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MICROFINANCE AND POVERTY IN INDONESIA: THE MACRO IMPACT OF PEOPLE'S CREDIT BANK

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Abstract. The purpose of this paper is to investigate the role of people's credit banks (BPRs), a predominant form of microfinance in Indonesia, in mitigating poverty. Using panel data from 31 provinces in Indonesia, this study employs static panel and panel models with instrument variables. Our findings substantiate that BPR credit significantly contributes to poverty reduction across various indices, including headcount poverty, poverty gap, and poverty severity measures. The empirical results offer valuable insights into the efficacy of targeted microfinance as a potent tool for poverty alleviation in developing economies.

Keywords: poverty, microfinance, credit, people's credit banks, provincial panel, Indonesia.

JEL Classification: E51, F62, G21, I13, O53.

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1. Introduction

The United Nations has recognised microfinance as a development tool for improving the well-being of people in poverty (United Nations, 2004). However, empirical evidence on the role of microfinance in poverty alleviation remains mixed (Beck et al., 2007; Khan et al., 2021; Ribeiro et al., 2022; Sharma et al., 2021; Tria et al., 2022; van Rooyen et al., 2012). Studies at the micro level, in particular, that examine the impact of microfinance services on clients who directly receive them have produced pessimistic results (Banerjee et al., 2015; Khandker et al., 2016; Maitrot & Niño-Zarazúa, 2017; Morduch, 2020). These findings contradict macro-level research which asserts microfinance has contributed to poverty alleviation (Buera et al., 2021; Félix & Belo, 2019; Imai et al., 2012; Islam & O'Gorman, 2019; Khandker et al., 2016).

It is critical to point out that all previous macro-level studies treat microfinance as a homogeneous entity. This is a major mistake because microfinance is a diverse entity (Remer & Kattilakoski, 2021; Sun & Liang, 2021). The various statuses of microfinance institutions (MFIs), whether formal, semi-formal, or informal, have different implications for the models, practises, and characteristics of the targeted clientele (Gloukoviezoff, 2016; Goldberg, 2005; Ledgerwood, 1998).

Informal MFI loans are small in size, have simple procedures, lack formal collateral, target lower-income groups, and typically rely on social instruments to assess the clients' reputation. Formal financial providers, on the other hand, have strict loan procedures, larger loan amounts, high transaction costs, require formal collateral, target middle to upper-income groups, and are strict in their financial services. Meanwhile, semi-formal financial providers offer products and services that bridge the gap between formal and informal institutions (Abrar et al., 2023; Beg et al., 2024; Gloukoviezoff, 2016; Krahnen & Schmidt, 2021; Ledgerwood, 1998; Sulemana et al., 2023).

Many studies have shown that MFI types have varying effects on internal performance as well as their ability to combat poverty. Ibrahim et al. (2018) found that the legal status of MFIs influences their internal performance in the case of countries in the Organisation of Islamic Cooperation (OIC), with MFIs charging higher interest rates on loans to clients being more likely to sustain their operations. Maeenuddin et al. (2023) noticed in Bangladesh that the type of MFI (bank or non-bank) and the extent of services provided to clients have a significant impact on the health and sustainability of MFIs. Furthermore, Ahmed and Kitenge (2022) noticed that the extent of services provided to clients influences the improvement of well-being through increased consumption and income. All of this highlights the fact that each type of MFI has different capabilities in terms of poverty alleviation. As a result, previous studies that combined various MFI types into a single analytical unit may have produced erroneous findings.

In light of this, the author is motivated to conduct a research study focusing on People's Credit Banks (BPRs) in Indonesia. The primary question in the research investigates whether microcredit provided by BPRs effectively alleviates poverty. The selection of BPRs as the primary research subject is motivated by their unique status as formal financial institutions expressly designed to serve low-income populations. Indonesia was chosen as an ideal context for this study because of its rich diversity in microfinance practises and its well-established and sustainable microfinance system (Johnston & Morduch, 2008; Robinson, 2002; Seibel & Parhusip, 1997). The findings of this focused investigation into BPRs are expected to serve as the foundation for assessing the distinct impact of different types of microfinance institutions on poverty alleviation. This is the focal point of the study.

This study presents three key aspects in addition to the specific research focus. First, given that BPRs are fully integrated into the financial system and have a widespread presence throughout Indonesian provinces, it focuses on macro-level impact analysis. According to Banto and Monsia (2021), Raihan et al. (2017), and Maksudova (2010), financial institutions with broad service coverage contribute significantly to macroeconomic performance. Second, unlike many previous studies that examined the impact of MFIs on various well-being indicators such as health, education, and social relationships (Batinge & Jenkins, 2021; Chhorn, 2021; DeLoach & Lamanna, 2011; Mahmud et al., 2022; Manko & Watkins, 2022; Ribeiro et al., 2022; van Rooyen et al., 2012), this study examines the impact of BPRs on poverty. It is critical to emphasise that BPRs are formal banking institutions subject to banking regulations, with their primary activities centred on aspects other than social and empowerment.

