# A Stress Test with Simultaneous Impact to the Banking System

**Aditya Anta Taruna*, Cicilia A. Harun†, Ramdani‡**

**Abstract**

*This paper tests a simultaneous approach in stress testing ST framework. Distress events that affect one bank could jeopardize other bank balance sheets. The affected bank, most likely, fails to satisfy its liabilities to other banks, thus potentially bringing down the other bank, too. In the current stress testing framework, this fact is often simplified. Usually, the ST treats simultaneous impact from failed banks sequentially. First, the ST calculates one bank's expected loss and then transmits it to another bank. While this treatment is common, we find that by implementing a simultaneous scenario to the banking system, we could estimate a more realistic result capturing the contagion effect amongst banks. Using an unprecedented crisis as a scenario, the COVID-19 pandemic, in the Indonesian banking system, we estimate a higher loss and number of failed banks compared to the current best practice ST framework. Here, we see that the results worsened because of the information channel, which the current best practice ST failed to capture.*

***keywords****: mathematical models, simulation modeling, financial economics*

*JEL clasification: C600, C630, G00*

* PhD Candidate in Economics at Crawford School of Public Policy, ANU

† Director at Bank Indonesia

‡ Analyst at Bank Indonesia

## 1. Introduction

In the banking sector, stress tests are utilized to gauge both the potential vertical (from the macroeconomy to the banking financial system) and horizontal (from bank to bank) impacts. These tests assess the resilience of banks when confronted with specific distress scenarios or shocks. By estimating the impact of these shocks on a bank's balance sheet, stress tests help to determine the level of resilience. The shocks are represented by scenarios comprising deteriorating macroeconomic conditions and/or specific distress conditions within the banking sector. Typically, these macroeconomic conditions involve declining GDP growth, heightened inflation, and currency depreciation. On the other hand, bank-specific scenarios encompass credit risk in specific sectors linked to the macroeconomic conditions, liquidity risk associated with potential deposit withdrawals or funding reductions, and market risk stemming from financial market distress. Subsequently, based on the results, regulatory authorities devise policy responses to ensure the resilience of banks and, more importantly, to mitigate the likelihood of such scenarios occurring.

In recent times, there has been a growing concern among financial authorities regarding macroprudential stress tests (MaPST). Unlike microprudential stress tests (MiPST), MaPST aims to assess the impact of scenarios not only on the banking system but also on the real economy (Anderson et al, 2008). MaPST takes into account individual impact, vertical impact, and horizontal impact. It evaluates the potential propagation and amplification of shocks in the financial system. In reality, horizontal impact may occur even before individual impact, especially in the case of systemic shocks (Shiller, 1995). When a shock originating from macroeconomic conditions or the financial system itself hits the financial system, banks may start to take defensive measures, causing horizontal impact to unfold.

In the event of a significant shock, banks have the ability to close off their credit lines to other banks, conserve liquidity, restrict credit extension to their most reliable debtors, and offload risky securities that could contribute to a decline in the value of risky assets and an increase in market risk. As a result, a bank that was initially stable could become distressed as a result of the shock spreading through horizontal transmission. Failing to recognize the importance of this horizontal impact relative to the vertical impact would lead to an underestimation of the shock's impact on the financial system. This addresses a criticism of MiPST's nature raised by Gordy (2003), which does not consider concentration risk. It is evident that a bank's portfolio is not solely impacted by a single systematic factor, as highlighted by Hashimoto (2009), who suggests that a bank's portfolio may be heavily concentrated in specific sectors, and a single systematic factor may not be adequate to explain the entire default dynamics. These assumptions could result in the underestimation or overestimation of a bank's capital level (Capital Adequacy Ratio). The main contribution of this research is to encompass all the aforementioned mechanisms and integrate them into the stress testing procedures conducted by financial regulatory authorities.

This paper focuses on the propagation and amplification mechanism within the framework, addressing a gap in the MiPST. Specifically, it examines the systematic pressure on the financial system. The paper assumes that the shock triggers panic in financial markets and leads to an over-extrapolation of the distress event, influenced by increasing uncertainties and worsening asymmetric information problems. As a result, propagation and amplification occur from the outset of the model. Incorporating this into our framework, we calculate the simultaneous impact of systematic factors on macroeconomic variables and banks' balance sheets. This module can then be integrated with other stress test modules that measure individual and vertical impacts.

In this paper, we posit that a bank's probability of default (PoD) is influenced not only by its portfolio, but also by other banks. Therefore, we employ a joint probability of default approach, specifically a copula method, to capture this dynamic. Our estimation takes into account all potential macroeconomic shocks (variables) and the dynamics of the banking system. A shock to one macroeconomic variable triggers reactions in other variables, as well as in the banking system. The dynamics of macroeconomics cause adjustments in a bank's PoD. Given the interconnected nature of banks, the adjustment of one bank's PoD disrupts the PoD of other banks. A standard stress test setup is insufficient to capture these interconnected reactions (Jakubik & Schmeider, 2008; Rösch, 2005).

In this paper, we also employ pair-wise copula correlation to analyze the butterfly effect or chain reactions that depict the transmission of risk from one source to another. In the realm of policy making, a simplified visualization of complexity can effectively convey the underlying issues, which can aid the decision-making process. The simplification in the pair-wise copula method facilitates the identification of the central network of interconnected factors and the paths of risk transmission. We leverage the insights provided by this method to assess the interconnectedness of the financial system by simplifying the connections of each factor.

Our stress test results are designed to closely mimic real-world dynamics, in contrast to the standard MiPST framework. This addresses the concerns raised by Gordy (2003). We chose to conduct the exercise using Indonesian banking data for two main reasons. First, stress tests are typically conducted within a specific jurisdiction, in our case, Indonesia. Therefore, we tailored the exercise to reflect the specific characteristics of the Indonesian financial system. When implementing this in a different jurisdiction, adjustments would be necessary, similar to how the IMF team customizes stress test exercises for the Financial Sector Assessment Program (FSAP). Second, Indonesian banking data is readily available to us and offers a level of detail that may not be accessible if we were to use data from other jurisdictions.

Utilizing the pair-wise copula method can assist in the decision-making process by simplifying the identification of interconnected factors and risk transmission paths within the central network. We employ the insights gained from this method to evaluate the interconnectedness of the financial system by streamlining the connections of each factor. Our stress test outcomes are tailored to closely replicate real-world dynamics, in contrast to the traditional MiPST framework.

The paper is organized as the following. Section 2 lays out the modeling of the stress test exercise using the joint probability estimation and present the illustration of the interconnectedness of the factors in the stress test using the pair-wise copula correlation. Section 3 describes stress scenario exercise, including risk transmission in our stress test framework. Section 4 discusses the results and robustness check developments. We conclude in Section 5.

## 2. Methodology and Data

### 2.1. Copula Method

In order to capture the impact of systematic factors and macroeconomic and sectoral influences on a bank's activities, we have developed an interdependency model among these factors. One common approach to modeling interdependencies among variables is through the use of copulas. Copulas are designed to link a set of variables into a joint distribution by capturing their dependence structure. The joint distribution copula is essentially a way to break down their individual distributions and their copula, which encapsulates the variables' dependence structure (Dalla, 2016). Furthermore, copulas can be viewed as a non-linear model, with the model's representation being provided by the joint distribution. The development of copula models has gained traction, particularly after the Global Financial Crisis in 2008. During the crisis, the

Gaussian copula failed to accurately assess the pricing of financial assets with low probabilities of default but complex dependence structures (Koziol, 2015).

Copula model was firstly introduced by Sklar's theorem which states that for a vector of random variables $\boldsymbol{X} = (X_1, X_2, \dots, X_n)$ with marginal cumulative distribution $F_i(x_i)$ and n-dimensional cumulative joint distribution $F(X_1, X_2, \dots, X_n)$, there exist n-dimensional copula $C$ such that

$$F(X_1, X_2, \dots, X_n) = C\big(F_1(x_1), F_2(x_2), \dots, F_n(x_n)\big) \tag{1}$$

If random variables are strictly increasing continuously, then there is exist inverse marginal cumulative distribution such that the copula is uniquely defined. Consequently, we can write copula representation in the following form

$$C(u_1, u_2, \dots, u_n) = F\big(F_1^{-1}(x_1), F_2^{-1}(x_2), \dots, F_n^{-1}(x_n)\big) \tag{2}$$

Therefore, copula is a function that maps a n-multidimensional uniform distribution generated through marginal distribution into a univariate uniform distribution. After formally defining copula, we can write a joint distribution of random variables as function of copula in an explicit form.

$$f(x_1, x_2, \dots, x_n) = c\big(F_1^{-1}(x_1), F_2^{-1}(x_2), \dots, F_n^{-1}(x_n)\big). f_1(x_1). f_2(x_2) \dots f_n(x_n) \tag{3}$$

Where $c(.)$ is a n-density distribution of $C(.)$.

The interaction between systematic factors could lead to an asymmetric property, which is crucial when modeling a random variable that produces extreme values on just one side. The Archimedean Copula (Joe, 1997) is commonly utilized to handle asymmetric random variables. One approach to capturing this asymmetric property is by using a multivariate copula model. Examples of this approach have been explored by Berg and Aas (2007) through the Nested Archimedean Copula method. This method constructs a multivariate copula model by decomposing it into a cascade of hierarchical bivariate copulas. However, this approach has specific conditions to ensure the resulting structure is a valid copula. These conditions include a decrease in the number of copulas at each layer, with the top layer containing only one copula. Additionally, all the inverse generator functions must be completely monotonic, and the degree of dependence must decrease with the level of nesting (Savu & Trede, 2006).

The Nested Archimedean Copula has a limitation because it relies on the Archimedean Copula setting, preventing the combination of symmetric and asymmetric copulas in one hierarchical copula construction. To address these issues, the Pair Copula Constructions (PCC) structure, initially proposed by Joe (1996) and further developed by Bedford and Cooke (2001, 2002), Kurowicka and Cooke (2006), and Aas et al. (2007), offers a solution by allowing the combination of bivariate copulas in a hierarchical structure that represents the joint distribution of random variables. While Nested Archimedean Copula allows the set-up of n-1 different copulas but is limited to the Archimedean copula family, PCC enables the set-up of n(n-1)/2 different copulas from any copula family.

PCC operates by determining the copula family for each combination of copulas among random variables. The copula family with the highest dependence structure is placed in the first layer as the unconditional copula distribution, with the rest being conditional copula distributions based on the previous layer. There are three types of PCC: Canonical Vine (C-Vine) and Drawable Vine (D-Vine) (Aas et al. 2007) have different specifications in the first layer (Figure 1). In a C-Vine, each layer has a node connected to edges, while in a D-Vine, there is no node connected to more than two edges for each layer. The third PCC is Regular Vine (R-Vine) (Dismann, 2010), which is more flexible than the previous structures, allowing for any kind of possible structures. The advantage of using R-Vine is that the structure is data-driven, making it possible to detect dependence clusters of random variables interconnected through some variables.

