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**Article Type:** Research Paper

# Dynamization Analysis of Capital Inflow, Credit Allocation, and Banking Performance using Panel Vector Autoregressive

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**THIS ARTICLE IS AVALILABLE IN:**
http://journal.umy.ac.id/index.php/esp

**DOI:** 10.18196/jesp.v23i2.16014

**CITATION:**
Ekananda, M. (2022). Dynamization Analysis of Capital Inflow, Credit Allocation, and Banking Performance using Panel Vector Autoregressive. *Jurnal Ekonomi & Studi Pembangunan, 23*(2), 245

**ARTICLE HISTORY**
**Received:**
29 Aug 2022
**Revised:**
19 Oct 2022
**Accepted:**
29 Nov 2022

**Abstract:** The direction of globalization and the integration of the financial system continue to increase, in line with the increasing capital flows, which is the focus of discussion in this research. This study applies panel data analysis to analyze banking behavior in order to improve its performance. The analysis uses panel data from 1991 to 2020 in 39 countries. Return on Equity (ROE) as a measure of the success of banking operations is determined by various interrelated factors. One of the variables closely related to banking performance is the share of non-financial business loans, the share of capital inflows entering the banking sector, and the share of capital inflows entering the non-bank sector. Economic variables that support good banking performance are GDP growth, bank concentration, inflation, leverage, and bank efficiency. This article applies a Panel Vector Autoregressive to capture the dynamization, and heterogeneity. The most exciting results were obtained by dividing the sample into subgroups, which helped the researcher understand each regime's different roles and transmissions. The changes in capital inflows to the non-bank sector will significantly reduce ROE and increase leverage for the next five periods. The results of the study imply that nowadays, bank managers should be aware while the changes in capital inflows change very quickly. Bank managers in countries with high capital inflows must always be aware of changes in capital inflows to the non-bank sector—steps to bank management by diversifying sources of funds efficiently from other parties in the transmission of credit channel.

**Keywords:** Capital Flow; Bank Performance; Leverage; Panel Vector Autoregressive; Dynamic Model
**JEL Classification**: E22; G20; G21; C23; C22



## Introduction

Banking performance is the final goal of banking, to gain market share and banking sustainability. During the Global Financial Crisis in 2007-2008, banking profits showed rapid development. One of the reasons is the efficiency and optimization of bank credit share. Sources of funding experienced changes and developments. Initially, domestic funding sources from the banking sector were still dominant. Several studies explained a relationship between the allocation of credit disbursement by banks and their performance's improvement. Optimal credit allocation will encourage better banking performance (Xu et al., 2018). This relationship can be dynamic and interdependent on various factors. Several factors that are often mentioned in various articles are banking capacity, interest rates, credit risk, trade openness, and capital inflow (Bezemer et al., 2017). The development of high capital mobility has resulted in corporations being able to choose funding sources other than bank credit. The flow of foreign capital into a country will impact the decreasing demand for credit from the corporations in the banking sector. Banks tend to shift their credit to the private sector (Zaiane & Moussa, 2021).

Bank credit allocation has shifted and now is marked by high growth in the individual sector. The impact of shifts in credit allocation includes stunted growth, disrupted economic stability, and financial fragility in a country. Changes in the allocation of bank credit have gained more attention because they can increase macroeconomic vulnerabilities and have negative impact to the economy. Beck et al. (2012), and Dunn and Ekici (2010) studied that a decline in credit for the corporate sector accompanied by an increase in personal credit will impact in lower savings rates and slow economic growth.

Several other kinds of literature state that high personal credit will increase external imbalances, primarily through exports (Büyükkarabacak & Krause, 2009), and have a more significant and more prolonged impact during crises and recessions (Alberto, 2016). The vulnerabilities are mainly transmitted through two transmission lines: the consumption channel (Dynan et al., 2012) and the investment channel (Chakraborty et al., 2013).

Economics between countries add to the complexity of capital flows. Global capital flows are increasingly mobile and spread through various means, including direct investment flows and portfolio investments (Ekananda & Suryanto, 2021). Samarina and Bezemer (2016) explained that various factors influence domestic banking credit distribution allocation. This marks the flow of foreign capital that enters the banking and corporate sectors. The development of capital inflows can be an incentive for a constrained saving economy. At the same time, portfolio investment can increase the allocation of consumer credit, which also increasing the vulnerability of financial system's stability.

This research gives new contribution to the previous literatures that have been conducted before as they tend to analyze the allocation of bank credit in terms of banking behavior (micro/internal factors), while other macro factors such as trade openness and capital inflows were not used in the analysis. Research on the impact of capital inflows generally uses data on total capital inflows. When viewed from the type and composition of capital inflows, each type has a different impact on banking performance (Ekananda, 2017). This difference is due to different transmissions which depends on the concentration and optimization of bank credit allocation. Igan and Tan (2015), using data from 1980to 2011, explained that capital inflows (non-FDI types) will encourage credit growth, and both individual and corporate loans. However, Igan and Tan (2015) did not look specifically at sectors that receive capital inflows. A year later, Samarina and Bezemer (2016) developed a study by looking at the Effict of capital inflows flowing in the banking sector and non-bank sector on corporate credit allocation. However, Samarina and Bezemer (2016) ignored the endogeneity and exogenous relationship between economic variables. Samarina and Bezemer (2016) had considered the heterogeneity of state banking factors by involving data from the Economic Monetary Union and The Organization for Economic Cooperation and Development (OECD) country groups.

The main contribution of this study is to look at the allocation of bank credit, which concerns the country's characteristics based on the level of globalization of its financial system (the share of foreign banks to total national banking) in order to fill the existing gaps and contribute to the previous literature. Therefore, this research intends to answer empirically and contribute to the previous literature by providing an integrated approach by examining the relationship between capital inflows and global banking credit allocation using the equation model.

**Theoretical background**

This study has an overview of the theories related to various economic agents. Theoretical studies will discuss the relationship between the flow of funds between economic agents. This includes banks, companies (firms), and individuals (households). The relationship between these three sectors can be explained from the supply and demand side. On the demand side, the condition of corporate and individual balance sheets and the availability of external funds are factors that influence the demand of credit for the corporate and individual sectors. Meanwhile, on the supply side, capital inflows/external funding, macroeconomic conditions, and banking sector characteristics are some of the factors that influence the supply of credit to the corporate and individual sectors (Freixas & Rochet, 2008).