Third, this study employs panel data derived from Indonesian provinces, which is a novel approach. Macro-level studies that put on specific MFI cases (BPRs) in a single country (Indonesia) are uncommon. Furthermore, previous macro-level empirical studies relied on aggregated data from multiple countries, which increased the risk of endogeneity issues due to significant differences in economic and financial systems across countries. Using panel data from administrative regions within a single country reduces these differences, increasing the robustness of the analysis.

The key finding of this study is that BPRs play a critical role in poverty reduction in Indonesia. Specifically, the credit provided by BPRs is effective in reducing poverty, as evidenced by a decrease in the proportion of the population living below and near the poverty line (headcount poverty reduction), an increase in the average expenditure of the poor, bringing them closer to the poverty line (poverty gap reduction), and a narrowing of expenditure disparities among the poor (poverty severity reduction).

The following sections of this paper are organised as follows: a literature review (Section 2), an explanation of the research methodology (Section 3), a description of the data (Section 3), the presentation and discussion of model estimation results (Section 4), and the conclusion (Section 5).

2. Literature review

2.1. The microfinance impact analysis

The units of analysis and the analytical methods used can be used to trace the choice between micro and macro-level analyses of the impact of microfinance on poverty (Ledgerwood, 1998; Odell, 2010). Individual clients who receive microfinance services are the focus of the micro-level impact analysis. The benefit of this unit of analysis is the ease with which clients can be defined and identified, allowing for rapid data collection via interviews or observations. The disadvantage of micro-level analysis is that the impact estimates are highly dependent on the clients' perceptions. Because it is not the primary goal, it is difficult to discern their effects on other stakeholders. Individuals, households, or businesses receiving microfinance services can be considered clients in micro-level impact analysis.

The macro-level impact analysis, on the other hand, goes beyond microfinance clients to include all stakeholders affected in a specific area. The establishment of microfinance institutions (MFIs) in a region may have an impact not only on the clients who benefit from their services, but also on other stakeholders through untraceable spillover effects. The increase in income and consumption among clients receiving microloans from MFIs can have a multiplier effect on the income chain of others. However, it is acknowledged that distinguishing between the primary and secondary impacts of MFI services is a difficult task (Ledgerwood, 1998; Raihan et al., 2017).

The literature recognises three methods for measuring the impact of microfinance: the experimental method, the quasi-experimental method, and the non-experimental method (Ledgerwood, 1998; Odell, 2010). The experimental method entails the creation of two groups at random: a treatment group and a control group. The treatment group is given a specific intervention (for example, microcredit), whereas the control group is not. Although the selection of both groups is not random, the quasi-experimental method attempts to mimic controlled experimental analysis. The non-experimental method employs non-experimental survey data to compare the impact of microcredit on poverty among those who receive and do not receive microloans.

Much of the research on the impact of microfinance on poverty over the last decade has used randomised controlled trials (RCTs). Many researchers believe that RCTs are the "gold standard" for assessing the effectiveness of an intervention (Gloukoviezoff, 2016; McHugh et al., 2017; Odell, 2010). This means that if RCTs are rigorously conducted in ideal conditions, they can eliminate selection bias and produce excellent internal validity, implying that the intervention is the only factor influencing the outcome (Tomlinson et al., 2015). Ideal conditions imply that the treatment and control groups are chosen at random, and that factors other than the intervention that affect the outcome are perfectly balanced for both groups (Deaton & Cartwright, 2016).

In practise, ideal conditions are difficult to achieve, so RCTs do not always produce accurate results. Imbalances in the factors underlying the treatment and control groups frequently cause major issues (Goldberg, 2005). The difficulty in ensuring the balance of factors underlying the treatment and control groups limits RCTs to short-term assessments, as RCTs may only detect short-term effects rather than long-term ones. Furthermore, RCTs are frequently tested in contexts and groups with distinct characteristics, rendering their findings inapplicable to other groups with distinct characteristics. These issues are frequently referred to as transportability issues (Deaton & Cartwright, 2016) or RCTs with low external validity (Tomlinson et al., 2015).

This study uses a non-experimental method and opts for a macro-level impact analysis for specific reasons. To begin, People's Credit Banks (BPRs) are an essential component of the Indonesian financial system, with BPR operations reaching all provinces. In this case, a macro-level impact analysis is preferable to a micro-level analysis. According to de Aghion and Morduch (2010), studies using data from large geographic areas and diverse contexts can yield more applicable conclusions than RCTs. Second, as Odell (2010) emphasises, before implementing a programme, the identification and evaluation structure of its impact through RCTs must be established. This means that RCTs cannot be used to evaluate already-running programmes. It is important to note that BPRs have been in place in Indonesia for quite some time. As a result, rather than an experimental method like RCTs, the appropriate method for assessing the impact of BPRs on poverty is a non-experimental method.

2.2. Microfinance and poverty

Greenwood and Jovanovic (1990) assert that financial development can enhance access to financial services for all population strata. Improvements in financial service access, in turn, have strong implications for development achievements such as economic growth, poverty, and income distribution (Beck et al., 2007; Ismail, 2021; Levine, 2021; Ravallion, 2001; Zhuang et al., 2009). Financial service access for poor groups becomes increasingly open as Microfinance Institutions (MFIs) develop. This is because the establishment of MFIs is essentially aimed at serving poor and low-income communities who cannot be served by formal financial institutions due to their weak ability to provide collateral and the high transaction costs for small loans (Batinge & Jenkins, 2021; Sharma et al., 2021).