### 2.2. Model and Transmission

In this study, our goal is to examine the impact of concentration risk and dependency relationships among macro and sectoral variables. The global financial crisis (GFC) served as a stark reminder of the interdependence between macroeconomic and sectoral elements. Additionally, research by Salmon indicates that a simple Gaussian copula is inadequate for capturing the dynamics of the GFC. Drawing from the GFC, we now recognize that stress or shock originating from a seemingly insignificant asset can have far-reaching effects on the entire financial system. Consequently, to comprehensively understand shock amplification and propagation, we include potential systematic factors from macroeconomic variables (such as GDP and exchange rate) and sectoral variables that banks may have significant exposure to. In addition to these variables, we also account for the presence of each bank's idiosyncratic factor, which is assumed to be independent for each bank. Let us assume $y_i$ is a bank's default profile at a specified point in time and assume that we have $n + k$ systematic factors which is divided into $n$ macroeconomic factors and $k$ sectoral factors. Thus, we could decompose $y_i$ as a set of systematic and idiosyncratic factors in the following expression:

$$y_i = \left(\sum_{j=1}^{n} \theta_{ij} X_{ij}^{m} + \sum_{h=1}^{k} \beta_{ih} X_{hj}^{s}\right) + \epsilon_i \tag{4}$$

where $\epsilon_i$ is the idiosyncratic factor from bank $i$ which follows $\epsilon_i \sim N(0,1)$ and independent across bank. $X_{ij}^{m}$ and $X_{ih}^{s}$ consecutively is $j$-th macroeconomic variable and $h$-th sectoral variables for bank $i$. In our further analysis, we make the assumption that macroeconomic and sectoral variables are interdependent, and their joint distributions will be modeled by copula. The systematic factors will be represented as a copula, allowing the bank default profile to be recognized as a copula as well. We assume that the systematic factors and idiosyncratic factors for each bank are independent, and the weights, ￼ and ￼, are to be determined based on the relative importance of a systematic factor for a particular bank. Additionally, we will impose restrictions or differentiate these coefficients based on groups of banks, considering factors such as capital position, ownership, credit specialty, or other forms of bank clustering that are of interest. For example, Indonesian banks are categorized into four groups based on the size of their tier 1 capital. According to Hashimoto's hypothesis (2009), large banks are more likely to be affected by macro variables than small banks.

When calculating macroeconomic weight, we analyze the bank's partial correlation between individual historical performance of portfolios of debt (POD) and the historical movement of macroeconomic factors. This is necessary because the bank's balance sheet does not explicitly provide information on the contribution of macroeconomic factors to POD. In contrast, the weight of sectoral factors will be evident in the bank's balance sheet, such as the credit disbursement to a specific sector. As a result, we examine the bank's balance sheet to determine the sectoral weights, which represent the credit allocation for each sector in the economy.

In the analysis, the systematic factor coefficients are deployed after transforming the vector of estimated coefficient ($\boldsymbol{\lambda_i} = [\boldsymbol{\theta}_i', \boldsymbol{\beta}_i']$) into a unit vector $\left(||\boldsymbol{\lambda}_i|| = 1\right)$ and standardize all the systematic factors and then construct a joint distribution. Hence, $y_i$ will have a zero means and a variance larger than 1 because the systematic factors are correlated to one another. The next step is to transform $y_i$ into an adjustment coefficient for an estimated POD in bank $i$. Adapting to Gordy (2003), the adjustment then takes a form as follow:

$$PD_i(X^m, X^s) = \min\{\max\{PD_0(1 - y_i), 0\}, 1\}. \tag{5}$$

Maximum and minimum constrains are imposed in order to ensure the resulting POD stay in default's nature domain and that the amount of failed credit will not exceed the amount of credit in the market. Since we standardize each systematic factor into standard normal distribution and commonly bank's POD is quite small (Jakubik, 2007; Lee & Rosenkranz, 2019) thus less likely to have value greater than 1 after the shock was given. According to these possibilities, we could derive the statistical properties of the $PD_i(X^m, X^s)$

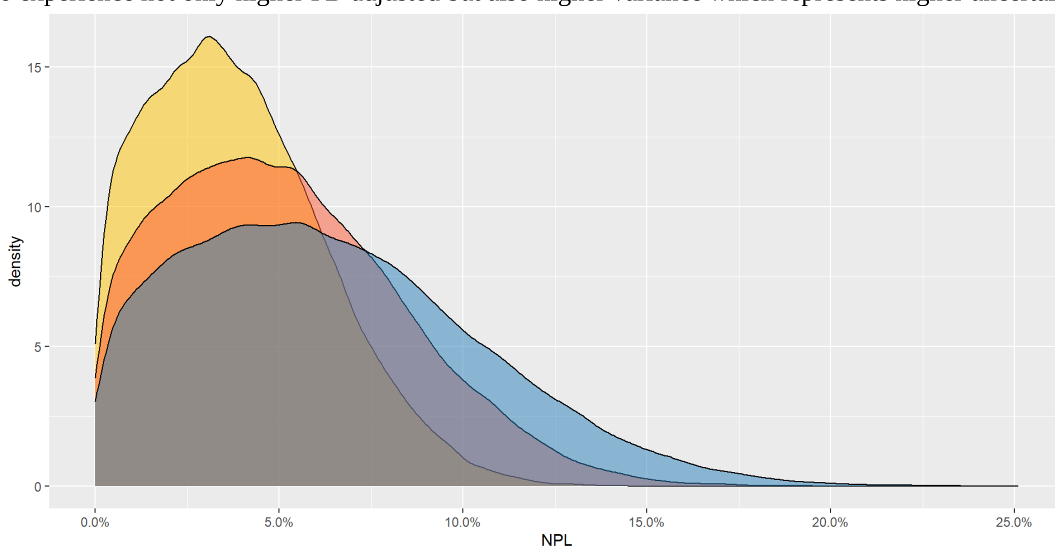
$$E\big(PD_i(X^m, X^s)\big) \approx E\big(PD_0(1 - y_i)\big) = PD_0\big(1 - E(y_i)\big) = PD_0 \tag{6}$$

$$Var\big(PD_i(X^m, X^s)\big) \approx Var\big(PD_0(1 - y_i)\big) = PD_0^2\big(Var(y_i)\big) > PD_0^2 \tag{7}$$

For the first property, $PD_0$ is equal to expectation of adjusted $PD$ and according to the law of large number, $PD_0$ could be approximated through averaging all time bank's $PD$. The second property shows that the variance of bank's adjusted $PD$ is a non-linear pattern, in terms of bank behavior in credit market. As consequences, bank with relatively high $PD$ behaviour is more likely to receive larger shock effect than those with relatively low POD even though they experience the same shock. These behaviors are shown by Figure 1.

**Figure 1: PD Adjusted for three different $PD_0$**

This graphs depict a comparison of PD adjusted for different $PD_0$ ($PD_0$= 2% with yellow, $PD_0$= 3% with orange, $PD_0$= 5% with blue). Futhermore, this graph provides an ilustration of Eq. (7) that bank with higher $PD_0$ would likely to experience not only higher PD adjusted but also higher variance which represents higher uncertainty.




If macroeconomic, sectoral, and idiosyncratic factors performed within a tranquil period, then the value of $y_i$ will be equal to zero. Thus, the value of adjusted POD will be equal with $PD_0$. If those factors performed quite well, then the value $y_i$ will be positive and at some extend lead to zero probability of default. However, if those factors performed bad in a distress period, then the value of $y_i$ will be lower than zero, thus the value of adjusted POD will be larger than $PD_0$.

$$PD_i(x^m_{stress}, x^s_{stress}) = \max\left\{PD_0\Big(1 - (-y_i^{stress})\Big)\right\} > PD_0 \tag{8}$$

In doing stress test which account for simultaneous shock, we establish scenario steps which follows Bonti et.al (2005):

1. Specify an economic stress scenario based on the characteristics of the bank's portfolio. For example, a percentage decline in the property sector. It is also possible to combine multiple scenarios into one, such as incorporating percentage declines in the agriculture and manufacturing sectors.
2. Translate the scenario into stress of systematic factors in the credit risk model. Once all variables are connected through their correlation values, the stress test scenario on a particular variable would propagate to other variables.

The algorithm above can be done by using a Monte Carlo simulation to generate a sample universe on a particular variable which meet stress scenario. Since each bank has different distribution in their lending, then a particular stress scenario would not give similar result across the banks. The important feature of this kind of stress test is the ability to put several variables into stress condition simultaneously and finally the median of $y_i$ will be taken as bank's response over all the shocks.

## 2.3. The Data

The correlation between macroeconomic indicators and a bank's Probability of Default (POD) has been explored in the literature, which connects the business cycle phase with banking stability (Louzis et al., 2010). During an economic expansion, a bank's POD tends to decrease because borrowers have a stronger capacity to repay their debts due to growing incomes or increased business revenues. Consequently, banks may become more willing to extend credit, potentially leading to the allocation of credit to lower-quality borrowers, thereby increasing the bank's POD when the economy begins to decline.

In our research, we focus on five key macroeconomic factors in Indonesia that significantly impact a bank's Probability of Default (POD). These factors include the policy interest rate, inflation, GDP, real effective exchange rate, and commodity prices. Specifically, the interest rate plays a crucial role in explaining a bank's POD, particularly in a floating interest rate environment. Additionally, GDP, as an indicator of economic capacity, greatly influences a bank's credit disbursement. It is widely recognized that GDP is a fundamental determinant of a bank's POD dynamics (Kjosevski et al., 2019). A rise in GDP results in higher income levels and increased business profitability for debtor firms, thereby enhancing debtors' ability to make payments and ultimately reducing a bank's POD (Andres C. and Bonilla O., 2012; Louzis et al., 2010).

Several studies have identified the interest rate as a primary determinant of a bank's probability of default (POD), including Lawrence (1995), Rinaldi & Sanchis-Arellano (2006), and Bofondi and Ropele (2011). Inflation also plays a crucial role in determining a debtor's ability to make payments. Its impact can manifest as increased input costs, leading to a higher bank POD (Curak et al., 2013), or it can be transmitted through central bank decisions to raise interest rates in order to combat inflation. In addition to inflation, we consider the exchange rate to explain a bank's dependency on the global economy. A bank's net foreign liability can raise default probability when the domestic currency depreciates, thereby weakening the repayment capacity of debtors with net foreign liability (Nucci and Pozzolo, 2001).

