used to classify individual banks based on their market values. One of the weaknesses of MES over CoVaR is that banks with greater liquidity have the greatest systemic risk. Therefore, CoVaR is ultimately preferred over MES due to using the SRISK method for econometric improvement.

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3. Data and Methodology

3.1. Data

To prove we utilize Indonesian banks and monthly macroeconomic data during 2002-2014, as shown in Table 1.

Table 1 Types and sources of data

No.	Data Type	Period	Source	Information
1	Balance Sheet, Profit & Loss, Cash-Flow	2002 - 2014	Bank Indonesia	Monthly data
2	Commercial Bank Periodic Report	2002 - 2014	Bank Indonesia or Financial Services Authorities	Monthly data of total asset value, book value of debt, and the book value of equity
3	SBI rate, JIBOR, CSPI Exchange rate	2002 - 2014	Bloomberg, BI, Yahoo Finance	Monthly data

It provides the complete monthly data of 119 Banks needed to conduct this study. The attributes analyzed include monthly balance sheet reports, income (profit & loss), and cash flow statements.

3.2. Methodology

The purpose of VaR and CoVaR measurements is to estimate the probability of underlying returns, using historical yield distributions, and estimated as parameter objects to fit a historical sample. Adrian & Brunnermeier's [2] methods and the *quantile regression* approach were used to estimate VaR and CoVaR.

The basis for calculating VaR and CoVaR is the change in the market value of the total assets generated by each bank and financial system, determined using stock price [2]. However, due to the limited list of banks, this research estimates the market value of assets based on iterations between the liability and equity markets derived from the cash flows of each unlisted bank as indicated by [19].

The calculation of individual VaR banks and the banking system requires knowledge of returns on bank assets. For an individual, it is derived from the market value of the bank at a given time, using the following Equation 1:

$$X_t^i = \left(\frac{A_t^i - A_{t-1}^i}{A_{t-1}^i} \right) \text{ and } X_t^{sys} = \left(\frac{A_t^{sys} - A_{t-1}^{sys}}{A_{t-1}^{sys}} \right) \text{ with } A_t^{sys} = \sum_i A_t^i \tag{1}$$

where X_t^{sys} = return of the market assets of the entire banking system;

A_{t-1}^{sys} = Market assets of the banking system at the last time.

For obtaining the time variation on the distribution between X^i and X^{sys}, this distribution is estimated as a function of a series of macro variables that can affect the amount of asset return. In this stage, the data processing technique used is Generalized Autoregressive Conditional Heteroscedastic or GARCH (1,1) regression. The GARCH model regression equation is used to estimate the return value of bank assets as follows:

$$X_t^i = \alpha^i + \beta^i M + \varepsilon_t^i$$
$$X_t^{sys} = \alpha^{sys} + \beta^{sys} M + \varepsilon_t^{sys} \tag{2}$$

where X_t^i = *Value at Risk* of bank *i* at observation *t*;

X_t^{sys} = *Value at Risk* banking system at the time of observation *t*

To estimate VaR values of individual banks, VaR and CoVaR systems of banking performed a regression using the model GARCH with a 99% confidence interval. Selection based on the confidence interval in calculating risk guidelines established by the Bank for International Settlements and Indonesia is 1%.

From Equation 2, the estimation coefficient was obtained, which was then used to calculate the value of individual VaR values and VaR for the banking system (Equation 3)

$$VaR_t^i = \hat{\alpha}^i + \hat{\beta}^i M$$
$$VaR_t^{sys} = \hat{\alpha}^{sys} + \hat{\beta}^{sys} M \tag{3}$$

Where VaR_t^i = *Value at Risk* of bank *i* at observation *t*

VaR_t^{sys} = *Value at Risk* banking system at the time of observation *t* with $VaR_t{}^{i}$ is the value at risk of bank *i* in period *t*, and $VaR_t{}^{sys}$ is the value at risk of the banking system in period *t*. M is a vector of macro variables including SBI rate, JIBOR, JCI, and ER *(Exchange Rate)*; all four are calculated in the value of their growth.

$$\text{sbi}_t = \frac{\text{sbi}_t - \text{sbi}_{t-1}}{\text{sbi}_{t-1}} \quad \text{jibor}_t = \frac{\text{jibor}_t - \text{jibor}_{t-1}}{\text{jibor}_{t-1}} \quad \text{ihsg}_t = \frac{\text{ihsg}_t - \text{ihsg}_{t-1}}{\text{ihsg}_{t-1}} \quad er_t = \frac{er_t - er_{t-1}}{er_{t-1}} \tag{4}$$