From a micro perspective, services provided by MFIs in the form of savings, credit, and payment systems directly contribute to poverty reduction (Asian Development Bank, 2000; Asian Development Bank Institute, 2001; Beck, 2015; Demirguc-Kunt et al., 2017; Tria et al., 2022). Savings in MFIs can be used by their owners as instruments to generate income in the form of interest, a source of funds for independent investment, to reduce the risk of selling productive assets when facing external shocks such as job loss, and to minimize the risk of high-interest debt. Similarly, credit provision by MFIs can increase borrower income through the creation of profitable new businesses, business diversification, business scale expansion, and technology improvements in economic activities. Furthermore, payment system services facilitated by MFIs can accelerate trade activities, impacting income increase. Additionally, savings and credit can also be used as buffers to prevent consumption from falling below the poverty line.

On a macro level, the presence of MFIs leads to the greater integration of the lower economic strata into the national financial system (Asian Development Bank, 2000). MFIs can function as institutional instruments to mobilize financial resources, which cannot be done by the formal financial sector. Moreover, various unsecured loan schemes offered by semi-formal and informal MFIs can address asymmetric information problems, which are major impediments to the financial sector in developing countries (Ahlin & Jiang, 2008; Buera et al., 2021). Consequently, increased mobilization of funds and reduced information asymmetry in financial markets will boost aggregate demand in the economy, thereby promoting economic growth, job creation, and poverty reduction (Banto & Monsia, 2021; Maksudova, 2010; Raihan et al., 2017).

Several researchers have developed theoretical models to assess the impact of microfinance. Ahlin and Jiang (2008) modelled the long-term impact of microfinance as a credit market improvement instrument on economic development through job type transformation. Their model demonstrates that job transformation from low to high quality facilitated by MFIs can promote economic growth and reduce poverty. Buera et al. (2012, 2021) integrated small-scale credit into a general equilibrium model. Their modelling shows that the majority of the benefits generated by microfinance are ultimately enjoyed by the poor and marginal entrepreneurs.

Islam and O'Gorman (2019) empirically calibrated Buera's et al. (2012) model for 21 countries to observe the impact of various microcredit policy alternatives. The results show that the impact of each policy alternative varies significantly between countries, concluding that no single credit policy can serve as a panacea for combating poverty. Imai et al. (2012) empirically tested the impact of microcredit on poverty levels using panel data from 48 countries and found that per capita microcredit affects the reduction of all poverty categories (headcount poverty, poverty gap, and poverty severity). This finding aligns with the study conducted by Félix and Belo (2019) for 11 Southeast Asian countries. Meanwhile, a study by Donou-Adonsou and Sylwester (2016) with 71 developing countries showed that microfinance credit does not play a role in reducing all categories of poverty. It can be concluded that most previous macro-level studies indicate that microfinance services play a significant role in reducing poverty levels.

A specific study to evaluate the impact of People's Credit Banks (BPRs) on poverty using provincial panel data in Indonesia was conducted by Devi (2016a, 2016b). Devi's (2016a) study examined the relationship between BPR assets and poverty levels using data from 27 provinces during 2000–2013 and, using Granger causality and cointegration tests, found no relationship between BPR assets and poverty, meaning BPRs do not affect poverty. Meanwhile, Devi's (2016b) study tested the impact of BPR credit on poverty levels in 27 provinces during 2000–2014 and, using two-stage least squares (2SLS) regression, found that per capita BPR credit affects poverty reduction in advanced and less advanced provinces but not in intermediate ones. Unfortunately, the application of the 2SLS method was not accompanied by an endogeneity test, thus questioning the reliability of the model. This is a weakness that will be corrected by the author's study.

3. Methodology

3.1. Statistical modelling

This study uses a small model with one equation where the model can be written as follows:

$$Pov_{it} = \alpha_0 + \alpha_1 Crdt_{it} + \alpha_2 Ycap_{it} + \alpha_3 Educ_{it} + \alpha_4 Unem_{it} + \varepsilon_{it}, \quad (1)$$

where *Pov* denotes poverty rate, *Crdt* is BPR credit per capita, *Ycap* is GDP per capita, *Educ* is education, *Unem* is unemployment rate, *i* is province, and *t* is year.

As mentioned in the literature review section, the contribution of BPR in fighting poverty can be represented by its three main services: mobilizing savings, channelling credit, and facilitating the payment system in the economy (Demirguc-Kunt et al., 2017). However, this study chooses credit as the representation of BPR as done by Félix and Belo (2019), Donou-Adonsou and Sylwester (2016), Imai et al. (2012). In addition, this study includes three additional independent variables as control variables (GDP per capita, education, and unemployment), which are intended to accommodate the varying levels of progress in Indonesian provinces (Ismail, 2021). It is expected that the coefficients of credit, education, and income or GDP per capita are negative, meaning that an increase in these three variables reduces poverty. Conversely, the unemployment coefficient is expected to be positive, because conceptually an increase in unemployment encourages poverty.