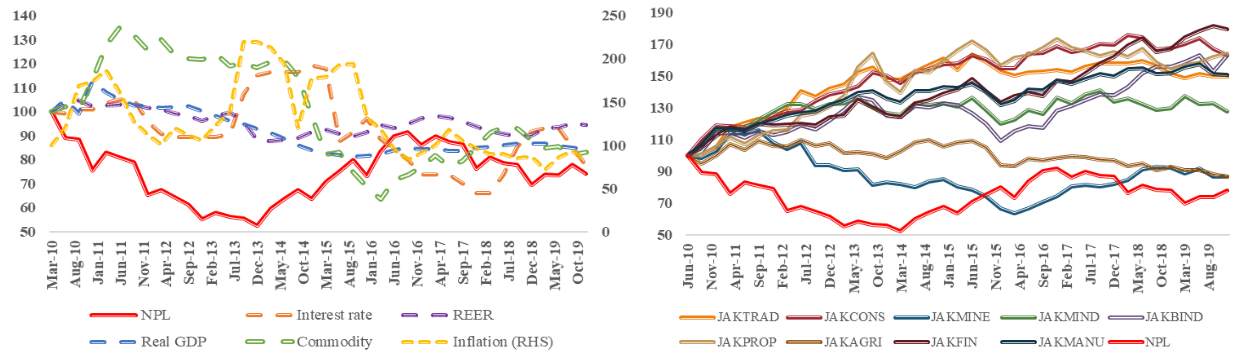
The fluctuation of world commodity prices also impacts a bank's Probability of Default (POD) by influencing the repayment capacity of debtor firms. In Indonesia, there is a negative correlation between commodity prices and the bank's POD. As commodity prices rise, the bank's POD tends to decrease (Agarwal et al., 2017).

We utilized the stock price movements of nine economic sectors to gauge market sentiment and real-time data, instead of relying directly on the Non-Performing Loans (NPL) for each sector. This decision was made because NPL measurements may be delayed and influenced by banks' risk management processes. To ensure that the stock price movements align with the sectoral NPL in the bank balance sheet data, we employed Partial Least Squared (PLS) analysis. This method allowed us to map the stock prices of the nine sectors to the closest NPL sectors. The use of stock price indices to determine a bank's Probability of Default (POD) is also supported by Hashimoto (2009). This mapping was necessary as the sectors represented in stock prices and NPLs are distinct. In Indonesia, the sectoral stock prices encompass trading, consumption, mining, miscellaneous industry, basic industry, property, agriculture, financial, and manufacturing, while the sectoral NPLs include agriculture, mining, manufacturing, electricity, construction, trading, transportation, financial corporations, government administration, and others. In practice, each sectoral NPL is a linear combination of the nine sectoral stock price sub-indices, and the linear combination form is selected to maximize their correlation. The data indicates that, in general, the movements in sectoral stock prices are associated with a bank's Probability of Default (POD) (Figure 4).[1]

These graphs depict comparison between NPL compared to macroeconomic factors (left) and sectoral factors (right).

**Figure 2: NPL dynamic compared to macroeconomic factors and sectoral factors**

These graphs depict comparison between NPL compared to macroeconomic factors (left) and sectoral factors (right) adjusted to 2010Q1 = 100. The graphs show sort of co-movement dynamic between NPL and two systematic factors.




## 3. Stress Test Exercise

The stress test scenario should accurately reflect a potential distress event in the financial system, whether it stems from macroeconomic factors or specific circumstances. It's important to note that replicating past distress events may not be the most effective approach for the current conditions. The reference point for the shock in the financial system may have changed, and the system may be facing new risks. Moreover, the risks that materialized in past crises, although unknown at the time, may already be factored into overall risk management by financial agents. Lastly, financial authorities are working to prevent a recurrence of past mistakes and crises by implementing regulations designed to mitigate similar emerging conditions.

It's important to consider the current economic conditions and potential risks that align with the country's economic trends (Cihak et al, 2019), despite any limitations. Any significant changes in macroeconomic variables could potentially create widespread stress within the system, affecting all active banks simultaneously.

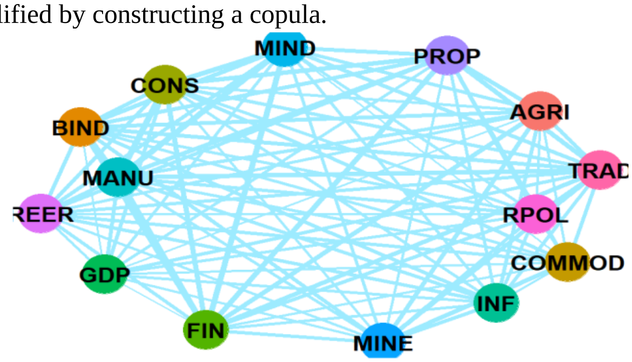
[1] All data used in this paper are ranging from Q 1 2010 to Q4 2019.

### 3.1. Pruning Macroeconomic Variables and Banking Industry Centrality

Adverse conditions could arise from various channels, whether from macroeconomic variables or from internal banking operations. A shock originating from one source could affect other elements of the system. For example, a disturbance in the capital market could lead to panic in other financial markets, setting off a chain reaction in the financial system. Figure 3 illustrates the extensive macroeconomic transmission linkages within the Indonesian financial system. These linkages are quite interconnected, so any type of shock, whether positive or negative, will impact other factors. Moreover, a shock that reverberates back to its point of origin could exacerbate the impact on the system.

**Figure 3: Systematic Factors Linkages**

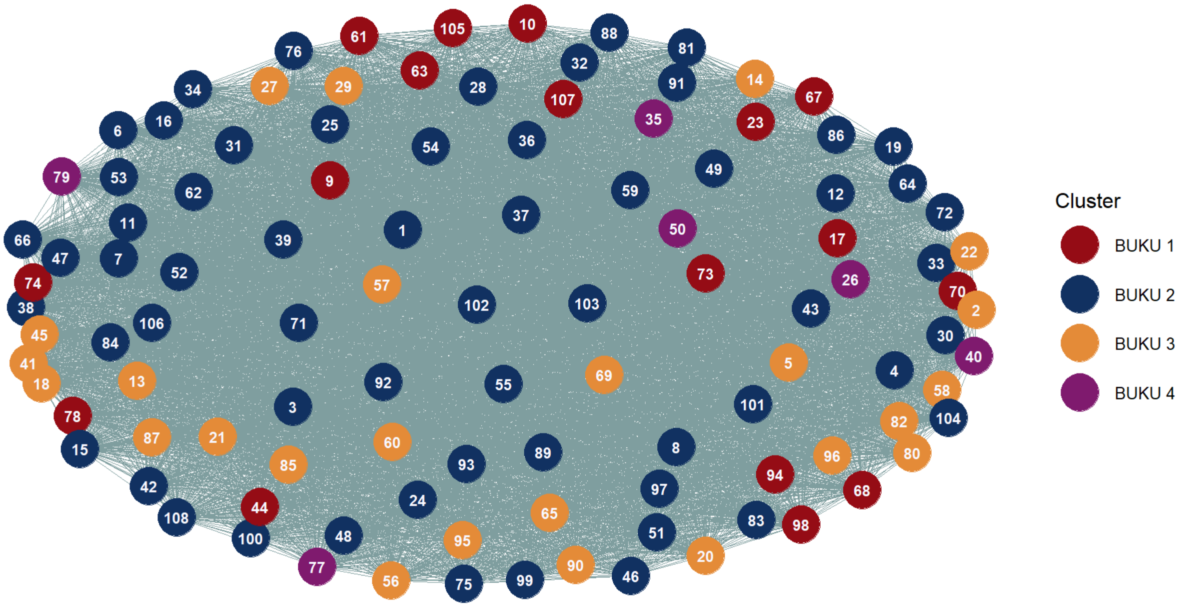
This graph depicts intercorrelation between systematic factors which govern the generating process of the data. Thicker connected line between two systematic factors indicates stronger relation between them. This complex intercorrelation will be simplified by constructing a copula.




The banking system in Indonesia is characterized by a high level of complexity. Currently, there are 110 active commercial banks, all of which are interconnected due to the evolving banking business model. The seamless execution of payments and digital transactions has led to increased interconnectedness among banks. As depicted in Figure 4, the Indonesian banking system exhibited significant interconnectedness in December 2019, both through direct and indirect linkages. In essence, this implies that any shock has the potential to propagate throughout the entire banking system.

**Figure 4: Banking System Network Representation**

This graph depicts banking system intercorrelation according to financing concentration to the economy and exposure to the systematic factors. This complex intercorrelation will be simplified by constructing a copula.

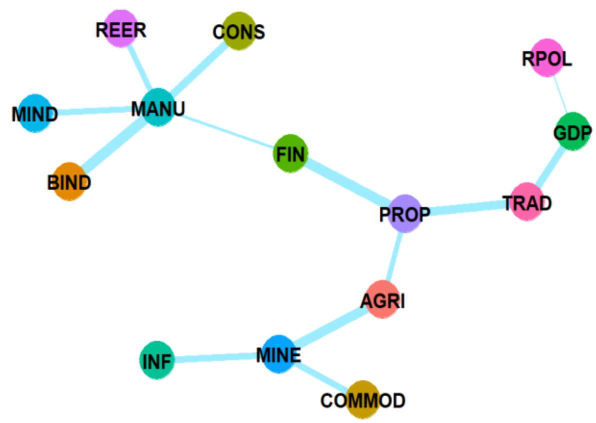



In order to fully capture the real dynamics, we have implemented a pruning technique to simplify the interconnections between macroeconomics and the banking system. Although the dynamics have been simplified, the stress testing framework will be able to mimic the true conditions. To reduce the 'less-significant' linkages in both macroeconomics and the banking system, we utilized pair construction copula (PCC).

Using this approach, Figure 5 displays the result of the pruning of the macroeconomics network. Shocks that impact the financial, property, and manufacturing sectors would have very high probabilities of being transmitted to other sectors. These sectors have the highest degree of centrality and can therefore be considered the most vulnerable sectors.