This model assumes that the public sectors (government and central bank) are not included. Each sector can be described as follows.; The private sector will allocate its income for consumption ($C_1$, $C_2$) and for saving (Sav) in the form of deposits in the DH bank and securities (bonds) BH, and will maximize its utility function by considering budget constraints:

$$\mathrm{Max\ U}(\mathrm{C}_1, \mathrm{C}_2) \tag{1}$$
$$\mathrm{C}_1 + \mathrm{BH} + \mathrm{DH} = \omega_1 \tag{2}$$

and

$$\mathrm{pC}_2 = \Pi_\mathrm{f} + \Pi_\mathrm{b} + (1 + \mathrm{r})\mathrm{BH} + (1 + \mathrm{r_d})\mathrm{DH} \tag{3}$$

Where $\omega_1$ represents the initial endowment of consumption, p is the price of $C_2$, $\Pi_f$ and $\Pi_b$ are a company and bank profits, r and $r_d$ are interest rates obtained from bonds and deposits. The corporation has the option of investing in level I, and the source of financing can be obtained from LF banking credit and by issuing BF securities, and the corporation will maximize profit:

$$\mathrm{Max}\ \Pi_\mathrm{f} \tag{4}$$
$$\Pi_\mathrm{f} = \mathrm{pf(I)} - (1 + \mathrm{r})\mathrm{BF} - (1 + \mathrm{r_L})\mathrm{LF} \tag{5}$$

and

$$\mathrm{I} = \mathrm{BF} + \mathrm{LF} \tag{6}$$

Where f is the production function and $r_L$ is the bank loan interest rate. The bank will choose its offer of LB credit, demand for DB deposits, and issuance of BB bonds to maximize profit:

$$\mathrm{Max}\,\Pi_b \tag{7}$$
$$\Pi_b = r_L LB - rBB - r_D DB \tag{8}$$

and

$$LB = BB + DB \tag{9}$$

Furthermore, in optimizing the allocation of credit, banks will consider the difference between the interest rates for consumer/personal loans and the interest rates for corporate loans (se = r – r*). It is assumed that these two types of credit have substitute properties. The supply of bank credit is a function of bank deposits and the interest rate differential, l = g(d, se). l is the supply of credit, d is the deposit, and se is the difference in interest rates for consumers and corporations (Brissimis et al., 2012).

The main factors that consider the demand for credit by the corporate and individual sectors include the cost of credit, which are the credit interest rates and economic activity. On the supply side, the ability and willingness to lend by banks are influenced by the condition of the sources of funds owned by banks (bank equity, total assets, deposits, and cost of external financing), banking capital position, costs of other alternative bank portfolios (e.g., the difference between interest rates), lending rates and T-bill rates), competition with other banks, and perceived risk (macroeconomic variables, non-performing loans) (Brissimis et al., 2012).

The theory and several kinds of literature described the factors that influence credit composition in the individual and corporate sectors including transaction costs and risk management (Beck et al., 2012). The individual sector is a debtor with a small credit limit (smaller size), it is generally the type of debtor that is difficult to evaluate and has low collateral compared to the corporate sector. This type of debtor causes banks to view the individual sector as a sector that has higher transaction costs and risks compared to the corporate sector.

Several kinds of literature studied the relationship between capital allocation and efficiency on banking performance: changes that occur in credit allocation will cause changes in banking income. Further, the composition of current loans and efficient bank management will increase revenue and improve banking performance. Souza (2016) stated that an increase in capital inflows will encourage an increase in asset prices as well, and loosen borrowing constraints. Improved performance has something to do with credit growth caused by economic growth. Further, high economic growth will increase capital inflow through banks and increase bank performance. Other researchers such as Raza et al. (2019), have used OECD data to find evidence that economic growth, good economic conditions, changes in credit allocation to the banking sector, and efficiency of banking management will improve banking performance.

There are two primary motivations for horizontal integration: increasing revenues and decreasing costs. The increase in income is obtained by expanding market share and increasing market power by setting interest rates above interest rates in a perfectly competitive market (Kopecky & Van Hoose, 2012). Market power increases because the number of companies decreases, so concentration increases (Tremblay & Tremblay, 2012). The merger paradox criticized this opinion about the increase in revenue. By using the Cournot model, where it is assumed that firms have constant and identical costs, prices are set above marginal cost with the output that produces the maximum profit from each firm under conditions of mutual attention to the reactions of its competitors. Bélanger and Edwards (2013) explained that the merger will not increase profits. This paradox can only be eliminated when the merging companies differentiate their products to have market power.

Meanwhile, cost reduction can be made by replacing a more efficient management system, implementing low-cost technology and business, and producing a product mix that provides economies of scope and economies of scale (Tremblay & Tremblay, 2012; Van Hoose, 2010). A study of bank mergers in the United States from 1985 to 1996 found that the increase in stock prices of consolidated banks was due to cost savings rather than anticipated increases in income (Klutse, 2020).

Several researchers also use panel data to prove their hypothesis about the relationship between capital inflows, credit growth, and the financial system. Igan and Tan (1995) used data from 33 countries from 1980 to 2011. This study is similar to the present research. The analysis is aimed at the consumer sector and corporate sector loans, capital inflows are expected to boost credit growth for the consumer and corporate sectors. The results of his research shows that FDI inflows do not affect credit growth.

Several researchers have discussed the variables that show the characteristics of the bank, such as efficiency, concentration, and leverage affect bank profits. Capital inflows that enter the banking system will be managed efficiently and generate higher profits.

Discussions about competition have been going on for a long time and continue to develop. Market structure is identified by the level of concentration or percentage of the entire market, controlled by some of the largest companies, the degree of differentiation, and barriers to market entry. Behavior is identified with the company's strategy that is related to price, production, investment, innovation, advertising, collusion, etc. Meanwhile, performance is identified with the company's efficiency and profitability (Bikker et al., 2012; Bélanger & Edwards, 2013).

Banking market concentration is a measure of competition in the banking industry. Various researchers have carried out various ways of measuring concentration. The most common measurement method calculates the total share of the five largest bank assets to total banking assets. Researchers who have applied this method include Bikker and van Leuvensteijn (2014). This method measures this. Concentration only occurs in the five largest banks. Other banks cannot compete because their asset growth could not keep up with the biggest banks. In this paradigm, competition will be stronger when the number of competing companies are less or more concentrated.

The banking industry allows for high concentration. Bikker and van Leuvensteijn (2014) explained that there are several characteristics related to the concentration of the banking market as follows. 1) tight competition between banks encourages consolidation to win the competition; 2) barriers to entry into the banking industry are quite high (economies of scale, regulations, accounting, and CAR regulations, solvency, high cost of product development, and size of financial institutions); 3) interbank interaction, transparency, and asymmetrical fee structure facilitate coordination actions; 4) most banking products are quite complex and have high switching costs, different services, and tariffs can exploit monopolistic competition; and 5) the existence of bank linkages with other financial institutions such as conglomerates to reduce competition, due to comprehension of risk information, good relations with customers. These five characteristics can restrain the growth of the number of banks in the industry. We can conclude that the higher concentration of the banking market will encourage banks to create better performance.

Banking efficiency will reduce production costs and overhead cost so that efficiency will generate greater profits. The more efficient a company is, the larger the company will grow, enabling contribution in determining prices, increasing market power, and ultimately increasing company profits (Thorley & Fulda, 2020). On the other hand, efficiency provides an opportunity to lower prices, and stimulate innovations, thereby opening up markets for new firms (Bikker & van Leuvensteijn, 2014).