3.2. Estimation strategy

Equation (1) will be estimated using two assumptions: the independent variable is exogenous and the independent variable is endogenous. For the assumption of exogeneity of independent variables, Equation (1) is estimated with three static panel methods: Common Effect (CE), Fixed Effect (FE), and Random Effect (RE). From the three estimations, the best one is selected through model selection test and its reliability is evaluated.

While the estimation for the assumption of endogeneity of the independent variable will be done with the instrument variable (IV) using the 2SLS (two stage least squares) method. Following Imai et al. (2012), this study views credit as an endogenous variable that is influenced by other variables that are not included in Equation (1). The presence of the endogeneity problem causes the assumptions of the OLS (ordinary least squares) method to be violated, which results in biased estimation results. Therefore, it is necessary to find another variable as a representation of the credit variable that has a strong correlation with the credit variable but is not correlated with the dependent variable (poverty). Of course, finding an instrument variable that has these characteristics is a difficult problem.

Campbell and Mankiw (1990) state that the best instrument of a variable is the variable itself and, therefore, they use the lag variable itself as the instrument. The decision on the length of the lag used varies widely from case to case and generally empirical evidence of reliability is one of the considerations (Campbell & Mankiw, 1990; Donou-Adonsou & Sylwester, 2016). The estimation for the value of the instrument variable as a representation of the credit variable ($\widehat{Crdt_{it}}$) is done using the following equation:

$$\widehat{Crdt_{it}} = \beta_0 + \beta_1 wCrdt_{it-1} + \beta_2 wCrdt_{it-2} + \beta_3 Ycap_{it} + \beta_4 Educ_{it} + \beta_5 Unem_{it} + \pi_{it}. \quad (2)$$

We follow Campbell and Mankiw (1990) and Donou-Adonsou and Sylwester (2016) by using two lags (lag 1 and lag 2) of the credit variable to predict the value of the instrument variable. The credit variable in Equation (2) is weighted (w) according to the proportion of the number of BPR offices in each province to the number of offices in all provinces for each year. Following Imai et al. (2012), we also include all control variables in Equation (2) as determinants of the credit instrument variable.

The estimation stages in the 2SLS method are, first, estimating the value of $\widehat{Crdt_{it}}$ in Equation (2) and, second, estimating equation (1) with the OLS method but the value of the variable Crdtit is replaced by the value of $\widehat{Crdt_{it}}$. It is important to emphasise that estimations conducted through the 2SLS method provide reliable results when they hold to two fundamental assumptions concerning the validity of instruments. ***Firstly***, instrument relevance requires that the instrumental variables be correlated with the endogenous regressors. In other words, these instruments should have significant impacts on the explanatory variables under consideration. Without this correlation, the risk of weak instruments rises, potentially resulting in failure to capture variations in endogenous variables (Andrews et al., 2019). ***Secondly,*** instrument exogeneity implies that the instrumental variables in a regression equation must be independent of the error term. This assumption ensures that the instruments are not influenced by factors affecting the dependent variable, reducing estimation bias. Violations of this assumption may result in biased coefficient estimates and inconsistent estimation results (Angrist & Krueger, 2001). To ensure that these assumptions are met, we use diagnostic tests such as the Wu-Hausman, Sargan, and Weak Instrument tests in our analyses.

3.3. Data: definition and sources

In this study, poverty is defined as the population living below the poverty line as measured by three indicators: (1) Head Count Index, which is the percentage of the population below the poverty line, (2) Poverty Gap Index, which is the average expenditure gap of each poor person against the poverty line, and (3) Poverty Severity Index, which is the distribution of expenditure among the poor. Credit is credit per capita, which is the value of credit in rupiah disbursed by BPRs divided by the total population. GDP per capita is the value of GDP in rupiah at constant 2010 prices divided by population. Education is literacy rate, which is the percentage of the population that can read for a certain age to the total population of a certain age. Unemployment is the percentage of the labour force that is unemployed to the total labour force. To avoid large differences in values for all variables, BPR loans per capita and GDP per capita are expressed in logs when estimating the regression equation.

Indonesia currently has 34 provinces. However, because data for all provinces is unavailable, this study uses data from 31 provinces, excluding three provinces (North Kalimantan, Riau Islands, and Bangka Belitung Islands). Data on poverty headcount are available from 2005 to 2019, while data on the poverty gap and poverty severity are available from 2007 to 2019. As a result, regression estimations for poverty headcount are carried out using a panel dataset compiled from 31 provinces between 2005 and 2019. Regression estimates for the poverty gap and poverty severity are based on a panel dataset spanning 31 provinces from 2007 to 2019.

Data on BPR loans and offices are collected from various editions of "Indonesian Economic and Financial Statistics" published by Bank Indonesia and "Indonesian Banking Statistics" published by the Financial Services Authority (OJK). Data other than bank loans and offices are collected from various editions of "Statistics Indonesia" published by Indonesian Central Bureau of Statistics (BPS).