**Figure 5: Pruned Systematic Factors**

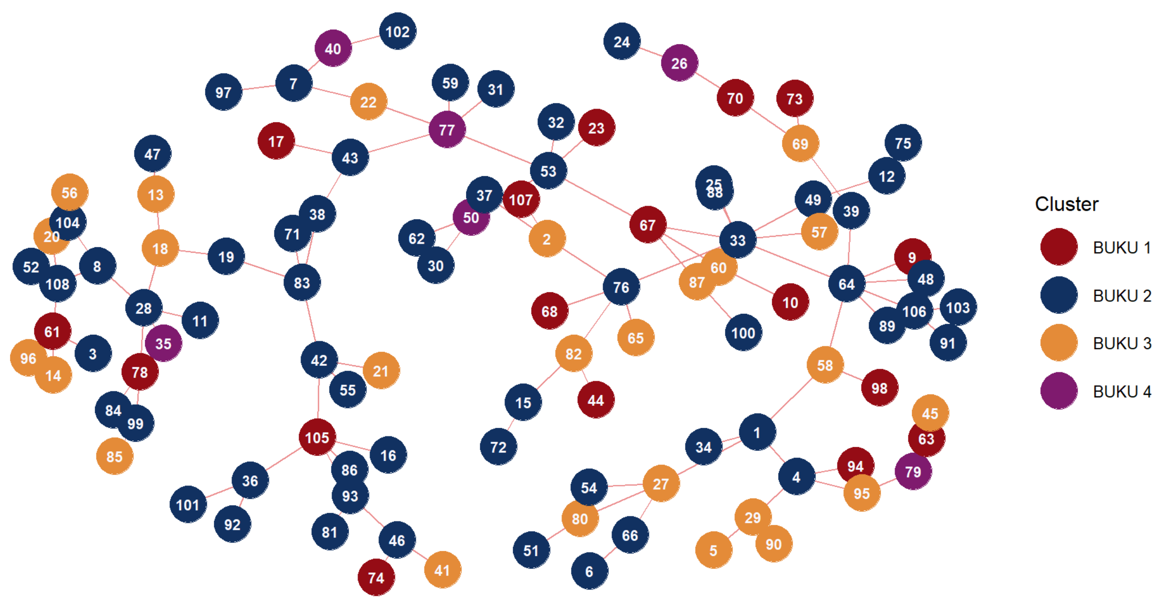
This graph depicts simplification of Fig. 3 by applying Prim's Algorithm. The result tells that financial sector have central role according to its position among systematic factors. In this data, financial sector strong has strongest relation to manufacture sector and property sector which represent financing relation between these sectors.




The banking industry underwent a similar treatment, using PCC to streamline the complex interconnections among banks. This process resulted in the simplified network shown in Figure 6. A comparison of the pruned network in Figure 6 with the original network in Figure 4 reveals that the pruned version is easier to explain while still offering valuable insights into the system dynamics.

**Figure 6: Simple Estimation of Banking Industry Interlinkages**

This graph depicts simplification of Fig. 4 by applying Prim's Algorithm. This simple estimation of banking system depends on financing concentration and exposure level to macroeconomics factors. Banks who have similarity in term of business risk appetite will be located on the same branch of the graph[2].




The underlying dynamics are quite intricate and thus challenging to observe and interpret. The Pruned Correlation Coefficient (PCC) enables us to discern crucial information. Both streamlined interconnections of macroeconomics and the banking system could form the

[2] the paper was written before OJK change the bank classification from BUKU to KBMI

foundation of our stress testing framework. These two networks can be updated as we gather more data in the future. Keeping the networks up to date is crucial for this framework, as we need to track the latest developments in the financial system, which can be influenced by industry and market structure, as well as the implementation of new business models.

### 3.2. A Plausible Scenario Design

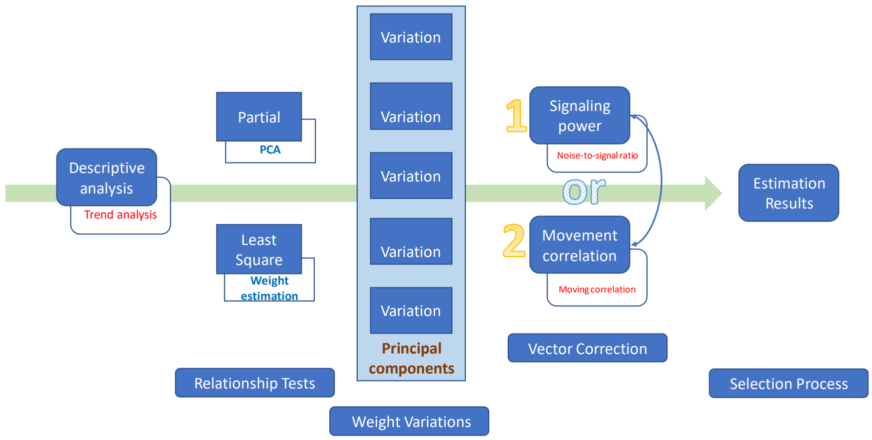
Converting a complex setup into a simpler one is just the first step; creating a realistic scenario is another challenge altogether. The two pruned networks, macroeconomics, and banking networks, remain independent of each other. In the previous section, we did not address how a shock in macroeconomic conditions would impact the banking industry. A shock to the macroeconomic conditions should have a ripple effect, large or small, on the banking system. With these considerations in mind, this section aims to establish the link for shock transmission.

To establish direct shock transmission, we utilize capital markets price signals. The most effective method for gauging the impact involves capturing shocks originating from global and domestic macroeconomic variables. As such, we employ stock market sectoral indices to illustrate the influence of macroeconomic variables alongside sectoral variables on the banking system. While some might propose using corporate sector performance mapped according to its business model instead of capital market data, this approach may offer a more accurate representation of the real sectoral performances of the economy. However, it's not the preferred option due to the lag in corporate data availability and the limited access to data from publicly listed corporations.

The use of stock market sectoral indices is not without complications. These indices do not perfectly correspond to sectoral categorizations in the banking industry. As a result, when a bank's performance on non-performing loans (NPL) is tied to its Portfolio of Derivatives (POD), we need to assess whether fluctuations in stock market sectoral indices could impact the performance of sectoral credits. In Figure 7, we outline a multi-step process for estimating the credit-sectoral relationship.

**Figure 7: Relationship Estimation Process**

This graph depicts process of extracting the dynamic of corporate sector performance through stock market sectoral indices. This estimation process used to switch availability of data where corporate sector performance data is always lagging into high frequency stock market data.




During PLS estimation, various eigenvector variations are generated based on the number of components. After conducting multiple trials, it was determined that selecting five components was most effective in capturing sectoral dynamics. Using more or fewer components resulted in poorer performance. While these components closely reflect real-world dynamics, some of the variable vectors show deviations from expected outcomes. For example, certain vectors may suggest that a negative shock to a particular sector would decrease the number of non-performing loans in that sector, based on banking data. This discrepancy indicates that the vector is likely incorrect and requires attention. The following methods outline the approaches used to rectify these vectors[3]:

1. Moving correlation (MC) between JCI sectors and credit sectors;
2. Signaling power (SP) – noise-to-signal ratio type 1 and type 2 error;
3. Authors' judgement on how the transmission should be. This approach is combining the above-mentioned first and second approach with the authors' judgement.
4. Squared value of estimated eigenvectors. This will move weight variation into the range of [0,1]. All together resulted in 100%.

After analyzing all the vector combinations, we determined that the final combination has the most significant negative impact on the banking system, so we opted to utilize this specific combination. As illustrated in Figure 8, each variable should accurately reflect real variable trends. Furthermore, upon mapping and comparing to the real variables, we observed that the squared eigenvectors provide the closest match to the real variable trends.

[3] Detailed explanation on each approach is on Appendix 1

**Figure 8: Mapping Bank's Credit Sector Using the Squared Eigenvectors**

These graphs depict comparison between bank's credit sector based using the squared Eigenvectors of corresponding PLS and real corporate sector data. The mapping able to mimic dynamic of real corporate sector data in term of correlation and trend-cycle of the data.

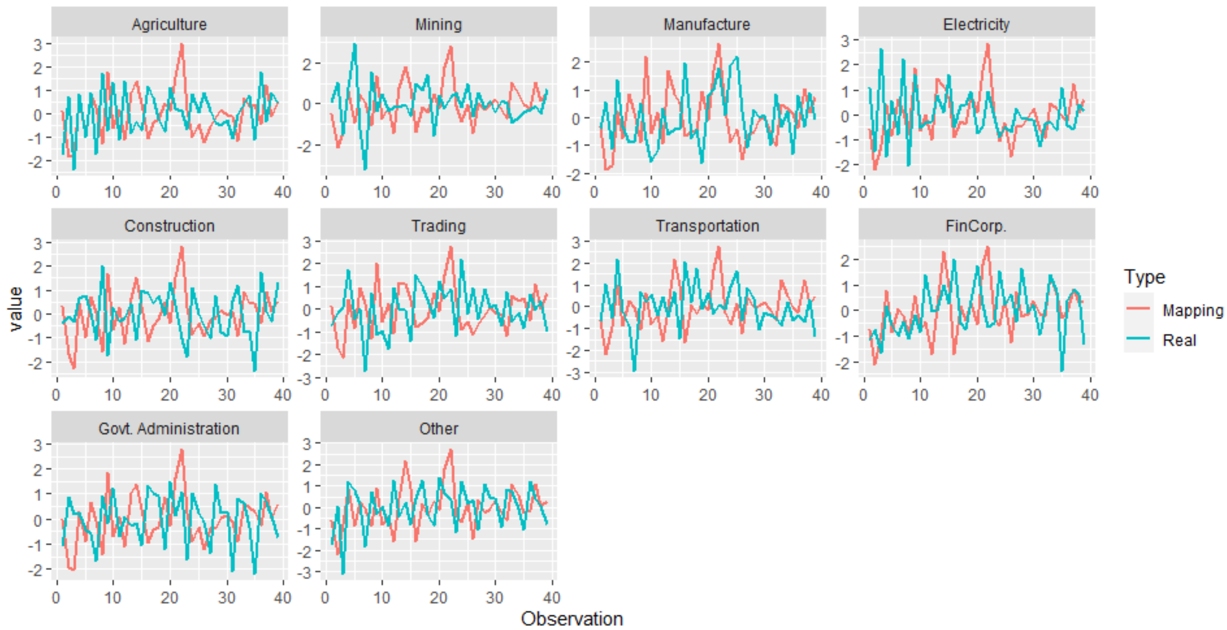



Table 1 also strengthens our argument, as it shows how all banks non-performing loans, both denominated in Rupiah and foreign currency, respond to a shock (systematic factor(s)). np (negative power approach), correl_all (all sample correlation), and squared approach capture all banks' reaction to the systematic factors. Based on this and previous mapping variable trend, we decided to use the squared eigenvectors, as variable weight, in translating the risk channel from the shock in the stock market to the bank's credit portfolio.