## Research Method

To answer the research objective or to analyze banking performance associated with the trend of increasing capital flows and credit allocation, this study will apply the panel data method using data on bank credit allocations in 43 countries in the world from year 1990-2016. The model used here refers to the framework of thought and empirical studies that have been conducted previously (Samarina & Bezemer, 2016). They looked at the relationship between capital inflows and bank credit allocation in 36 European countries in the year 1990to 2011. This study focuses on the trend of increasingly integrated global financial systems. To that end, the analysis will compare the relationship between capital inflows and bank credit allocations between groups of countries based on the share of foreign banks. Further, this study also complements the independent variables used, including the capital flow matrix and control variables, and bank characteristics, as done by (Bezemer et al., 2017). Apart from the selection of variables, investigating the dynamics between capital inflows and bank credit allocation has not been analyzed yet in global countries with a broader timeline coverage, 1990-2020. Data analysis was conducted using secondary data obtained from several sources, including IMF, BIS, CEIC, BPS, Bank Indonesia, and World Bank data.

Explanatory variables consist of two groups, which are bank characteristics variables, and macroeconomic variables. The use of explanatory variables refers to the theoretical framework as described earlier. Macro variables are inflation, exchange rate, economic growth, and deregulation. Variables related to bank characteristics are efficiency, concentration, capital inflow, share of non-financial business loans to total bank loans (credit allocation), and leverage. Banking concentration as an explanatory variable follows the research of Bikker and van Leuvensteijn (2014) and Han et al. (2017), Banking leverage (Ferrante, 2015), Banking efficiency follows the research conducted by Bikker and van Leuvensteijn (2014). Capital inflows in the banking sector and the corporate sector are used in the present research, by observing the research conducted by Igan and Tan (1995), Calderón and Kubota (2019), Durdu et al. (2013), Lane and Milesi-Ferretti (2010), and Souza (2016). Using ROE, the performance variable follows several researchers, namely ROE (Pagratis et al., 2014), and Raza et al. (2019).

**Table 1** Variable List

| Variable | Description | Unit | Explanation |
|---|---|---|---|
| $CrNFB_{it}$ | Share of non-financial business loans to total bank loans | % total kredit | BIS (Bank for International Settlements) |
| $BInfl_{it}$ | Share of capital inflows (portfolio equity, debt, and other investment loans) entering the banking sector to GDP | % GDP | BoP – IMF |
| $NBInfl_{it}$ | Share of capital inflows (portfolio equity, debt, and other investment loans) entering the non-bank sector to GDP | % GDP | BoP – IMF |
| $Concr_{it}$ | Concentration is calculated from the total share of the top 5 largest bank assets to total banking assets | % total aset | World Bank |
| $Effic_{it}$ | Efficiency is calculated from the ratio of total revenue to costs | % | World Bank |
| $GDPcap_{it}$ | GDP per capita | USD | World Bank |
| $Inf_{it}$ | Inflation is calculated from annual CPI growth | % (yoy) | IMF - WEO |
| $ExRate_{it}$ | The exchange rate of LCU (local currency units) against the U.S. dollars | LCU/USD | IMF - IFS |
| $Leverage_{it}$ | The ratio of total bank credit to total deposit | % | World Bank |
| $dereg_{it}$ | Credit market deregulation index | Index | Fraser Institute's Economic Freedom Indicators |
| $ROE_{it}$ | Bank return on equity | % *before tax* | World Bank |

The data that will be used in this research is panel data, a combination of cross-section and time-series data. Wooldridge (2010) and Greene (2018) explains several advantages of using panel data: paying attention to heterogeneity, more complete information, less possibility of collinearity between the variables studied, and more degrees of freedom and efficiency. The data used are from 39 countries in the span of 30 years (1991-2020). Deregulation is measured as the index from three components: ownership of banks, an extension of credit, and interest rate controls/negative interest rates. We obtained this from Fraser Institute's Economic Freedom Indicators. The index is the average of all components, with an index of 1 – 10.

The Table 2 is a descriptive statistic that consists the average, 50% of percentile, standard deviation, and coefficient of variation. The data is calculated using 1,170 observations, with 39 countries and 30 periods from 1991 – to 2020. Globally, the average corporate credit allocation for banking reached 41.83% (total credit), with the share of capital inflows in the non-bank sector being more extensive than the share of capital inflows in the banking sector.

**Table 2** Descriptive Statistics

| Var | Average | Perc 50% | StDEv | Var | Average | Perc 50% | StDEv |
|---|---|---|---|---|---|---|---|
| CrNFB | 39.86 | 37.44 | 10.55 | ROE | 11.06 | 11.37 | 5.76 |
| BInfl | 85.50 | 27.57 | 218.55 | GDPCap | 26,048 | 28,067 | 18,541 |
| NBInfl | 204.92 | 29.88 | 966.19 | Inf | 11.43 | 2.52 | 31.57 |
| Concr | 75.01 | 76.22 | 14.53 | ExRate | 323.51 | 2.09 | 1,393 |
| Leverage | 100.46 | 94.95 | 40.25 | dereg | 8.41 | 8.58 | 0.99 |

The Std Dev value indicates a variable with a level of volatility or a tendency to change. The larger the value, the more volatile the variable. Based on Table 2, changes in capital inflow in the banking sector and the non-bank sector are the most volatile. The Table indicates that the volatility of capital inflows is higher, which indicates that capital inflows tend to be short-term.

This research is expected to produce responses that occur 1) contemporaneous and 2) lag time, which are responses that occur at some time after the impulse. Some things to note are the order because it uses the Cholesky method. The variables arranged to form a sequence in the Cholesky orthogonalization structure show the total impact between variables when shock occurs.

The research uses data from various countries. The diversity of countries can be seen from the large deviation of GDP. The analysis strategy uses all data followed by analysis for divided data (Table 3). Distribution of data according to the country with nominal GDP, the share of capital inflow to the non-bank sector GDP (NBInfl), and the share of capital inflow to the banking sector (BInfl). All data is divided into two by the average threshold. We expect a specific IRF pattern to fit this grouping.

**Table 3** Variables and Thresholds

| Variable | Category | Number of Country | Obs | Threshold |
|---|---|---|---|---|
| | All | 39 | 1092 | |
| Nominal GDP per Capita | High | 19 | 532 | 26,047.67 |
| | Low | 20 | 560 | |
| Share of capital inflow to the banking sector to GDP (BInfl) | High | 32 | 896 | 85.50 |
| | Low | 7 | 196 | |
| Share of capital inflow to non-bank sector to GDP (NBInfl) | High | 19 | 532 | 29.88 |
| | Low | 20 | 560 | |
| Leverage | High | 19 | 532 | 94.95 |
| | Low | 20 | 560 | |

This research gives new contribution for the previous literatures. This study uses panel data estimation techniques. According to Ekananda (2016) and Greene (2018), some of the purposes of using panel data include; first, panel data can determine the heterogeneity of banking originating from various countries. Second, panel data analysis considers unobserved variables. Third, able to reduce inter-variable collinearity.Fourth, panel data estimation can minimize the bias generated by individual aggregation because there are more data units. The methodology used in this study uses a vector autoregressive (VAR) model to obtain a response in the presence of shock from several regression variables. Responses in the next period will record the combined impact over time. Therefore, the response in the next period is very dependent on the lag structure, variable stationarity, and the role of exogenous variables in the VAR model. The use of the Fixed Effict model on PVAR is expected to be able to capture unobserved variables sourced from various banks. According to the model created by Abrigo and Love, (2016) and Yang and Lee, (2021), the panel VAR method. The STATA application has adopted an algorithm for heterogeneity and dynamics in Vector Autoregressive.