3.4. Statistical description

People's Credit Banks (BPRs) now operate in all Indonesian provinces. Figure 1 depicts the average per capita credit values in 31 provinces from 2005 to 2019. The top five provinces with the highest average per capita credit values are clearly Bali, Jambi, Yogyakarta, Lampung, and Maluku. West Sulawesi, Bengkulu, Gorontalo, Aceh, and North Maluku, on the other hand, have the lowest average per capita credit values.

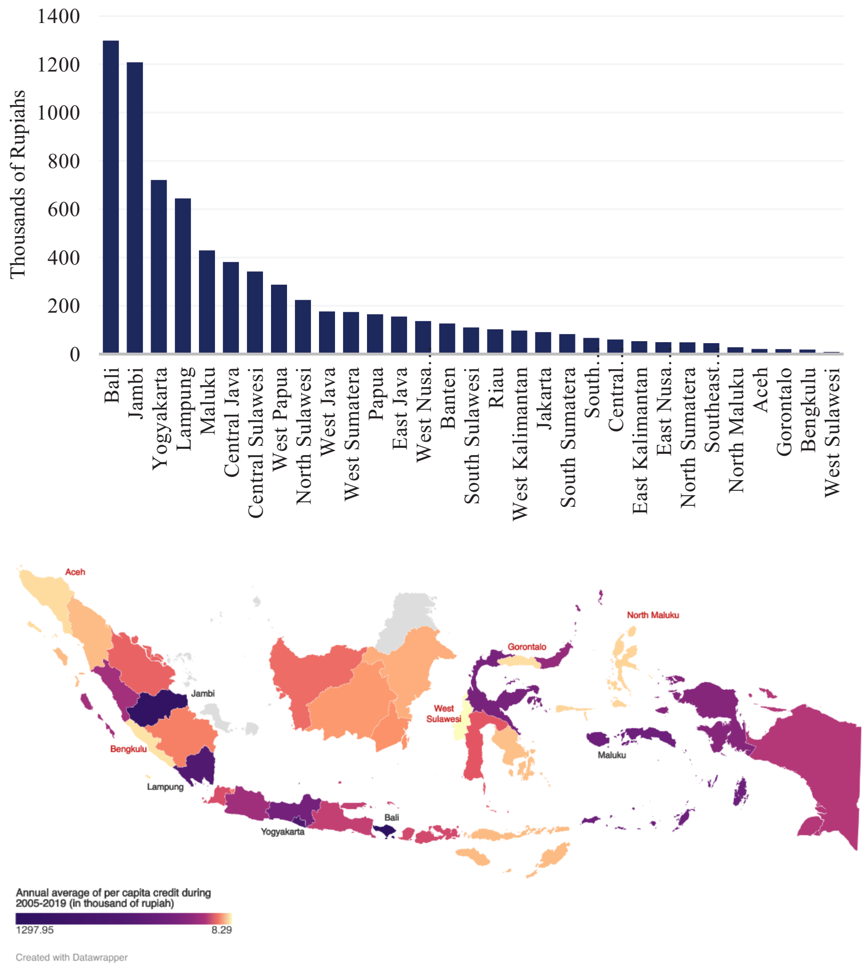

Figure 1. Annual average of per capita BPR credit during 2005–2019 by Province (in thousands of rupiah) (source: researcher's calculation results based on Bank Indonesia in various series)

Table 1 presents a description of the variability of research variables. Education has the lowest coefficient of variation (0.61%). This suggests that the level of education (literacy rates) in Indonesia is relatively consistent across provinces. The variable of credit per capita, on the other hand, has the highest coefficient of variation (165.206%). This demonstrates Indonesia's significant variation in credit per capita across provinces. According to the observed data, the lowest credit per capita (minimum) value is Rp0.051 million (in Central Kalimantan province in 2005), while the highest (maximum) value is Rp258.760 million (in Bali province in 2019). Furthermore, the coefficient of variation for the headcount poverty rate is relatively high (54.817%), with an average poverty rate per province of 14.32%. Jakarta province had the lowest headcount poverty rate (3.42% in 2019), while West Papua province had the highest (41.52% in 2006). Meanwhile, per capita income and unemployment rates have coefficients of variation of 84.576% and 46.429%, respectively. As a result, it is possible to conclude that economic diversity among Indonesian provinces is quite high.

Table 1. Description of research variables (source: author's calculations)

Variable	Coefficient of Variation	Mean	Standard Deviation	Minimum	Maximum
Pov	54.817	14.032	7.692	3.420	41.520
Crdt	165.206	20.250	33.455	0.051	258.760
Ycap	84.576	33.040	27.944	8.058	173.918
Educ	0.610	94.300	5.759	64.530	99.870
Unem	46.429	6.539	3.036	1.400	18.910

Table 2 shows the correlation between the research variables. All other variables have negative correlations with the poverty headcount variable *(Pov)*. Our expectations are met by the negative correlations between poverty and BPR credit *(Crdt)*, per capita income *(Ycap)*, and education *(Educ)*. A decrease in poverty is expected to be accompanied by an increase in per capita credit, per capita income, and education. In contrast, the negative correlation between poverty *(Pov)* and unemployment *(Unem)* is unexpected. In an ideal world, an increase in unemployment would be accompanied by a decrease in poverty rates. It is important to note, however, that correlation does not imply causation. In the following regression analysis, the causal relationships between poverty and influencing variables will be investigated. Table 2 additionally demonstrates the relationships between independent variables like per capita credit, per capita income, education, and unemployment. It is clear that the correlations between the independent variables are weak.