**Table 1: Number of Bank's Negative Response to Negative Shock of Systematic Factors in Rupiah**

This table provides number of banks who has negative response to negative shock of systematic factors in rupiah. This table used to check consistency of bank response to systematic shock. Squared Eigenvectors approach fit the consistency criteria that almost all banks will response negatively to negative shock of systematic factors.

| Variable | NM | PP | NP | PM | Correl_all | Squared |
|---|---|---|---|---|---|---|
| RPOL | 59 | 59 | 54 | 54 | 57 | 102 |
| REER | 33 | 33 | 38 | 38 | 33 | 108 |
| INFLATION | 42 | 42 | 24 | 24 | 35 | 0 |
| GDP | 105 | 105 | 90 | 90 | 93 | 105 |
| COMMOD | 44 | 44 | 90 | 90 | 84 | 108 |
| TRAD | 90 | 90 | 75 | 75 | 82 | 108 |
| CONS | 108 | 108 | 75 | 75 | 67 | 108 |
| MINE | 2 | 2 | 108 | 108 | 101 | 108 |

| | | | | | | |
|---|---|---|---|---|---|---|
| MIND | 108 | 108 | 106 | 106 | 79 | 108 |
| BIND | 108 | 108 | 107 | 107 | 108 | 108 |
| PROP | 108 | 108 | 96 | 96 | 103 | 108 |
| AGRI | 60 | 60 | 108 | 108 | 92 | 108 |
| FIN | 108 | 108 | 107 | 107 | 96 | 108 |
| MANU | 108 | 108 | 106 | 106 | 86 | 108 |

**Table 2: Number of Bank's Negative Response to Negative Shock of Systematic Factors in Foreign Currency**

This table provides number of banks who has negative response to negative shock of systematic factors in rupiah. This table used to check consistency of bank response to systematic shock. Squared Eigenvectors approach fit the consistency criteria that almost all banks will response negatively to negative shock of systematic factors.

| Variable | NM | PP | NP | PM | Correl_all | Squared |
|---|---|---|---|---|---|---|
| RPOL | 31 | 31 | 31 | 31 | 31 | 54 |
| REER | 37 | 37 | 32 | 32 | 33 | 54 |
| INFLATION | 34 | 34 | 21 | 21 | 35 | 0 |
| GDP | 51 | 51 | 50 | 50 | 51 | 54 |
| COMMOD | 36 | 36 | 40 | 40 | 37 | 54 |
| TRAD | 48 | 48 | 39 | 39 | 46 | 54 |
| CONS | 54 | 54 | 50 | 50 | 50 | 54 |
| MINE | 29 | 29 | 53 | 53 | 39 | 54 |
| MIND | 54 | 54 | 54 | 54 | 49 | 54 |
| BIND | 54 | 54 | 48 | 48 | 50 | 54 |
| PROP | 54 | 54 | 35 | 35 | 50 | 54 |
| AGRI | 42 | 42 | 49 | 49 | 39 | 54 |
| FIN | 54 | 54 | 48 | 48 | 51 | 54 |
| MANU | 54 | 54 | 50 | 50 | 50 | 54 |

### 3.3. Implementing the Shock to the Banking System

The banking stress test involves simulating extreme but plausible financial system shocks on a bank's balance sheet. According to Adrian et al (2020), one approach to estimating extreme shocks is through the use of the tail risk method. Tail risk typically arises from events with a low probability of occurrence but with the potential to cause significant financial losses when they do occur. These low probabilities are associated with the lower or upper percentiles of a distribution, making tail risk the bottom percentile of each variable.[4]

We have identified unique characteristics for each variable (refer to Table 3) and have estimated the best-fitted distribution for each based on our dataset. In Figure 9, you can see the fitted distribution of each variable, represented by the theoretical distribution (depicted by the blue

[4] Lower percentiles in normal distribution is at the left tail.

area). The majority of the fitted distributions closely resemble the actual data distribution. These distributions enable us to estimate the tail risk associated with each variable. Furthermore, the tail risk takes into account the relationships between variables, with each variable having distinct tail events.

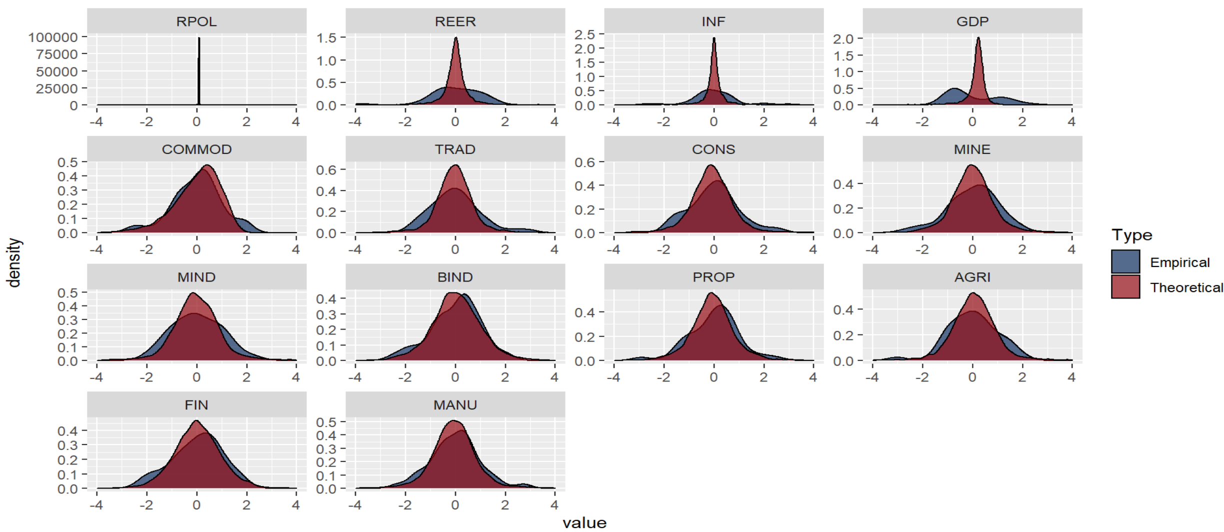
**Table 3: Fitted Distribution of Systematic Factors**

This table provides information about fitted distribution of systematic factors which also captures information about high order moment of distribution such as kurtosis and skewness to recognize fat tail distribution. Fat tail distribution important to characterize severe but plausible criteria in stress testing. The result shows that all systematic factors have fat tail distribution and asymmetric distribution compared to standard normal distribution.

| Variable | Distribution | μ | Σ | η | T | Perc. 0.5% | Perc. 99.5% |
|---|---|---|---|---|---|---|---|
| RPOL | Skew Power Exponential | 0.09 | 2.20E-26 | 1.10 | 0.09 | -134.16 | 197.27 |
| REER | T-Family | 0.0075 | 0.23 | 1.47 | - | -4.32 | 4.34 |
| INF | T-Family | -0.002 | 0.14 | 1.11 | - | -6.38 | 6.38 |
| GDP | Skew t Distribution Type 4 | 0.21 | 0.17 | 1.00 | 3.00 | -11.52 | 1.18 |
| COMMOD | Skew t Distribution Type 4 | 0.14 | 0.70 | 2.91 | 913.99 | -4.16 | 1.95 |
| JAKTRAD | Normal Exponential t | -0.03 | 0.55 | 1.50 | 2.00 | -3.80 | 3.75 |
| JAKCONS | Normal Exponential t | -0.08 | 0.67 | 1.50 | 2.00 | -4.60 | 4.42 |
| JAKMINE | Normal Exponential t | -0.01 | 0.66 | 1.50 | 2.00 | -4.50 | 4.47 |
| JAKMIND | Normal Exponential t | -0.04 | 0.76 | 1.50 | 2.00 | -5.16 | 5.08 |
| JAKBIND | Logistic | 0.02 | 0.55 | - | - | -2.92 | 2.97 |
| JAKPROP | T-Family Type 2 | -0.06 | 1.01 | 3.64 | - | -3.41 | 3.27 |
| JAKAGRI | Normal Exponential t | 0.05 | 0.70 | 1.50 | 2.00 | -4.65 | 4.76 |
| JAKFIN | Logistic | 0.01 | 0.54 | - | - | -2.85 | 2.87 |
| JAKMANU | Normal Exponential t | -0.05 | 0.72 | 1.50 | 2.00 | -4.94 | 4.82 |
| - | Standard Normal | 0.00 | 1.00 | - | - | -2.57 | 2.57 |

**Figure 9: Fitted Distribution of Systematic Factors**

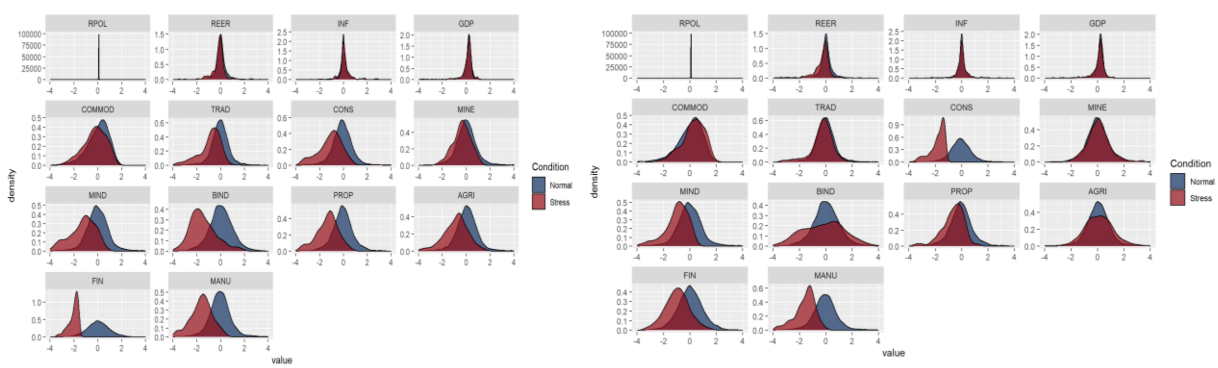
This graph depicts comparison between empirical and theoretical distribution of systematic factor based on optimum fitted distribution according to Table 3. The fitted distributions especially for sectoral variable able to fit the empirical distributions closely.




As mentioned earlier, we have identified two key systematic factors in the stock market: JAKFINANCE and JAKCONSUME sectors. The impact of these sectors ripples through the financial system, creating a complex chain reaction. In Figure 10, the left side illustrates the response of each variable to JAKCONSUME, while the right side shows the variable responses to JAKFINANCE. As depicted in Figures 10 (Left) and 10 (Right), a shock occurring in the banking system leads to a shift in distributions towards a left-skewed distribution. A left-skewed distribution indicates an increased probability of the variable being in a distressed condition, as the mean also shifts to a lower value within the distribution.

**Figure 10: Impact of Stress Test Scenario to Systematic Distribution**

These graphs depict impact of shock of a systematic factor to other systematic factors. The left graph provides impact of negative shock of JAKFIN and the right graph provides impact of negative shock of JAKCONS. Response of all systematic factors to these shocks are consistent with economics theory which transmits shocks across variables.