This section will describe the PVAR versus VAR matrix. The fundamental difference between PVAR and VAR lies in the data structure that adopts behavior between individuals and dynamic behavior between variables. The PVAR used the estimator concept proposed by Yang and Lee, (2021), in the case of a VAR panel, a data set consists of i = 1,2,…., N individuals. Each individual has t= 1,2,3,…T period. The following is an example of model 1, where the W matrix consists of 6 endogenous variables BInfl, NBInfl, CrNFB, Effic, Concr, and ROE. The arrangement of the PVAR(1) equations which consist of 5 equations, is:

$$dBInfl_{it} = \beta_{10} + \beta_{11} dBInfl_{it-1} + \beta_{12} dNBInfl_{it-1} + \cdots + \alpha_{15} ROE_{it-1} + \varepsilon_{effec,it}$$
$$dNBInfl_{it} = \beta_{20} + \beta_{21} dBInfl_{it-1} + \beta_{22} dNBInfl_{it-1} + .. + \alpha_{25} ROE_{it-1} + \varepsilon_{concr,it}$$
$$\ldots$$
$$ROE_{it} = \beta_{50} + \beta_{51} dBInfl_{it-1} + \beta_{52} dNBInfl_{it-1} + \cdots + \alpha_{55} ROE_{it-1} + \varepsilon_{roe,it} \tag{10}$$

Where $dBInfl_{it}$ and $dBInfl_{it-1}$ are vector, the dimension is $[T-(m+2)+1]Nx1$.

$$dBInfl_{it} = \begin{bmatrix} dBInfl_{1,m+2} \\ \ldots \\ dBInfl_{N,m+2} \\ dBInfl_{1,m+3} \\ \ldots \\ dBInfl_{N,m+3} \\ \ldots \\ dBInfl_{1,T} \\ dBInfl_{N,T} \end{bmatrix}, dBInfl_{it-1} = \begin{bmatrix} dBInfl_{1,m+1} \\ \ldots \\ dBInfl_{N,m+1} \\ dBInfl_{1,m+2} \\ \ldots \\ dBInfl_{N,m+2} \\ \ldots \\ dBInfl_{1,T-1} \\ dBInfl_{N,T-1} \end{bmatrix} \tag{11}$$

The variable $dBInfl_{it}$ is arranged as a column vector consisting of the first individual to N individuals in the m+1 year, then the column arrangement repeats below it for the first individual to N individuals in the m+3 year, and so on, the first individual to N individuals in the year m+3 to T. Then the vector has dimensions [T-(m+2) + 1]Nx1. The vector $dBInfl_{t-1}$ is arranged in the same way, but the data starts from time to m+1 to T-1. The variable m is the desired amount of lag. The other variables, $Effic_{it}$ and $ROE_{it}$, are arranged similarly, but the data starts from time to m+1 to T-1. The independent variable vectors $Effic_{it-1}$, and $ROE_{it-1}$ have dimension [T-(m+2)+1]Nx1.

$$Effic_{it-1} = \begin{bmatrix} Effic_{1,m+1} \\ \dots \\ Effic_{N,m+1} \\ Effic_{1,m+2} \\ \dots \\ Effic_{N,m+2} \\ \dots \\ Effic_{1,T-1} \\ Effic_{N,T-1} \end{bmatrix} \text{ and } ROE_{it-1} = \begin{bmatrix} ROE_{1,m+1} \\ \dots \\ ROE_{N,m+1} \\ ROE_{1,m+2} \\ \dots \\ ROE_{N,m+2} \\ \dots \\ ROE_{1,T-1} \\ ROE_{N,T-1} \end{bmatrix} \quad (12)$$

We can see that the dependent variables are arranged sequentially according to the individual, then repeated at different times. We combine all the independent variables in one equation in the next step. The matrix to the right of the first (independent) equation is denoted as $W_{dBInfl,t-1}$ with dimension [T-(m+2)+1]Nx[T-(m+2)+1]xK. The matrix $W_{dBInfl,it-1}$ is a diagonal block consisting of a matrix w. Here $W_{dNBInfl,it-1} = W_{\mathrm{dCrNFB},it-1} = W_{Effic,it-1} = W_{ROE,it-1}$ according to variable name. The matrix format is

$$W = \begin{bmatrix} w_{m+1} & 0 & 0 & 0 & 0 \\ 0 & w_{m+2} & 0 & 0 & 0 \\ 0 & 0 & w_{m+3} & 0 & 0 \\ 0 & 0 & 0 & \dots & \dots \\ 0 & 0 & 0 & \dots & w_T \end{bmatrix} \quad (13)$$

Matrix $w_{m+1}$ and $w_{m+2}$ have Dimension [T-(m+2)+1]xK consists of data lag variables $\mathrm{dBInfl}_{it}$, $\mathrm{dNBInfl}_{it}$, $\mathrm{dCrNFB}_{it}$, $\mathrm{Effic}_{it}$,and $\mathrm{ROE}_{it}$ that is

$$w_{m+1} = \begin{bmatrix} 1 & dBInfl_{1,m+1} & dNBInfl_{1,m+1} & \dots & ROE_{1,m+1} \\ 1 & dBInfl_{2,m+1} & dNBInfl_{2,m+1} & \dots & ROE_{2,m+1} \\ 1 & dBInfl_{3,m+1} & dNBInfl_{3,m+1} & \cdots & ROE_{3,m+1} \\ 1 & & & \cdots & \\ 1 & & & & \\ 1 & dBInfl_{N-1,m+1} & dNBInfl_{N-1,m+1} & \cdots & ROE_{N-1,m+1} \\ 1 & dBInfl_{N,m+1} & dNBInfl_{N,m+1} & \cdots & ROE_{N,m+1} \end{bmatrix}$$

$$\text{sampai } w_T = \begin{bmatrix} 1 & dBInfl_{1,T} & dNBInfl_{1,T} & \dots & ROE_{1,T} \\ 1 & dBInfl_{2,T} & dNBInfl_{2,T} & \dots & ROE_{2,T} \\ 1 & dBInfl_{3,T} & dNBInfl_{3,T} & \cdots & ROE_{3,T} \\ 1 & & & \cdots & \\ 1 & & & & \\ 1 & dBInfl_{N-1,T} & dNBInfl_{N-1,T} & \cdots & ROE_{N-1,T} \\ 1 & dBInfl_{N,T} & dNBInfl_{N,T} & \cdots & ROE_{N,T} \end{bmatrix} \quad (14)$$

Next, we combine all the equations into the matrix $A_{it}$. Matrix $A_{it}$ is dependent and $A_{it-1}$ is independent with dimension [T-(m+2)+1]MxNx1. For five variables, where M is the number of variables, and N is the number of sections, then the dimensions of the matrix $A_{it}$ and $A_{it-1}$ are [T-(m+2)+1]5Nx[T-(m+2)+1 ]MxK. The matrix format $A_{it-1}$ is

$$A_{it-1} = \begin{bmatrix} W_{dBInfl,it-1} & & \\ & \dots & \\ & & W_{ROE,it-1} \end{bmatrix} \tag{15}$$