Table 2. Correlation between research variables (source: author's calculations)

Variable	*Pov*	*Crdt*	*Ycap*	*Educ*	*Unem*
Pov	1				
Crdt	–0.135	1			
Ycap	–0.302	–0.050	1		
Educ	–0.569	0.008	0.184	1	
Unemp	–0.003	–0.293	0.207	0.219	1

4. Result and discussion

4.1. Model estimation results

The estimation results using the static model are presented in Table 3, which contains three important pieces of information. The first information presents the model selection results to select the best estimation result. By using a combination of three test tools (Chow-test, Hausman-test and Lagrange Multiplier-test), it is found that the RE is the model that produces the best estimation compared to the CE and FE. This is true for all poverty categories (headcount poverty, poverty gap, and poverty severity).

The second set of information presents the estimation results of Equation (1) using the Random Effects (RE) model. Table 3 illustrates that the coefficient for credit is negative and statistically significant at the 1% level for the poverty headcount index and at the 5% level for the poverty gap and severity indices, aligning with our expectations. Meanwhile, the coefficients of the control variables generally align with expectations, although there are some

Table 3. Estimation of Equation (1) with static model

	Dependent variable:		
	Poverty Headcount	Poverty Gap	Poverty Severity
Model Selection Test:			
Chow-test	F = 15.292; df (1;2) = 120; 268; p-value = 0.00; RE selected	F = 2.026; df (1;2) = 120; 212; p-value = 0.00; FE selected	F = 2.844; df (1;2) = 120; 212; p-value = 0.00; FE selected
Hausmann-test	X^2= 5.890; df = 4; p-value = 0.208; RE selected	X^2 = 7.108; df = 4; p-value = 0.130; RE selected	X^2 = 8.582; df = 4; p-value = 0.072; RE selected
Lagrange Multiplier-test	X^2= 1759.7; df = 1; p-value = 0.000; RE selected	X^2= 728.17; df = 1; p-value = 0.000; RE selected	X^2= 770.16; df = 1; p-value = 0.000; RE selected
Selected Models	RE	RE	RE
Estimation of Equation (1):			
	RE	RE	RE
Intercp	81.027*** (7.796)	18.809*** (3.195)	6.231*** (1.103)
Crdt	−1.088*** (0.163)	−0.215** (0.075)	−0.068** (0.025)
Ycap	0.387 (0.739)	0.364 (0.298)	0.215* (0.103)
Educ	−0.649*** (0.069)	−0.192*** (0.027)	−0.075*** (0.009)
Unem	0.399*** (0.062)	0.082* (0.034)	0.028* (0.012)
TSS	1328	211	23
RSS	3808	297	34
R^2	0.651	0.290	0.309
Adj-R^2	0.648	0.282	0.302
F-stat	778.43	145.37	160.15
N	423	367	367
Classic assumption check			
No serial correlation	DW = 1,186; p-value = 0.00; assumptions violated	DW = 0.551; p-value = 0.00; assumptions violated	DW = 0.521; p-value = 0.00; assumptions violated
Homoscedasticity	BP = 10.202; df = 4; p-value = 0.037; assumptions violated	BP = 20.261; df = 4; p-value = 000; assumptions violated	BP = 15.105; df = 4; p-value = 0.00; assumptions violated

Note: Significance level: * p < 0.1, ** p < 0.05, *** p < 0.01. TSS – total sum squares, RSS – regression sum squares, parentheses under the coefficient show the standard error, and N – number of observations, DW – Durbin-Watson, BP – Breusch-Pagan.

deviations. Specifically, the coefficient for education is significantly negative at the 1% level across all poverty indicators, while the coefficient for unemployment is significantly positive at the 1% level for the poverty headcount and at the 10% level for the poverty gap and severity indices, consistent with expectations. However, the effect of per capita income is not as anticipated, as all coefficients for per capita income are positive. Notably, these coefficients are not statistically significant for the poverty headcount and poverty gap regressions, but they are significant at the 10% level for the poverty severity regression.

The third information reports the fulfilment test of classical assumptions for the selected estimation methods. The test results show that all estimations using the RE violate classical assumptions characterized by the presence of serial correlation and heteroscedasticity in all poverty categories. This indicates that the estimation results with the RE method are statistically biased and inefficient. Thus, the estimation results using the static panel model cannot be used as a strong basis for assessing the effect of BPR on poverty.

For this reason, the discussion needs to be shifted to estimation with the IV method. Table 4 displays the 2SLS method estimation results for Equation (1). It is critical to examine the Wu-Hausman, Sargan, and Weak Instrument tests to assess the reliability of the 2SLS estimation results. The null hypothesis of the Wu-Hausman test is that the independent and dependent variables have no correlation. The 2SLS method is not the best choice if the null hypothesis is accepted. The p-values obtained from the tests are remarkably low, as illustrated in Table 4, with 0.000003 for headcount poverty, 0.0008 for poverty gap, and 0.000008 for poverty severity. These findings lead to the rejection of all null hypotheses, indicating a significant correlation between the independent and dependent variables, confirming the accuracy of the 2SLS estimation.