Equation 5 is used to estimate CoVaR_t^i the result used to determine the coefficient of the return on the banking system. It is substituted in the estimation result of VaR_t^i the coefficient $\gamma^{sys|i}$ as shown in the following Equation 5:

$$X_t^{sys} = \alpha^{sys|i} + \beta^{sys|i} M + \gamma^{sys|i} X_t^i + \varepsilon_t^{sys|i}$$

$$\text{CoVaR}_t^i = \hat{\alpha}^{sys|i} + \hat{\beta}^{sys|i} M + \gamma^{sys|i} \text{VaR}_t^i \tag{5}$$

where CoVaR_t^i = *Conditional Value at Risk*, CoVaR of the banking system at bank *i*;

$\hat{\alpha}^{sys|i}, \hat{\beta}^{sys|i}, \hat{\gamma}^{sys|i}$ = Estimated parameters

Furthermore, the systemic risk contribution to the banking system of each bank is calculated using Equation 6.

$$\Delta\text{CoVaR}_t^i = \text{CoVaR}_t^i - \text{VaR}_t^{sys} \tag{6}$$

The magnitude ΔCoVaR_t^i is a measure of the risk contribution of each bank to systemic risk in the entire banking system at a particular time.

3.2.1. Financial Linkage Analysis

The following steps were used to analyze the financial relationship between banks:

a. Estimate the equation CoVaR (A|B), which is the *Value at Risk* of bank A that is conditioned on the *Value at Risk* of bank B using Equation 7 [20]:

$$X_t^A = \alpha + \beta^A M + \gamma X_t^B + \varepsilon_t^{A,B} \tag{7}$$

with X_t^A and X_t^B denoting return on assets of banks A and B, respectively.

b. The parameters α, β, and γ in the estimation results are then used to calculate CoVaR (A|B) by substituting the *Value at Risk* bank B from Equation 3 into (6).

Therefore, the CoVaR (A | B) estimate is:

$$\text{CoVaR(A|B)}_t = \hat{\alpha}^A + \hat{\beta}^A M + \hat{\gamma}\,\text{VaR}_t^B \tag{8}$$

c. The level of marginality or change ΔCoVaR (A|B) is the difference in CoVaR (A|B) with *Value at Risk* of bank A at a certain number of observations. That illustrates several advantages of the *Value at Risk* for bank A separated and used to determine B, as shown in Equation 9.

$$\Delta\text{CoVaR(A|B)}_t = \text{CoVaR(A|B)}_t - \text{VaR(A)}_t \tag{9}$$

The estimate Equation 9 is used as a relative measurement tool to determine banks that generate greater shocks.

d. *Financial linkage* analysis of interbank dynamics is accomplished by measuring the percentage change of the *Value at Risk* of an individual bank given the action or response of A or B at a 99% confidence interval:

$$\%\ \Delta\text{CoVaR(A|B)}_t = \frac{\text{CoVaR(A | B)}_t - \text{VaR(A)}_t}{\text{VaR(A)}_t} \tag{10}$$

Equation 10 represents the additional risk value percentage at a certain time interval *(time_varying)*. When the *Value at Risk* of bank B is integrated at the middle, using a 99% confidence interval under conditions of *distress* or *default*, there are no possible ways to differentiate the banks at their default conditions. Therefore, its default probability is calculated to estimate the default risk of one bank to another.

4. Result and Analysis

4.1. Probability of Default Estimate

Banks' role as an intermediary institution makes it inseparable from idiosyncratic *inherent* risks associated with everyday business activities. Therefore, it is increasingly important to have reliable predictive measurement methods to avoid bank defaults and have higher degrees of transmission.

Merton [8] introduced the default model by modifying the Black-Scholes model of the option price [21]. This model was modified and developed by Olddrich Vasicek and Stephen Kealhofer as the VK [22]. Subsequently, the VK model was modified by KMV, a financial consulting firm in the United States, and renamed KMV. This model calculates Expected Default Frequency (EDF), which is likely to fail over the coming years for companies in which shares are traded. The value of EDF requires the price of equity and certain items in the company report.