PVAR is condensed into

$$A_{it} = \beta_0 + \sum_{l=1}^{m+1} \beta_{lt} A_{it-l} + \delta X_{it} + \varepsilon_{it} \tag{16}$$

Matrix $X_{it}$ is an exogenous variable

$$X_{it} = [dInf_{it} \quad LnGDPCap_{it} \quad dExRate_{it} \quad LnConcr_{it}] \tag{17}$$

Greene (2018) states that the unbiased estimator for $\beta$ is:

$$\hat{\beta} = (W_{it-1}'V^{-1}W_{it-1})^{-1}W_{it-1}'V^{-1}Y_{it} = \left(\sum_{i=1}^{n}\sum_{j=1}^{n}\sigma^{ij}W_i'\right)^{-1}\left(W_j\sum_{i=1}^{n}\sum_{j=1}^{n}\sigma^{ij}W_i'Y_j\right) \tag{18}$$

Impulse response function in standard VAR can be formed after the estimation process. In summary, PVAR is iterated under conditions of stable PVAR parameters. The iterated PVAR model will form 3 parts, which are the average element , the estimated parameter matrix A and $e_{it-j}$ pure innovation or in the form of a forecast shock $\varepsilon_{it}$ to pay attention to the contemporaneous impact on PVAR (Enders, 2005).

$$G_{it} = \mu + \sum_{j=1}^{\infty} A_1^t e_{it-j} = \mu + \sum_{j=1}^{\infty} \phi_j \varepsilon_{it-j} \tag{19}$$

If the PVAR consists of 2 variables (M=2), and $\beta$ is the estimated PVAR parameter and $\alpha$ is the contemporaneous parameter matrix parameter, then the IRF form is as follows.

$$\begin{bmatrix} dBInfl_{it} \\ ROE_{it} \end{bmatrix} = \begin{bmatrix} \overline{dBNInfl}_{it} \\ \overline{ROE}_{it} \end{bmatrix} + \sum_{i=1}^{\infty} \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}^i \frac{1}{(1-\alpha_{12}\alpha_{21})} \begin{bmatrix} 1 & -\alpha_{12} \\ -\alpha_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{dBInfl,it-1} \\ \varepsilon_{ROE,it-1} \end{bmatrix} \tag{20}$$

Equation 20 explains how Impulse (rightmost epsilon notation) will produce a response from time to time on the rightmost variables (ROE and Inflation). This way, the researcher obtained a dynamic analysis of the inflation and ROE variables due to disturbances. (Hamilton, 1994). Contemporaneous impact with Cholesky's orthogonalization structure becomes

$$\text{become} \begin{bmatrix} 1 & 0 \\ -\alpha_{21} & 1 \end{bmatrix} \tag{21}$$

Transmission and order using the Cholesky method will produce two kinds of analysis, which are 1) analysis of responses that occur contemporaneous and 2) responses that occur in the next period after the impulse occurs. Estimation, determination of maximum lag, measurement of PVAR stability adopted using the STATA program created by Abrigo and Love (2016). They also apply the matrix structure proposed by Yang and Lee, (2021) to estimate the parameter.

The method for panel vector Autoregressive has progressed and has been applied to various studies. The estimation steps are similar to the standard VAR method: model selection, stability measurement, and variable stationarity. Testing the VAR model using time series data and Panel VAR using panel data are very different. We need to test the unit root panel and select the fixed Effict or Common Effict model for the panel data. The unit root panel test emerged on time-series data from the unit root test. The main difference from unit root testing on time series data is that, we have to decide on the asymptotic behavior of the time series according to the time dimension and the cross-sectional dimension. Recent literature shows that panel-based unit root tests have higher power compared to unit root tests based on individual time series. The method used for the panel unit root test is Shahbaz et al. (2014) or Pesaran (2007). The method for the panel unit root test considers the basic specifications of the ADF. Where: $H_0$: null hypothesis if panel data has unit root $H_1$: panel data does not have a unit root.

We apply the VAR panel model selection procedure developed by Abrigo and Love (2016). The model selection method calculates the coefficient of determination of the overall model, Hansen's statistic (Hansen, (1982) in Lee (2014), and the corresponding p-value. The model selection criterias are all based on the J Hansen statistic. It requires the number of moment conditions to be greater than the number of endogenous variables in the model. The selection begins by using the most restrictive sample VAR panel model estimation with the highest order of lag used, for all models to be estimated by the program.

This study tested the stability to ensure that the selected VAR model was stable. Appropriate stability will determine proper Impulse response function (IRF) and variance decomposition (VD) analysis. This research's test procedure followed Abrigo and Love (2016). They measure the stability of the VAR panel by calculating the modulus of each eigenvalue of the estimated model. Lütkepohl (2005) and Hamilton (1994) explain that the VAR model is stable if all the modulus of the companion matrices are all less than one.

## Result and Discussion

Referring to (Samarina & Bezemer, 2016), the following are the methods and data sources used in this study. The scope of the research covers some global countries within the timeframe of 1991to 2021. There are 39 (thirty-nine) selected countries in the world that are included in this study. The selection of countries and the research period mainly considering the availability of data, especially data on capital inflows for the banking sector and the non-bank sector, which data were sourced from the IMF.

The present research needs to do a panel unit root test to ensure the stationarity of all panel data. We apply the method conducted by Im et al. (2003) before. The unit root test panel uses the Kao Residual Cointegration Test (result in the Table 4) on the variables used in the study. User-specified lag length at first lag indicates that the Null Hypothesis is rejected at HAC variance 8.734871 and t statistic -2.920052. Table 4 show the another test for non panel. Levin, Lin & Chu also showed the cpintegration accour. Data then will show the cointegration.

**Table 4** Unit Root Test

| Kao-Engle Granger (Panel Data) | t-Statistic | Prob. |
|---|---|---|
| ADF | -2.920052 | 0.0017 |
| Residual variance | 6.603591 | |
| HAC variance | 8.720901 | |
| **Non Panel Data** | | |
| Levin, Lin & Chu t* | -6.98558 | 0.0000 |
| Im, Pesaran and Shin W-stat | -23.7195 | 0.0000 |
| ADF - Fisher Chi-square | 577.660 | 0.0000 |
| PP - Fisher Chi-square | 733.439 | 0.0000 |

Null Hypothesis: No cointegration

Simulation scenario will need to be conducted if there is a change share capital inflow to the non-bank sector to GDP (NBInfl). For all models, the exogenous variables consist of GDP growth (gGDP), Inflation (Inf), Exchange Rate (ExRate), and Concentration (Concr). Using all data, consisting of 39 countries from 1991 to 2020.

This study uses panel data considering the heterogeneity at the banking level of OECD countries. The estimated parameters result in analysis that captures unobservable factors outside the model. The fixed Effict method is applied to capture unobservable—factor problems outside the model. The use of all data will result in an analysis derived from the heterogeneity of all banks in OECD countries. However, sometimes grouping the data according to the data level will provide a more in-depth analysis. This study divides the analysis according to the level of data (high and low) GDP per capita, capital inflows to banks, and leverage ratios. This research will analyze all data during the initial stage to produce a response that all banks will accept in the involved countries. Thus, there are 4 PVAR models to be analyzed. Model testing was also carried out on all PVAR models.