### 3.4. Covid-19 Crisis Path

In 2020, there was an unprecedented financial crisis triggered by a health crisis, leading to economic and financial turmoil (World Health Organization (2020)). To understand the impact of the Covid-19 crisis on the banking system, we developed two scenarios: one with moderate impact and the other with severe impact. These scenarios outline the macroeconomic path of Covid-19 on Indonesia's real sectors.

For the sectoral factors, we utilized historical returns from the Global Financial Crisis period for each sector, with the assumption that there would be no intervention from financial authorities, no credit restructuring programs by banks, and no other actions taken in response to the shock.[5]

**Table 4: COVID-19 Assumptions**

This table provides information about the COVID-19 assumptions which address that the pandemics would lead to global supply chain disruption transmit to lower GDP growth and higher inflation, besides the impact of social distancing and restriction of socio-economy activities.

| Indicator | National Budget Assumption | Scenario | |
|---|---|---|---|
| | | Moderate | Severe |
| GDP Growth (%, yoy) | 5.3 | 2.3 | -0.4 |
| ICP Price (%, yoy) | 63 | 38 | 31 |
| Exchange Rate (%, yoy) | baseline | moderate | Severe |
| Inflation (%, yoy) | 3.1 | 3.9 | 5.1 |
| Nominal GDP (Trillion Rp) | 17,464.70 | 16,829.80 | 16,574.90 |

## 4. Results, Discussion and Robustness Check

### 4.1. Results and Discussion

Each scenario presents three stress test results: (i) the impact of macroeconomic conditions on the banking system; (ii) the impact of stock market shocks (one sector at a time) on the banking system; and (iii) a combined scenario of macroeconomic and sectoral shocks. A macroeconomic shock may or may not lead to a shock in the stock market. The same applies to a sectoral shock affecting the overall financial system. The combined scenario aims to account for the possibility of deteriorating macroeconomic conditions and sectoral shocks occurring simultaneously.

The simulation results indicate that the Covid-19 scenario has the potential to significantly impact the financial system. In the moderate scenario, it led to a minimum of 60 banks falling

[5] In real practice, financial authorities will intervene thus making the shock impact milder.

below the Basel III CAR requirement of 10.5%. The impact was even more pronounced in the severe scenario, with at least 73 banks failing to meet the Basel III CAR requirement. These estimates were derived using a combination of macroeconomic and sectoral shocks. Table 5 provides a summary of the Covid-19 impact on Indonesia's financial system in both the moderate and severe scenarios. It also highlights the least severe impacts on the financial system caused by individual shocks, whether macro or sectoral.

**Table 5: Covid-19 impacts to Indonesia Financial System**

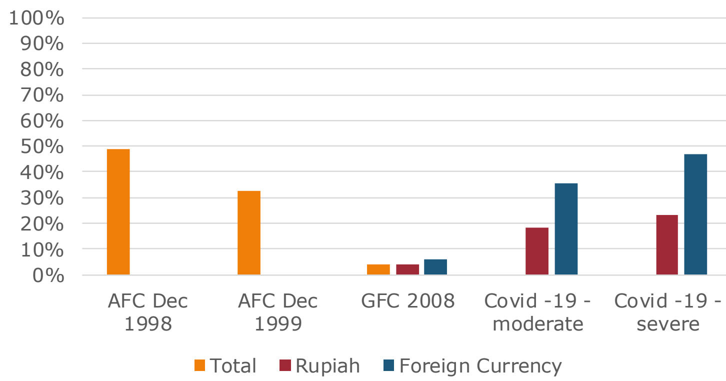
This table provides stress testing result based on Covid-19 scenario assumption which divides the result based on two different CAR threshold. Most of failed banks suffer huge loss if sectoral factor worsening which is depend on bank financing concentration.

| CAR Threshold 10.5% | | | CAR Threshold 8% | | |
|---|---|---|---|---|---|
| **Systematic Factor** | **Moderate** | **Severe** | **Systematic Factor** | **Moderate** | **Severe** |
| Macro | 5 | 16 | Macro | 2 | 12 |
| Sectoral | 47 | 66 | Sectoral | 32 | 61 |
| Joint M-S | 60 | 73 | Joint M-S | 51 | 70 |

The Covid-19 pandemic has led to a significant increase in non-performing loans as of March 2020. A combination of deteriorating macroeconomic conditions and distressed stock markets has had a major impact on the banking system. Stock market distress was triggered by the sudden reversal of global investors seeking safety, leading to a liquidity shock in the financial system. The lack of production capability in the corporate sector has hindered their repayment capability, contributing to the rise in non-performing loans. In a moderate scenario, non-performing loans have risen to 18.25% (Rupiah denominated) and 35.57% (foreign currency), and in a severe scenario, they have reached 23.24% (Rupiah) and 46.84% (foreign currency). These values are nearly as high as the non-performing loan levels during the Asian Financial Crisis, where the total non-performing loans reached 48.6% in December 1998 and 32.8% in December 1999. Additionally, the estimated values exceed the non-performing loan levels during the Global Financial Crisis, which only reached 5.8% for non-performing loans in Rupiah and 5.8% in foreign currency. Figure 11 illustrates the non-performing loan levels in the Asian Financial Crisis, Global Financial Crisis, and the Covid-19 scenario.

**Figure 11: NPL Dynamics in three-stressed condition**

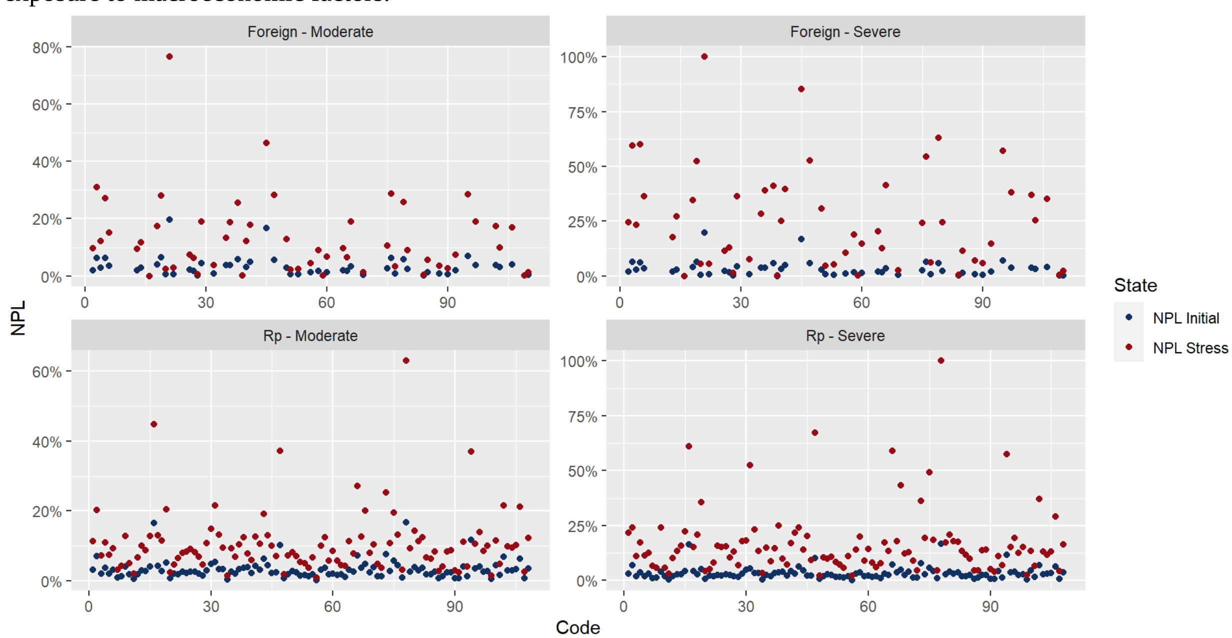
This graph depicts the comparison between the stress test result with two major economic crises, The GFC and The AFC. The result based on the pandemics scenario produces more severe impact to financial system rather than impact of The GFC, the stress test result is comparable with the impact of the AFC in 1998.




The impact of Covid-19 on the banking system in Indonesia is detailed in Figure 12. In the moderate scenario (Figure 12 – Left), the Covid-19 impact has caused the non-performing loans (NPL) of almost every bank to exceed 5%, which is the average level of NPL during the Global Financial Crisis (GFC) in 2008. In the severe scenario, the number of banks with NPL ratios significantly above 5% increases to almost every single bank. Additionally, 10% of the banks' NPL increases to 100%. In this situation, regardless of the size of the bank's capital adequacy ratio (CAR).

**Figure 12: Individual Response to COVID-19 Scenario**

These graphs depict impact of stress test scenario to individual bank in term of domestic currency credit and foreign currency credit. Bank with higher initial NPL will suffer nonlinearity due to financing concentration to certain sector and high exposure to macroeconomic factors.

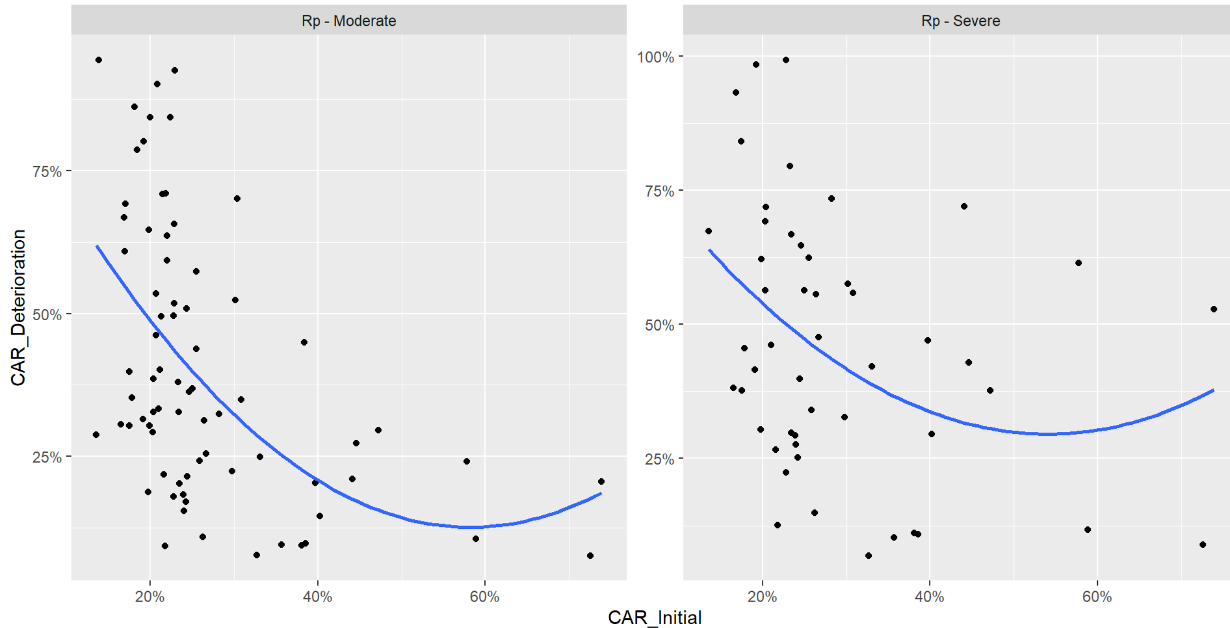



The stress test findings indicate that the Covid-19 crisis and subsequent financial shock could have a significant impact on Indonesia. There is a possibility of a widespread collapse of the entire banking system. Any level of shock, regardless of its magnitude, is likely to spread from one bank to another, exacerbating the distress. In a moderate scenario, approximately 50% of active banks may face a substantial credit shock, while in a severe scenario, the entire system could fail. Although this stress test does not consider potential interventions by financial authorities, the results suggest the urgency of designing and implementing appropriate policy responses. Authorities should take proactive measures to mitigate the situation before it escalates. Additionally, they should prepare for potential economic downturn resulting from the Covid-19 pandemic.