According to Merton [8], several factors are responsible for the various levels of systemic risk in each bank, such as market value and asset return volatility. These variables are the main gauge of a bank's default probability level. However, the problem with this sort of scrutiny is that observations indicating a default are unavailable until a bank is in default. The banking business activities are the management of risk and highly sensitive to confidence. Therefore, it is important to make probabilistic assessments of possible defaults.

The results of the estimated probability of default for several sample banks are shown in Table 2, which describes the probability of default of each bank along with its standard deviation and the soundness rating of each bank based on the average probability of default. To maintain the practicality of the report, not all banks were analyzed in this research. However, a full list can be provided upon request.

Table 2 Probability of default and bank rating (AAA= (0–5%); AA= (5–15%); A= (15–25%); BBB= (25–35%); B= (35–50%); B= (50–65%); CCC= (65–75%); CC= (75–85%); C= (85–95%); D=95% +)

Bank ID	Mean Probability of Default	Standard Deviation	Rating	Ranking
2	37.5%	8.56%	BB	8
8	34.9%	4.81%	BBB	6
9	42.7%	3.31%	BB	18
14	18.7%	7.03%	A	3
16	51.4%	3.02%	B	43
28	48.2%	4.77%	BB	30
147	48.7%	7.62%	BB	34
427	18.2%	6.69%	A	2
441	56.2%	2.34%	B	65
451	42.4%	14.29%	BB	14
553	66.8%	1.49%	C	92
566	67.7%	2.37%	C	94

As mentioned previously, this research uses CoVaR to analyze and measure systemic risk in the Indonesian banking industry. It first calculated VaR for individual and overall banking systems before CoVaR calculations.

4.2. VaR for Individual Bank and the VaR System

It is necessary to identify the risks contained in the banking system in the early stages of systemic risk measurement. According to [2], the high risk in the market or system defines the parameters in which linked individuals tend to spread adverse impacts to other institutions. A bank generates individual systemic risk as part of a system instead of the aggregate ones contained in the banking system as a whole.

After calculating the probability of default, the risk value of each bank is measured using a 99% confidence level. VaR acts as a measure of the risk of an entity, which is estimated using the GARCH (1.1) model. That is in line with [23], using the previous SBI, JIBOR, IDX return, and the IDR/USD exchange rates as control variables capable of affecting bank asset returns. Table 4 shows the estimated results and brevity values of 119 banks.

Table 3 Estimation of VaR equality of individual bank and VaR systems

Bank ID	Return Assets	SD	VaR	Coefficient Estimation Model GARCH (1,1) Macro Variable Lag 1				
				C	SBI-1	JBR-1	ISHG-1	ER-1
2	1.42%	3.78%	-7.23%	0.016	0.016	-0.107	-0.050	0.079
8	0.69%	2.25%	-4.65%	0.005	0.122	-0.058	0.035	0.143
9	0.75%	2.84%	-5.87%	0.008	0.011	-0.052	-0.026	0.116
14	1.05%	1.36%	-2.13	0.009	-0.090	-0.037	0.010	0.099
16	0.92%	2.54%	-5.07%	0.009	0.084	-0.036	-0.031	0.051
28	1.69%	3.45%	-6.32%	0.019	-0.276	0.077	-0.132	0.004
147	2.37%	3.87%	-6.63%	0.023	-0.059	-0.053	-0.004	-0.034
427	2.43%	2.82%	-4.16%	0.024	-0.210	0.001	0.013	0.077
441	1.52%	5.40%	-11.00%	0.019	0.152	-0.233	-0.183	-0.284
451	2.74%	3.67%	-6.00%	0.026	-0.049	-0.077	-0.034	-0.078
553	2.71%	8.46%	-16.34%	0.039	-0.162	-0.203	-0.364	-0.305
566	2.23%	10.03%	-21.24%	0.020	-0.519	0.336	-0.007	-0.091
System	1.09%	1.44%	-2.28%	0.011	0.062	-0.057	-0.031	0.010
Average	1.98%	9,88%	-21.26%					

The average VaR of the entire banking system was recorded at -21.42%, while its operational definition is the value of the risky tail of assets at a 99% confidence level. According to [2], the more negative the VaR value, the greater the bank risk.

4.3. Risk Contribution of Individual Bank on the Banking System

CoVaR illustrates the interconnectedness between the VaR of each bank and the banking system. The estimated value from each bank is determined using the GARCH (1,1) approach. The constants and coefficients of the resulting model are then substituted on the macro variables and the estimated value of the individual VaR of each bank. Therefore, CoVaR values of individual banks are obtained instead of the overall banking system's risk.