This study divides the two samples by calculating all data's 50% percentile value. We did not choose the mean as the divisor because percentiles divide according to the data distribution (Anderson et al., 2017). In the following procedure, this study calculates the average of the variables by country. Then, any average variable above the percentile value will be considered as the upper regime and the lower regime in other parts. 19 countries have higher per capita GDP levels than 20 other countries. The GDP per capita threshold is 26,047.67. Nineteen countries have higher capital inflows to banks than 20 other countries. The threshold value of the capital inflow to the bank to GDP ratio is 85.50 percent. Nineteen countries have high leverage ratios, they have higher leverage compared to the other 20 countries. The leverage ratio threshold is 94.95438 percent.

We apply the model selection procedure developed by Abrigo and Love (2016). A suitable option is PVAR(1) model that could represent all PVAR models. We Assume that the dynamics between variables occurred one period ago. Economic agents generally consider banking performance and economic developments in the previous period. The results of stability checks showed that the modulus is smaller than 1. PVAR(1) showsed a stable model. Long-term simulation is expected to go to a steady-state position. The measuring stability will follow the procedure from Abrigo and Love (2015). Table 5 shows the test on all of the data model and the model with the distribution of the GDP regime, where the real, imaginary, and modulus values are below 1.

**Table 5** Real, Imaginary and Modulus

| Kao-Engle Granger (Panel Data) | t-Statistic | Prob. |
|---|---|---|
| ADF | -2.920052 | 0.0017 |
| Residual variance | 6.603591 | |
| HAC variance | 8.720901 | |
| **Non Panel Data** | | |
| Levin, Lin & Chu t* | -6.98558 | 0.0000 |
| Im, Pesaran and Shin W-stat | -23.7195 | 0.0000 |
| ADF - Fisher Chi-square | 577.660 | 0.0000 |
| PP - Fisher Chi-square | 733.439 | 0.0000 |

Null Hypothesis: No cointegration

Table 6 shows tests on other models. The real, imaginary, and modulus values are all below 1. We can conclude that the models analyzed in this study are all stable. This stability follows the procedure determined by Lütkepohl (2005) and Hamilton (1994).

**Table 6** Real, Imaginary and Modulus

| Upper BInfl | | | Lower BInfl | | | Upper Leverage | | | Lower Leverage | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Real** | Imag | Modulus | Real | Imag | Modulus | Real | Imag | Modulus | Real | Imag | Modulus |
| **0.529** | -0.116 | 0.542 | 0.583 | 0.056 | 0.589 | 0.711 | 0.000 | 0.711 | 0.624 | 0.056 | 0.624 |
| **0.529** | 0.116 | 0.542 | 0.583 | -0.056 | 0.589 | 0.412 | 0.000 | 0.412 | 0.397 | -0.056 | 0.397 |
| **0.276** | 0.000 | 0.276 | -0.235 | 0.000 | 0.235 | -0.012 | 0.172 | 0.173 | -0.098 | 0.000 | 0.098 |
| **-0.223** | 0.000 | -0.223 | 0.118 | 0.000 | 0.118 | -0.012 | -0.172 | 0.173 | 0.082 | 0.000 | 0.082 |
| **0.028** | 0.000 | 0.028 | -0.037 | 0.000 | 0.037 | 0.070 | 0.000 | 0.070 | -0.021 | 0.000 | 0.021 |

Figure 1 on the left describes the response of bank performance (ROE) to shock of the share of capital inflows to the non-bank sector to GDP (NBInfl). The increased flow of funds to the non-banking sector, such as corporation from outside the bank sectors,caused banks to face competition. Figure 1 on the left shows the ROE responding negatively. This study related with Ben Salah Mahdi and Boujelbene Abbes (2018). Further, figure 1 shows the Credit allocation (CrNFB) responding negatively in the early period. Credit allocation, which is defined as the share of non-financial business loans to total bank loans. Figure 1 on the right describes the response of efficiency (the ratio of total revenue to costs). In line with the decline in banking performance, the bank's total income from credit will decrease (Anggraeni & Berniz, 2022).

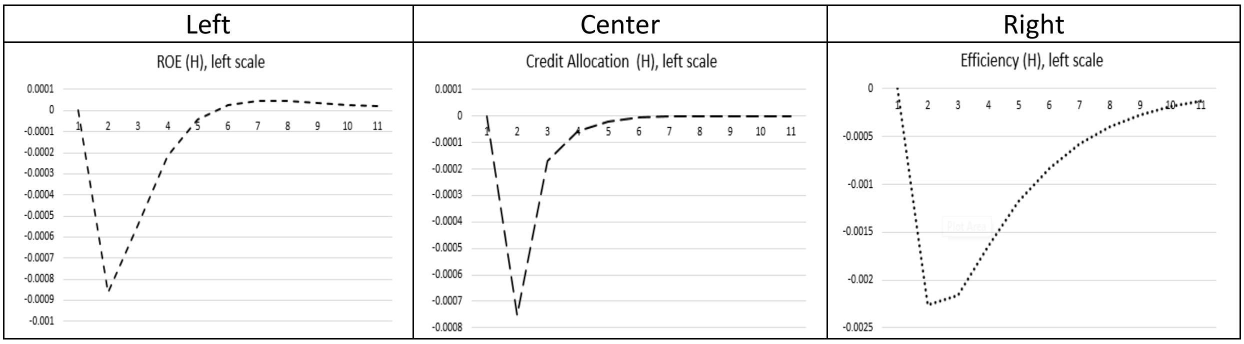


**Figure 1** Response of ROE, CrNFB, and Efficiency to capital inflow to non-bank sector to GDP

If in the previous simulation, the research assumes that the response occurs at all economic levels. In reality, the level of the economy and the challenges in each country are different. This study simulates the response that occurs at different levels of GDP per capita. A total of 19 countries have higher per capita GDP levels compared to the 20 other countries. The GDP per capita threshold is 26,047.67. The data processing results explain that Figure 2 shows the Response of ROE, CrNFB, and efficiency to NBInfl according to GDP per capita level. The vertical axis measures the response of each variable due to impulse capital inflow to the non-bank sector (NBInfl). By combining IRF at high and low GDP per capita levels, we can see the difference in response.