Figure 12 also indicates that certain banks undergo a significant increase in non-performing loans (NPL) when transitioning from moderate to severe scenarios. However, this analysis only captures a single moment in time. We haven't accounted for the potential further spread and intensification of the process, which could lead to an even more dire situation. This finding aligns with existing literature on financial crises, suggesting that the escalation of distress within the banking system can result in a much more catastrophic outcome. It's crucial for all stakeholders to act swiftly to mitigate risks and prevent greater losses, rather than assuming that the situation will resolve itself. In instances where banking stress tests fail to incorporate simultaneous shocks in systemic variables, regulators should contemplate introducing non-linearity into the scenarios as the crisis evolves into a more severe state (Harun et al, 2020). This adjustment may help address the potential non-linear responses of banks to prolonged distress scenarios.

**Figure 13: CAR Deterioration based on initial CAR for adverse Scenarios**

These graphs depict nonlinear pattern of CAR after simulation which state that a bank with lower capital buffer will suffer more capital loss than a bank with larger capital buffer position.




In order to identify the pattern of deterioration, we conducted a detailed analysis of individual banks' performance. Figure 13 illustrates that the deterioration of the capital adequacy ratio (CAR) is significantly more pronounced when the severe scenario is applied. It is noteworthy that banks with a low CAR (those positioned on the left of the horizontal axis) consistently experience more severe deterioration in both scenarios. Conversely, banks with a relatively higher CAR experience a lower degree of deterioration. This information can serve as an early warning for regulators when a cluster of banks begins to exhibit weak liquidity. Bank supervisors should take note that the likelihood of survival for these banks under adverse conditions is significantly lower compared to banks with a relatively higher initial CAR. These findings underscore the utility of stress tests as a supervisory tool for bank regulators to assess the ability of banks to withstand simultaneous shocks in both macroeconomic and sectoral variables.

### 4.2. Robustness Check

The impact of Covid-19 suggests two key points: first, financial authorities should intervene to mitigate the impact, and second, the severity of Covid-19 is significant, with implications for the banking system. While the pandemic's impact on the banking system is substantial, we conduct several robustness checks to assess the framework's sensitivity. We have designed two different scenarios for these checks. They are:

1. The 50% value of moderate Covid-19 scenario. This scenario tries to check framework sensitivity and observe its result;
2. The 2013 Taper Tantrum scenario. In this case, we use the historical Taper Tantrum data as scenario, but implement all the parameters estimated from Covid-19 scenario, since we do not have a sufficient sample data if we trimmed the data to just before the Taper Tantrum in June 2013.

The robustness checks indicate that the estimation results fall within an acceptable range. In each scenario, non-performing loans (NPL) values increase, attributed to the distress scenarios imposed on the banking system. Table 6 presents the estimation statistics for each scenario. It is noteworthy that the absence of intervention and policy response from financial authorities results in even higher NPL values in each scenario. This situation is deemed acceptable as it necessitates the banking system to solely rely on its liquidity and capital buffer.

**Table 6: Robustness check results**

These table provides impact of simulations based on different scenarios including systematic factors condition during Taper Tantrum in 2013. The robustness checks show that the estimation result are within tolerable range and furthermore able to figure out dominant shock when the crises occurred.

| **Scenario** | | **Realized** | | **Covid-19 Baseline** | | | |
|---|---|---|---|---|---|---|---|
| | | **Apr-20** | **Jun-13** | **Macro** | **Sectoral** | **Joint M-S** | |
| NPL Aggregate | Rp (%) | 3.05 | 1.97 | 4.05 | 3.04 | 4.07 | |
| | Forex (%) | 2.02 | 1.41 | 3.19 | 2.39 | 3.20 | |
| | Total (%) | 2.89 | 1.88 | 3.92 | 2.95 | 3.94 | |
| CAR Deterioration | < 10.5% | | | 3 | 2 | 3 | |
| | < 8.0% | | | 2 | 2 | 2 | |
| **Scenario** | | **50% Moderate** | | | **Taper Tantrum** | | |
| | | **Macro** | **Sectoral** | **Joint M-S** | **Macro** | **Sectoral** | **Joint M-S** |
| NPL Aggregate | Rp (%) | 2.99 | 7.37 | 7.37 | 2.99 | 8.73 | 9.04 |
| | Forex (%) | 3.36 | 5.65 | 5.65 | 2.36 | 6.84 | 7.08 |
| | Total (%) | 2.91 | 7.13 | 7.13 | 2.90 | 8.46 | 8.76 |
| CAR Deterioration | < 10.5% | 2 | 17 | 17 | 2 | 25 | 23 |
| | < 8.0% | 1 | 10 | 10 | 1 | 18 | 20 |

## 5. Concluding Remark

The primary focus of this research is to illustrate the significant impact of simultaneous shocks on the financial system. It is common for authorities to use stress test exercises solely as a supervisory tool to assess capital gaps. However, by incorporating the scenario of simultaneous shocks in macroeconomic and real sectoral variables, we demonstrate that when a distress event spreads rapidly and causes damage in other areas of the economy due to interconnected transactions or information, the resulting distress is much more severe. This addresses the criticism that stress test exercises fail to accurately capture the panic and loss of confidence in financial markets.

It is crucial to capture tail events in order to illustrate the most catastrophic outcomes. While the stress test is not a predictive tool, it serves as a means to measure what we refer to as a severe but plausible financial market disaster resulting from multiple systematic shocks. It may be hard to imagine that shocks could occur in two or more factors simultaneously, but the Covid-19 pandemic, which simultaneously halted nearly all economic activities, exemplifies such an event. Therefore, having a tool that can simulate such scenarios within the macroprudential stress test framework would be valuable.

# References


Aas, Kjersti., Czado, Claudia., Frigessi, Arnoldo., Bakken, Henrik., 2009. Pair-copula Constructions of Multiple Dependence. Insurance: Mathematics and Economics 44(2), 182-198.

Adrian, Tobias., Morsink, James., Schumacher, Liliana., 2020. Stress Testing at the IMF. International Monetary Fund Working Papers No. 20/04.

Anderson, Ron., Danielsson, Jon., Baba, Chikako., Das, Udaibir S., Kang, Heedon., Segoviano, Miguel., 2018. Macroprudential Stress Tests and Policies: Searching for Robust and Implementable Frameworks. IMF Working Paper No. WP/18/197.

Bedford, Tim., Cooke, Roger M., 2001. Probability density decomposition for conditionally dependent random variables modeled by vines. Annals of Mathematics and Artificial intelligence 32(1-4), 245-268.

Bedford, Tim., Cooke, Roger M., 2002. Vines: A new graphical model for dependent random variables. Annals of Statistics 1031-1068.

Berg, Daniel., Aas, Kjersti., 2007. Model for Construction of Multivariate Dependence: A Comparison Study. The Norwegian Computing Center.

Bofondi, Marcello., Ropele, Tiziano., 2011. Macroeconomic determinants of bad loans: evidence from Italian banks. Bank of Italy Occasional Paper 89.

Bonilla, Carlos A. O., 2012. Macroeconomic determinants of the non-performing loans in Spain and Italy. Unpublished doctoral dissertation, Departement of Economics, University of Leicester.

Bonti, Gabriel., Kalkbrener, Michael., Lotz, Christopher., Stahl, Gerhard., 2005. Credit Risk Concentrations under Stress. Journal of Credit Risk 2(3), 115-136.

Čihák, Martin., Oura, Hiroko., Schumacher, Liliana., 2019. What Is Stress Testing? Checking The Health of Banks is Crucial to Financial Stability. Financial and Development September.

Curak, Marijana., Pepur, Sandra., Poposki, Klime., 2013. Determinants of non-performing loans–evidence from Southeastern European banking systems. Banks & bank systems, (8, Iss. 1), 45-53.

Daul, Stephane., De Giorgi, Enrico, G., Lindskog, Filip., McNeil, Alexander., 2003. The Grouped t-Copula with an Application to Credit Risk. SSRN 1358956.

Diamond, Douglas, W., Dybvig, Philip, H., 1983. Bank runs, deposit insurance, and liquidity. Journal of political economy 91(3), 401-419.

Dißmann, Jeffrey, F., 2010. Statistical inference for regular vines and application.

Dißmann, Jeffrey, F., Brechmann, Eike, C., Czado, Claudia., Kurowicka, Dorota., 2013. Selecting and estimating regular vine copulae and application to financial returns. Computational Statistics & Data Analysis 59, 52-69.

Frey, Rudiger., McNeil, Alexander, J., Nyfeler, Mark., 2001. Copulas and Credit Models. Risk 10.111114.10.

Friedman, Milton., Schwartz, Anna, J., 1867. A monetary history of the United States. 1960.

Glasserman, Paul., Li, Jingyi., 2005. Importance Sampling for Portfolio Credit Risk. Management Science 51(11), 1643-1656.

Gordy, Michael, B., 2003. A Risk-factor Model Foundation for Rating-based Bank Capital Rules. Journal of Financial Intermediation 12, 199-232.

Gordy, Michael, B., Lütkebohmert, Eva., 2013. Granularity Adjustment for Regulatory Capital Assessment. International Journal of Central Banking 9(3), 33-70.

Jakubik, Petr., 2007. Macroeconomic environment and credit risk. Czech Journal of Economics and Finance (Finance a uver) 57(1-2), 60-78.

Jakubık, Petr., Schmieder, Christian. 2008. Stress testing credit risk.

Joe, Harry., 1996. Families of m-variate distributions with given margins and m (m-1)/2 bivariate dependence parameters. Lecture Notes-Monograph Series 120-141.