ΔCoVaR measurement describes the relationship between the levels of an individual bank's risk (VaR) of the banking system's systemic risk contribution. Table 4 describes the calculation results ΔCoVaR for each bank with a low correlation between individual and systemic risk contribution. This result shows that banks with high VaR values are not necessarily big contributors to systemic risk and vice versa.

That is understandable because individual bank VaRs measure how much losses an institution can suffer due to common factors, such as inflation, interest, exchange, and market rates. Individual VaR is related to the marginal loss distribution of the portfolio. This assumption relates to the joint distribution of losses suffered by all market participants and how they are transmitted in the system [24].

Bank 8 with VaR is ranked 114 (VaR -4.6%) is the most systemic bank based on ΔCoVaR. That suggests that the quality of risk management in the bank internal described by VaR does not necessarily reflect the bank's systemic risk. Therefore, as stated in previous research, this reinforces the need to use systemic risk indicators that differ from inherent bank risk.

Table 4 Individual risk and systemic risk contribution

Bank ID	**Individual Risk**		**Systemic Risk Contribution**		
	VaR	**Ranking**	**Δ COVAR**	**Ranking**	**% Δ COVAR**
2	-7.2%	101	-2.03%	3	89.11%
8	-4.6%	114	-2.58%	1	113.27%
9	-5.9%	109	-2.24%	2	98.49%
14	-2.1%	119	-1.27%	15	55.72%
16	-5.1%	112	-1.50%	7	66.02%
28	-6.3%	107	-1.46%	8	64.18%
127	-12.8%	62	-0.83%	32	36.27%
427	-4.2%	117	-0.59%	56	26.09%
441	-11.0%	77	-1.76%	4	77.20%
451	-6.0%	108	-0.52%	62	22.78%
553	-16.3%	40	-0.96%	26	42.23%
566	-21.2%	30	-1.31%	12	57.33%
Average				25.38%	

4.4. Calculation Results $\Delta CoVaR_{A|B}$

The focus of attention and discussion surrounding the systemic risk literature is the threat generated by a bank. When it is in a state of financial distress, its impact tends to disrupt the stability of the whole banking system. That is because it is a business that relies on trust. Therefore, the failure of a bank leads to panic, which is indirectly a form of contagion. This study finds an important role in explaining the strategies used by banks to determine a market. The amount of each contribution to the bank against others is influenced by many things. Based on the calculation of CoVaR in the previous section, it has been shown that one of the main contributing factors is the number of assets owned by the bank.

This research contributes to explaining how a bank's position can be accounted for in the market. It also performs calculations for indicators $\Delta CoVaR_{A|B}$ for each bank for all pair-wise. Table 7 illustrates the mean changes of $\Delta CoVaR_{A|B}$ of twelve systemically important banks, which yields an overview of the systemic risk each bank poses against another.

Table 5 shows that bank 2 has wide and varied systemic influences. The influence on the bank's systemic 8 ($\Delta CoVaR_{2 | 8)}$ amounted to 67.0%, while that of bank 2 to 9 ($\Delta coVaR_{2|9)}$ was at 54.7%, and by showing the relationship of systemic influence between each bank becomes a banking system.

Many people think the problem of systemic importance emerges because a bank becomes "too big to fail." It suggests that the largest banks, such as bank 2, bank 8, bank 9, and bank 14, are systemically important because the banks in the BUKU 4 concentration (CR4) are dominant in economically significant financial markets [25].

A clear threshold occurs when individual bank failures become an undefined systemic crisis. That is achieved by computing that banks with total assets above a certain percentage (ξ) tend to go bankrupt within a short period [26]. According to [27], a threshold is used to make groups of institutions systematically important, such as the probability that an economic or financial shock can de-capitalizing accounting institutions, in aggregate, 20% of banking assets. The ΔCoVaR A|B threshold of 20% applied to one dozen Indonesian banks are systemically important. Additional tests suggest that bank size positively affects the potential risk a bank generates.