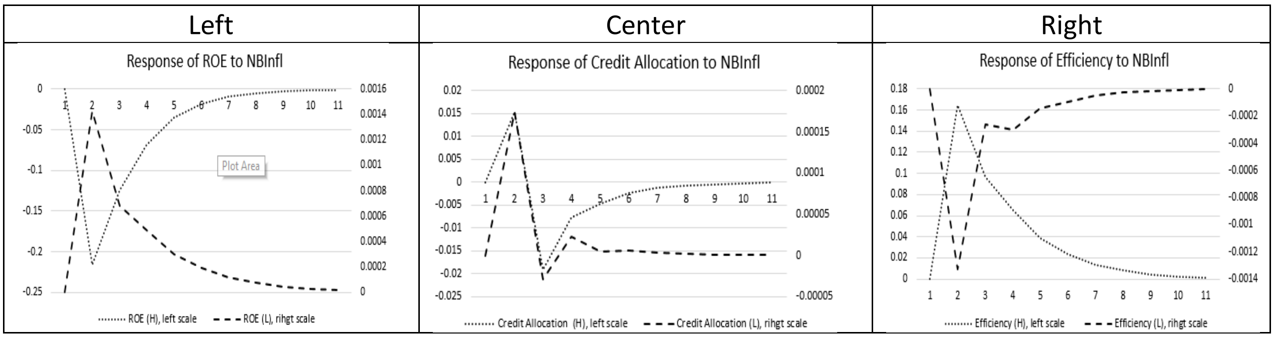


**Figure 2** Response of ROE, CrNFB, and Efficiency to NBInfl at high and low GDP per capita

Figure 2 on the left describes the response of ROE to NBInfl. The left axis describes the ROE response at high GDP. The right axis describes the ROE response at low GDP. Changes in share capital inflows and banking ROE in countries with high GDP negatively respond. These results explain that banks in countries with high GDP experience performance pressures, so ROE has a negative impact. In contrast, banks in countries with low GDP experience a positive performance boost so that ROE has an increasing impact. This result can be explained by the presence of Ekananda and Suryanto (2021).

Figure 2 explains the negative credit allocation response due to a shock to share capital inflows to the non-bank sector (NBInfl). This result is the same as the IRF for banking in general (middle figure 1). The increase in capital inflows to the non-bank sector initially put pressure on credit allocation. For a more extended period, credit allocation resulted in a negative response. Banks in all countries have experiences for not being accepted or receiveing a negative response at the beginning of the period. The response returned to negative after briefly experiencing a positive response. The right-hand response unit is much smaller than the left-hand response unit. We conclude that, in general, the response to credit allocation is negative—the conclusion following the credit allocation response for all data. The resultant response amplitude is dominated by the credit allocation response of banks in countries with high GDP (Hoang et al., 2021).

Figure 2 on the right side describes the efficiency of the response. The right-hand response unit is much smaller than the left-hand response unit. The resultant response amplitude is dominated by the efficiency response of banks in countries with high GDP. This resulted in the credit allocation response for all data. This study wants to deepen understanding in banking behavior regarding banks' high and low share of capital inflows (BInfl). The high share capital inflow to banks (BInfl) indicates high capital inflow to the banking sector. The banking sector will take advantage of capital inflows to credit channeled to the real sector. Placement of funds through credit will improve banking efficiency and performance. A total of 19 countries have higher capital inflows to banks than 20 other countries. The threshold value of the capital inflow to the bank to GDP ratio is 85,49897 percent. The data processing results explain that Figure 3 shows the Response of ROE, CrNFB, and Efficiency of the capital inflow to the non-bank sector and GDP according the level of Binfl (Hoang et al., 2021). By combining IRF at high and low GDP per capita levels, we can see the difference in response.

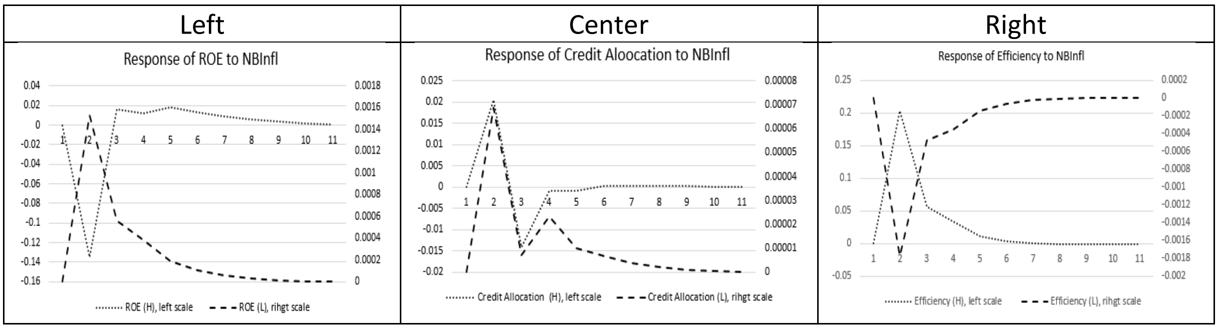


**Figure 3** Response of ROE, CrNFB, and Efficiency to capital inflow to the non-bank sector (NBInfl) at high and low share of capital inflow to banks (BInfl)

Figure 3 on the left describes the response of ROE to NBInfl. The change in capital inflow share and banking ROE in countries with high capital inflow to banks shows a negative response. From the beginning of the period to the end of the simulation, the ROE response was negative. The ROE response was also negative for banks with low capital inflow. The main difference occurs at the beginning of the simulation. At the beginning of the simulation, banks with higher capital inflows showed a negative response, while banks with lower capital inflows ROE, responded positively with low values. Banks dominated the resultant response with high capital inflows to banks. These results explain that banks with high capital inflow experience a faster decline in ROE compared to banks with low capital inflows. These results can be explained by the presence of Ekananda (2017) and Xu et al. (2018).

The increase in capital inflows to the non-bank sector initially suppressed credit allocation in the banking group with high capital inflows to banks. In the banking group with low capital inflow to banks, there was a positive response but with a small value which could be seen on the Figue 3 in the middle.. Banks nominated the total response from both groups with high capital inflows to banks (Vukas et al., 2022). This result is the same as the IRF for banking in general (middle figure 1). We conclude that, in general, the response to credit allocation is negative. The resultant response amplitude is dominated by the credit allocation response of banks in countries with high GDP.

Suppose we look at the response efficiency of all data, we can see thatthe response shows negative from the beginning to the end of the period. The response efficiency value is small—figure 3 on the right of response efficiency for different banking groups. If banks with high capital inflows (to banks) start with a response of up to 0.2, the response value starts negatively in banks with low capital inflows to banks.

This study wants to observe further on banking behavior regarding high and low leverage. High leverage shows the high total credit to the total deposit. Distribution according to leverage is crucial because it relates to the company's ability to create profits and performance (Hoang et al., 2021 and Vukas et al. 2022). The higher the leverage, the higher the liabilities the banking sector must bear. Leverage also showcases the bank's ability to utilize deposits that can be channeled as credit—that is why good credit management results in a good performance. This study is in relation to Ben Salah Mahdi and Boujelbene Abbes (2018) studies. A total of 19 countries have high leverage ratios, higher leverage than 20 other countries. The leverage ratio threshold is 94,95438 percent. The data processing results explain that Figure 4 shows the Response of ROE, CrNFB, and Efficiency to capital inflows to the non-bank sector according to leverage. By combining IRF at high and low leverage levels, we can see the difference in response.