Joe, Harry., 1997. Multivariate models and multivariate dependence concepts. CRC Press.

Juodis, Mindaugas., Valvonis, Vytautas., Berniunas, Raimondas., Beivydas, Marijus., 2009. Measuring Concentration Risk in Bank Credit Portfolios using Granularity Adjustment Practical Aspects. Society of Actuaries in Ireland.

Hashimoto, Takashi., 2009. Asset Correlation for Credit Risk Analysis – Empirical Study of Default Data for Japanese Companies. Working Paper Series No. 09-E-3. Bank of Japan.

Ivanov, Eugen., Min, Aleksey., Ramsauer, Franz., 2017. Copula-Based Factor Model for Multivariate Asset Returns. Econometrics 5(2).

Kjosevski, Jordan., Petkovski, Mihail., Naumovska, Elena., 2019. Bank-specific and macroeconomic determinants of non-performing loans in the Republic of Macedonia:

Comparative analysis of enterprise and household NPLs. Economic research-Ekonomska istraživanja 32(1), 1185-1203.

Koziol, Phillip., Schell, Carmen., Eckhardt, Meik., 2015. Credit risk stress test testing and copulas – is the Gaussian copula better than its reputation?. Discussion Paper No. 46. Deutsche Bundesbank.

Kurowicka, Dorota., Cooke, Roger, M., 2006. Uncertainty analysis with high dimensional dependence modelling. John Wiley & Sons.

Lawrence, Emily, C., 1995. Consumer default and the life cycle model. Journal of Money, Credit and Banking 27(4), 939-954.

Nucci, Franceso., Pozzolo, Alberto, F., 2001. Investment and the exchange rate: An analysis with firm-level panel data. European Economic Review 45(2), 259-283.

Rinaldi, Laura., Sanchis-Arellano, Alicia., 2006. Household debt sustainability: What explains household non-performing loans? An empirical analysis.

Rösch, Daniel., 2005. An empirical comparison of default risk forecasts from alternative credit rating philosophies. International Journal of Forecasting 21(1), 37-51.

Rosenkranz, Peter., Lee, Junkyu., 2019. Nonperforming Loans in Asia: Determinants and Macrofinancial Linkages. Asian Development Bank Economics Working Paper Series (574).

Salmon, Felix., 2012. The formula that killed Wall Street. Significance 9(1), 16-20.

Savu, Cornelia., Trede, Mark., 2010. Hierarchies of Archimedean copulas. Quantitative Finance 10(3), 295-304.

Schönbucher, Philipp, J., 2000. Factor Models for Portfolio Credit Risk. Department of Statistics, Bonn University.

Schönbucher, Philipp, J., Schubert, Dirk., 2001. Copula-Dependent Default Risk in Intersity Models. Working Paper. Department of Statistics. Bonn University.

Shangquan, Ghao, 2000. Economic Globalization: Trends, Risks and Risk Prevention. CDP Background Paper No. 1.

Shiller, Robert, J., 1995. Conversation, information, and herd behavior. The American economic review 85(2), 181-185.

Tirole, Jean., 2011. Illiquidity and all its friends. Journal of Economic Literature 49(2), 287-325.

Valle, Luciana, D., De Giuli, Maria, E., Tarantola, Claudia., Manelli, Claudio., 2016. Default probability estimation via pair copula constructions. European Journal of Operational Research 249(1), 298-311.

World Health Organization. 2020. Coronavirus Disease (COVID-2019). Situation Reports.

# APPENDIX I - Vectors Correction Approaches Explanations

Moving correlation approach uses 20 day moving correlation between JCI sectors and credit sectors. The correlations indicate how sectoral credits respond to all the conditions that influence the dynamics of sectoral JCI. Furthermore, when a shock caused JCI sector to plummet, the correlation value should change accordingly. Table 1 shows corrected vector of stock price and NPL eigenvectors using moving correlation approach. 02129488545, 02129052895

**Table 7: Estimated Vector Using Moving Correlation**

This table provides rule of vector estimation using moving correlation, 1 indicates that the vector should be negative regardless what the PLS estimated. Negative vector indicates negative shock to bank's credit portfolio.

| Variabel | NPL Agri. | NPL Mining | NPL Manu. | NPL Elect. | NPL Const | NPL Trad. | NPL Trans | NPL FinCorp | NPL Govt Adm | NPL Other |
|---|---|---|---|---|---|---|---|---|---|---|
| JAKTRAD | 1 | 1 | - | - | 1 | - | 1 | - | 1 | - |
| JAKCONS | - | 1 | - | - | 1 | - | 1 | 1 | 1 | - |
| JAKMINE | 1 | - | 1 | 1 | 1 | 1 | 1 | 1 | 1 | - |
| JAKMIND | - | 1 | - | - | - | - | 1 | - | - | - |
| JAKBIND | 1 | 1 | - | - | 1 | - | - | - | 1 | - |
| JAKPROP | 1 | 1 | 1 | - | 1 | 1 | 1 | - | 1 | - |
| JAKAGRI | - | 1 | - | 1 | - | - | - | - | - | - |
| JAKFIN | 1 | 1 | 1 | - | 1 | 1 | 1 | 1 | - | - |
| JAKMANU | - | 1 | - | - | - | - | 1 | - | - | - |

Similar to moving correlation approach, signaling power approach tries to capture the dynamics of the interaction among variables. This approach was done to capture day-to-day dynamics between two might-be-related variables. Signaling power estimates the relation between two variables, one as the reference and the other as the intertwined variable. For example, when a negative return happens in stock market, it can be determined whether it will cause an increase in bank's non-performing loans or not. As shown by Figure 11, the corrected vectors of the eigenvectors from the signaling power shows a different set of vectors than the ones estimated using moving correlation.[6]

[6] We use four types of signaling power: (i) negative power; (ii) positive power; (iii) positive medium; and (iv) negative medium uses sectoral JCI negative return instead of positive return to capture the co-movement. Both negative and positive power capture type 1 error of sectoral JCI index return changes to explain bank's NPL ratio increase (negative and positive return respectively), while the medium types tries to capture sectoral JCI return and increase in bank's NPL co-movement (using negative and positive return for each medium signaling power).

**Table 8: Signaling Power Vector Estimation**

This table provides rule of vector estimation by signaling power. 1 indicates that the vector should be negative regardless what the PLS estimated. Negative vector indicates negative shock to bank's credit portfolio.

| Variabel | NPL Agri. | NPL Mining | NPL Manu. | NPL Elect. | NPL Const | NPL Trad. | NPL Trans | NPL FinCorp | NPL Govt Adm | NPL Other |
|---|---|---|---|---|---|---|---|---|---|---|
| JAKTRAD | - | 1 | 1 | 1 | - | - | - | - | - | - |
| JAKCONS | - | - | - | - | - | - | - | - | - | - |
| JAKMINE | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| JAKMIND | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| JAKBIND | - | - | - | - | - | - | - | - | - | - |
| JAKPROP | - | - | - | 1 | - | - | - | - | - | - |
| JAKAGRI | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| JAKFIN | - | - | - | - | - | - | - | - | - | - |
| JAKMANU | - | - | - | - | 1 | 1 | - | 1 | - | 1 |

The combined moving correlation and signaling power needs a particular step involving seeking for the eigenvector combination that has more than 4 negative vectors (before forced/corrected). Moreover, even though the combination might have more than four negative eigenvectors, if any of the positive eigenvector value were significantly higher than any of the negative eigenvectors, we need to change the positive significant vector into negative. This approach requires several fuzzy logic steps to be applied into the algorithm.[7] Figure 12 points out vector estimation results of the combined approach.

**Table 9: Combination of MC and SP approaches**

This table provides rule of vector estimation by using combination of MC and SP approaches. 1 indicates that the vector should be negative regardless what the PLS estimated. Negative vector indicates negative shock to bank's credit portfolio.

| Variabel | NPL Agri. | NPL Mining | NPL Manu. | NPL Elect. | NPL Const | NPL Trad. | NPL Trans | NPL FinCorp | NPL Govt Adm | NPL Other |
|---|---|---|---|---|---|---|---|---|---|---|
| JAKTRAD | - | - | 1 | - | 1 | 1 | 1 | - | 1 | 1 |
| JAKCONS | - | 1 | 1 | - | - | 1 | 1 | - | - | - |
| JAKMINE | - | - | - | - | - | - | - | - | - | - |
| JAKMIND | 1 | - | - | - | - | - | - | - | - | - |
| JAKBIND | 1 | - | - | - | - | - | - | - | - | - |
| JAKPROP | 1 | 1 | 1 | - | 1 | 1 | 1 | - | 1 | - |
| JAKAGRI | 1 | - | - | - | 1 | 1 | - | 1 | - | 1 |
| JAKFIN | - | - | - | - | - | - | - | - | - | - |
| JAKMANU | 1 | - | 1 | - | - | - | - | - | - | - |

[7] For fuzzy logic explanations please refer to Appendix 1.

In the last approach, we squared all eigenvector values. This approach converts all eigenvector variant into a range of [0,1]. A total value of all converted eigenvectors will be one. In this approach, all squared eigenvectors are forced to have a negative vector. In Table 4, the left columns of each sectoral NPL illustrate the vectors of each eigenvector estimated from PCA, and the right columns mark the squared eigenvectors value. In this approach, since all squared eigenvectors have positive vector, we change the vectors of all squared eigenvector into negative.

**Table 10: Eigenvector Manipulation Using Squared Method**

This table provides rule of vector estimation by Eigenvector Manipulaton Using Squared Method. 1 indicates that the vector should be negative regardless what the PCA estimated. Negative vector indicates negative shock to bank's credit portfolio.

| Variabel | NPL Agri. | NPL Mining | NPL Manu. | NPL Elect. | NPL Const | NPL Trad. | NPL Trans | NPL FinCorp | NPL Govt Adm | NPL Other |
|---|---|---|---|---|---|---|---|---|---|---|
| JAKTRAD | - | - | - | 1 | - | - | 1 | 1 | - | 1 |
| JAKCONS | 1 | - | 1 | 1 | - | - | - | 1 | 1 | - |
| JAKMINE | - | - | - | 1 | - | - | - | - | - | - |
| JAKMIND | - | - | 1 | 1 | - | - | 1 | 1 | 1 | - |
| JAKBIND | - | - | 1 | 1 | - | 1 | 1 | 1 | 1 | 1 |
| JAKPROP | - | - | - | 1 | - | - | - | 1 | - | - |
| JAKAGRI | - | - | - | 1 | - | - | 1 | - | - | 1 |
| JAKFIN | 1 | - | 1 | 1 | - | - | 1 | 1 | 1 | 1 |
| JAKMANU | - | - | 1 | 1 | - | - | - | 1 | 1 | - |