Table 5. Twelve systematically important banks Mean Changes of $\Delta CoVaR_{A|B}$ (Mean: $\bar{x} = \Sigma\, p_x .\, x_i$, where p_x = Probability of Default of individual bank)

Covar A|B	2	8	9	14	16	28	147	427	441	451	553	566	Mean
2	*0.0%*	67.0%	54.7%	26.3%	31.4%	14.2%	51.0%	7.7%	28.9%	24.2%	27.6%	46.7%	22.1%
8	61.5%	*0.0%*	55.6%	40.2%	37.1%	31.0%	23.9%	0.9%	33.7%	8.3%	20.2%	42.0%	23.0%
9	53.4%	62.8%	*0.0%*	40.1%	30.7%	43.2%	34.5%	7.8%	45.4%	17.4%	30.8%	41.8%	27.0%
14	29.5%	55.2%	42.0%	*0.0%*	19.2%	35.8%	15.5%	5.9%	18.0%	14.6%	33.8%	36.3%	20.8%
16	32.0%	38.3%	34.3%	15.7%	*0.0%*	39.5%	30.0%	12.8%	11.7%	14.1%	15.5%	40.0%	21.3%
28	19.1%	36.4%	44.0%	32.0%	46.1%	*0.0%*	12.2%	-9.0%	37.5%	9.7%	32.8%	20.7%	23.1%
147	54.6%	47.1%	39.0%	16.9%	33.8%	11.0%	*0.0%*	50.6%	39.8%	26.8%	34.1%	28.7%	25.4%
427	15.2%	12.9%	31.3%	17.7%	41.1%	-3.7%	45.3%	*0.0%*	75.9%	71.9%	-17.5%	63.0%	20.2%
441	30.8%	41.1%	41.2%	13.3%	26.9%	34.1%	33.1%	17.3%	*0.0%*	34.3%	38.9%	43.4%	22.8%
451	43.9%	41.7%	39.2%	16.8%	38.7%	15.4%	30.9%	60.0%	41.5%	*0.0%*	31.0%	51.9%	21.5%
553	45.8%	33.8%	38.5%	31.9%	27.8%	38.3%	31.2%	-11.1%	44.3%	28.2%	*0.0%*	40.4%	21.0%
566	40.7%	41.8%	30.4%	22.1%	23.1%	10.6%	27.6%	16.4%	26.3%	26.5%	31.5%	*0.0%*	20.3%

Suppose that a data set contains the Calculated values of % Δ CoVaR (A|B), $x_1, x_2, \dots, x_i$, occurring with Probability of Default, $PoD_1, PoD_2, \dots, PoD_k$; respectively.

(i) For a population N observations, therefore; $N = \sum_{i=1}^{k} PoD_i$

(ii) Expected Value, E(X), of a Discrete Random Variable X is defined as folows:

$E(X) = \mu_x = \sum_x x\, .\, PoD_x\,(x)$

where the notation indicates that summation extends over all Probability of Default values X of % Δ CoVaR (A|B). The expected value of the random variable is called its **population mean** and is denoted by $\boldsymbol{\mu_x}$. Therefore, the expected value of a random variable % Δ CoVaR (A|B) is the sum of the products of each value of the random variable of % Δ CoVaR (A|B) with that value's Probability of Default of each bank. It becomes the main novelty of this research, which integrates Probability of Default derived from Merton Model [8] into the mean of the threshold of 20% Δ CoVaR (A|B) when calculating Systemically Important Bank determination.

5. Conclusions

In conclusion, this research bridges Ayomi & Hermanto's [23] gap in using CoVaR to calculate systemic risk in the Indonesian banking system. Firstly, the scope of the data used reflects the real condition of the Indonesian banking industry. That is shown from the use of population data of all banks and market risk premiums that fluctuate according to market conditions. Secondly, this research considers the transmission of crisis transmission from outside the Indonesian financial system. Therefore, adding the exchange rate as one of the independent variables in the estimation is required.

A Merton model [8] was used to gauge the commercial banks' probability of default, which was quantified to determine each bank's risk value, including its contribution to the whole banking systemic risk. Finally, the financial linkage among banks was measured to determine the value in contributing risk. 12% of ΔCoVaR (A|B) threshold was applied in Indonesian banks, and the empirical results showed that the overall size is not the only factor in determining systemic risk.

A limitation of the research aside from the bank size is the possibility of market perception. Behavioral economics research includes the market perceptions made and the mechanisms that drive depositors' choices. Richard H. Thaler, the economics noble prizewinner of 2017, showed how these human traits systematically affect individual decisions and market outcomes [28] allowing to analyze systemic risk determinants more comprehensively.

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