Table 4. Estimation results of equation (1) with IV

	Dependent variable:		
	Poverty Headcount	Poverty Gap	Poverty Severity
Intercept	123.592*** (7.817)	23.661*** (2.265)	7.653*** (0.824)
Crdt	–2.125*** (0.507)	–0.510*** (0.139)	–0.186*** (0.051)
Ycap	–2.666*** (0.586)	–0.353* (0.158)	–0.021 (0.058)
Educ	–0.620*** (0.062)	-0.127*** (0.017)	-0.050*** (0.006)
Unem	–0.033 (0.112)	0.015 (0.033)	0.009 (0.012)
Wu-Hausman test	0.000003	0.00008	0.000008
Sargan test	0.667	0.753	0.591
Weak Instrument test	3×10^{-17}	4×10^{-16}	4×10^{-16}
Wald Test	4×10^{-35}	1×10^{-17}	4×10^{-16}
R^2	0.233	0.080	0.022
Adjusted R^2	0.225	0.069	0.010
N	387	344	344

Note: Significance level: * p < 0.1, ** p < 0.05, *** p < 0.01. Parentheses under the coefficient show the standard error, N – number of observations.

The Sargan test is used to test the validity of the instrument variables as a whole. The null hypothesis of the Sargan test is that there is no systematic correlation between the instrument variables and the residuals in the first stage estimation (estimation of Equation (2)). The test results in Table 4 show that the p-value is quite high, where the values are 0.667 for headcount poverty, 0.753 for poverty gap, and 0.591 for poverty severity. These test results show that the null hypothesis for all poverty categories is accepted, so the instruments used in this study are valid.

The last test is the Weak Instrument test. This test aims to determine whether the instrument variable has strong enough power to overcome endogeneity problems. The null hypothesis of this test states that instrumental variables are weak and have no significant correlation with endogenous variables. The test results in Table 4 show that the p-values are very small, namely 3×10^{-17} for headcount poverty, 4×10^{-16} for poverty gap and severity. These results imply the rejection of the null hypothesis, so it can be said that the instrument variables chosen in this study are able to overcome the endogeneity problem of the estimation results for all poverty categories.

Based on the results of these three tests, it can be said that estimation using IV is able to overcome endogeneity problems so that it can produce reliable estimates. In addition, as written in Table 4, the Wald test for estimation with IV also shows significant results for all poverty categories. And more importantly, the estimation results with IV produce coefficient signs which are all in accordance with theoretical predictions, where the coefficients for credit, income and education are negative while the unemployment coefficient is positive. Therefore, the estimation results using IV can be used as a guide for assessing the impact of BPR on poverty in Indonesia.

4.2. Discussion

As shown in Table 4, it is clear that the credit coefficient is negative and significant. This result applies to all poverty categories. This proves that credit disbursed by BPRs is able to reduce provincial poverty rates in Indonesia. Furthermore, not only is it able to reduce the proportion of people living below the poverty line (reducing the poverty headcount), BPR credit is also able to reduce the average expenditure gap of the poor against the poverty line (reducing the poverty gap), and is able to narrow the expenditure distribution of the poor (reducing the severity of poverty).

This illustrates that BPR credit has a high quality in fighting poverty in Indonesia. Through BPR credit, the poor who are close to the poverty line have a greater chance of rising above the poverty line and becoming free from poverty. Likewise, for the poor who are far below the poverty line, BPR credit increases their chances of rising above the poverty line. In addition, BPR credit also reduces expenditure inequality among the poor themselves.

The above findings are in line with the Indonesian government's policy that has positioned BPRs as financial service providers for the grassroots and MSMEs that cannot be served by large-scale formal finance. What has been launched by the government since 1992 is the right policy. Lending by BPRs has proven to be able to contribute to reducing poverty levels in Indonesia. From the perspective of Banking Law No. 7/1992, BPRs are formal banking institutions that must apply banking principles in their operations, such as collateral requirements for borrowers. However, these rigid practices do not prevent BPRs from participating in the fight against poverty in Indonesia.

The findings of this study also prove that Indonesia has other microfinance providers, besides Bank Rakyat Indonesia's Village (Unit BRI-Unit Desa), that can reduce the burden of problems experienced by all categories of the poor in Indonesia. So far, the success of microfinance in Indonesia has often been attributed to the success of BRI-Unit Desa, which has service coverage to all corners of the country coupled with healthy financial performance (Patten et al., 2001; Robinson, 2002; Rosengard et al., 2007). It should be noted that many other large-scale commercial banks in Indonesia currently have MSME divisions, just as Bank Rakyat Indonesia (BRI) has an MSME division called BRI-Unit Desa. The vastness of the microfinance market in Indonesia seems to be one of the attractions for commercial banks to enter the microfinance market. Despite having to contend with the MSME divisions of many commercial banks, BPRs with a relatively small share of loans can still play an important role in fighting poverty in Indonesia.