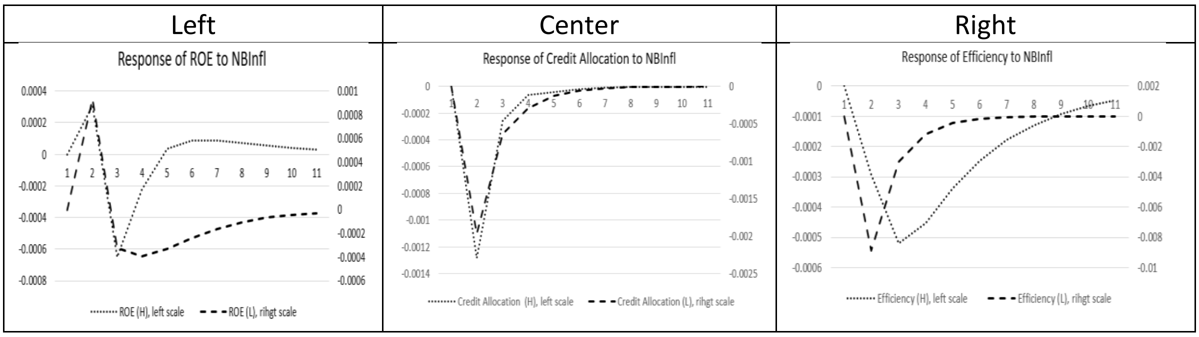


**Figure 4** Response of ROE, CrNFB, and Efficiency to capital inflow to the non-bank sector to GDP (NBInfl) at high and low of Leverage

Figure 4 on the left describes the shock on the share of capital inflows to the non-bank sector on GDP (NBInfl) in response to bank performance (ROE). The change in share capital inflows and banking ROE in high-leveraged countries shows a negative response. From the beginning of the period to the end of the simulation, the ROE response was negative. For banks with low leverage, the ROE response is also negative. The main difference occurs at the beginning of the simulation. At the beginning of the simulation, banks with high leverage showed a negative response, while ROE responded positively for banks with lower leverage,. Highly leveraged banks dominate the resultant response. These results explained that banks with highher leverage actually experience a faster decline in ROE than banks with low leverage. These results can be explained by the presences of Hoang et al., (2021) and Vukas et al. (2022).

All banking groups showed a negative response. The result is the same as using the data. We can conclude that the difference in leverage is not the trigger for lowering credit allocation (Figure 4 middle). The total responses from both groups show the same results as the IRF for banking in general (Figure 1 middle). We conclude that, in general, the response to credit allocation is negative. If we look at the response efficiency of all data, the response shows negative from the beginning to the end of the period (Figure 4, right). The same results were obtained for the banking group in accordance to their leverage.

Currently, the increase in capital inflow to non-banks is growing rapidly as an alternative funding source. When capital inflows to banks are getting more expensive, capital inflows to non-banks are becoming a source of funding with higher demand. Banks are under pressure to channel their funds through credit transmission, which then reducing bank profits. The results of this study support the past study conducted by Bezemer et al. (2017). A negative shift occurred in non-financial business loans as this sector received funds directly outside the bank's line of credit. There is pressure on banks to gain profits from lending. Meanwhile, when interest and operating costs are increased, they might result in lower efficiency as the profit ratio to costs. IRF studies on all samples reflect responses in heterogeneous situations that are more diverse. These results support Raza (2019) research in OECD countries.

By dividing the sample data according to the 50% percentile group, we can analyze more deeply in a more integrated economic situation. Research by Raza (2019) shows heterogeneity between FDI and economic growth in OECD countries. The data grouping into several countries according to FDI and economic growth rates shows more analytical results.

The research results using panel data are more interesting than time series data if we summarize the responses from various sub-samples. Generally, the third to eleventh-period response corresponds to the response to all data. We start the discussion from the ROE response. Table 7 column ROE summarizes Figures 2 to 4 left side. The ROE response of countries with GDP per capita, the share of capital inflow to banks, and high leverage are always negative. Response ROE is positive for low levels. The data processing results correspond to the negative ROE response in the total sample. The negative ROE response in the total sample is caused by the negative ROE response in countries with high GDP per

Capita. The Countries with high GDP per capita, the Changes in capital inflows to the non-bank sector significantly disrupted the development of lending to the non-banking sector. These results follow the research of Igan and Tan (1995).

**Table 7** Summary of response variables to NBInfl

| Response | ROE | | | CrNFB | | | Leverage | | |
|---|---|---|---|---|---|---|---|---|---|
| | 0-2 | 3-5 | 6-11 | 0-2 | 3-5 | 6-11 | 0-2 | 3-5 | 6-11 |
| TOTAL sample | - | - | 0 | - | - | 0 | - | - | 0 |
| GDPperCap : High | ---- | -- | 0 | ++ | - | 0 | ++ | + | 0 |
| GDPperCap : Low | + | + | 0 | -- | - | 0 | - | - | 0 |
| share of capital inflow to banks : High | --- | -- | 0 | ++ | - | 0 | ++ | + | 0 |
| share of capital inflow to banks : Low | ++ | + | 0 | -- | - | 0 | - | - | 0 |
| Leverage: High | -- | -- | 0 | -- | - | 0 | -- | - | 0 |
| Leverage : Low | ++ | + | 0 | -- | - | 0 | -- | - | 0 |

## Conclusion

Several studies have used the panel VAR (PVAR) model to calculate the IRF by considering the impact of specific country characteristics due to the shock transmission of economic variables. This article investigates the response to ROE as a variable of bank performance, the share of non-financial business loans to total bank loans, and bank efficiency due to changes in capital inflow to the non-bank sector. This study is interesting because the change of share capital inflow to the non-bank sector occurs in current capital flows. The greater the mobility of funds, the greater possibility to change the model to the banking sector or directly to the non-bank sector.

We use data from 39 countries from the year 1990–2020. The trend of globalization and financial system integration that continue to increase in line with increasing capital flows is the focus of discussion in this research. This study has analyzed the dynamic vector Autoregressive model on panel data. The use of panel data is to deepening the research on banking performance that considers the diversity of banking between countries. We divided the research data into sub-sample upper and lowered regimes based on the 50% percentile value. The aim is to obtain interesting differences in characteristics and taking them into account to the characteristics of countries and characteristics according to the regime of GDP per capita, leverage, and capital inflow.

All PVAR models show stability on the order of one (p=1), so we can analyze the response of banking performance due to changes in credit allocation. Changes in capital inflows in the non-bank sector significantly affected the allocation of bank credit. In line with the hypothesis, an increase in non-bank capital inflows negatively correlates with bank credit allocation. In general, an increase in the allocation of bank credit has led to higher bank profits.

IRF analysis on the sub-sample data according to the upper and lower regimes is under the IRF analysis on all data. Analysis of the sub-sample helps deepen the analysis at the upper and lower regime levels. All analyzes focused on changes in the share of capital inflows to the non-bank sectorand the response to ROE as a variable of bank performance, the share of non-financial business loans to total bank loans, and bank efficiency.

At the beginning of the period, the shock share of capital inflows were responded negatively by ROE and credit allocation. Negative responses occur in various variable regimes of GDP per capita, the share of capital inflow to banks, and leverage. We can conclude that changes in the share of capital inflows cause changes in bank performance at various levels of the regime. An increase in the share of capital inflows to the non-bank sector will affect bank performance. The decline in bank performance and bank efficiency decreases. This phenomenon applies at various levels of the regime. The most interesting results were obtained by dividing the sample into subgroups, which helped the researcher understand each regime's different roles and transmissions. The GDP per capita is high. Banks can utilize all resources at a high GDP per capita without being affected by internal banking conditions. At low GDP per capita, the economy's ability is challenging to support inefficient banking and weak resources. In a situation where the share of capital inflow to banks is high, banks in any situation can continue to develop their business without disrupting their profits.

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