The results of the research that took the case of BPRs in Indonesia in general turned out to be in line with the results of previous research conducted by Buera et al. (2021), Félix and Belo (2019), Islam and O'Gorman (2019), and Imai et al. (2012). As mentioned earlier, the studies conducted by Félix and Belo (2019) and Imai et al. (2012) came to the same conclusion as the authors' study, where microfinance was able to reduce three categories of poverty. However, the results of this author's study contradict the study conducted by Donou-Adonsou and Sylwester (2016) which revealed no impact of microfinance credit on all poverty categories.

We now turn to the impact of control variables. Unlike credit, which has an effect on all poverty categories, the effect of control variables only applies to certain poverty categories. As shown in Table 4, per capita income has a significant and negative effect on the headcount poverty group and the poverty gap but no effect on the poverty severity category. This means that an increase in per capita income can, first, lift the poor who are below and close to the poverty line out of poverty and, second, increase the expenditure or income of the poor who are far below the poverty line to get closer to the poverty line. However, the increase in per capita income is not able to minimize the distribution of expenditure among the poor.

The results of the variation in the effect of per capita income on poverty seem to be in line with the study conducted by Suryahadi et al. (2009) who found that the impact of economic growth on poverty in Indonesia is uneven. The distribution of the impact of growth still depends on, among other things, the location where the poor are located (in villages or in cities) and what sectors have strong growth (agriculture, industry, or services). Growth in the agricultural sector in rural areas has a strong impact on rural poverty reduction. Meanwhile, the growth of the services sector in urban and rural areas is able to reduce poverty rates in all sectors. Unfortunately, the author's research is not as detailed as that of Suryahadi et al. (2009). This researcher only underlines that the finding of non-uniform income effects from this study is indeed in line with the growth phenomenon that occurs in Indonesia.

The effect of education and unemployment in this study is very clear. As shown in Table 4, education (as measured by literacy rate) has a negative and significant effect on all poverty categories. This means that improvements in basic education in Indonesia have been able to contribute significantly to the reduction of all poverty categories. The opposite is true for the unemployment variable. It is evident that unemployment does not affect all categories of poverty.

4.3. Implications

This study finds that People's Credit Banks (BPRs) significantly contribute to poverty alleviation in Indonesia. BPRs are formal financial institutions regulated by banking regulations and are not part of Microfinance Institutions (MFIs). Therefore, BPRs must implement strict procedures similar to those of general banks when providing credit services to their customers. However, this strict service process does not prevent BPRs from contributing to the fight against poverty. This indicates that BPRs can be a model of formal banking for other countries wishing to develop new instruments to combat poverty. The success of BPRs also shows that Indonesia has other formal financial institutions, besides BRI-Unit Desa, that can be relied upon to combat poverty.

It must be understood that microfinance services in Indonesia are not only provided by formal banking institutions (such as BPRs and conventional banks through SME divisions) but also by various types of MFIs with highly diverse characteristics, adding complexity to Indonesia's microfinance system (Holloh, 2001; Indonesia Financial Services Authority, 2016; Seibel, 2005; Soemitra et al., 2022; Steinward, 2013). An important question arises: do all types of microfinance in Indonesia contribute to poverty alleviation? Although the author's research finds the impact of BPRs on poverty, other studies have yielded pessimistic findings. For example, a study by Takahashi et al. (2010) revealed that one of the MFIs in Indonesia initiated by a Community Self-Help Organization (BPR-Yayasan Bina Swadaya) has not contributed to poverty reduction. Similarly, a study by Adam and Lestari (2017) found that the government-sponsored microcredit assistance program for Small and Medium Enterprises (*Kredit Usaha Rakyat*, KUR) has not shown significant results in alleviating poverty.

These findings suggest that not all types of microfinance in Indonesia contribute to poverty reduction. Consequently, further studies are needed to examine the impact of each type of microfinance on poverty. This recommendation seems applicable not only to Indonesia but also to other countries with high levels of microfinance complexity. As pointed out by Sun and Liang (2021), Remer and Kattilakoski (2021), Gloukoviezoff (2016), Odell (2010), and Goldberg (2005).

5. Conclusions

Microfinance is a complex fact as it involves many dimensions. Each country has its own unique type of microfinance so that microfinance practices differ greatly between countries. Microfinance studies that are conducted by combining several countries into one unit of study have a great potential to eliminate the role of each MFI. Therefore, this study is conducted in order to see the impact of BPR on poverty in Indonesia. BPR is chosen as the object of study because BPR is one of the most popular types of microfinance providers in Indonesia and Indonesia is one of the largest microfinance countries in the world.

This study uses static panel approach and variable instrument. It is found that the variable instrument approach with the 2SLS method provides more reliable estimation results than the static panel approach. The empirical results of this study show that credit channelled by BPRs is able to reduce poverty in Indonesia in a quality way. That is, not only is it able to release poor status for the poor who are below and close to the poverty line, but BPR credit is also able to increase the expenditure of the poor who are far below the poverty line to approach the poverty line, and is able to narrow the distribution of expenditure among the poor themselves.

This study has yielded additional findings in addition to BPR's contribution to poverty reduction. Basic education, which prevents illiteracy, helps to reduce poverty in all categories. Unemployment does not help alleviate poverty in all categories. Meanwhile, per capita income does not impact all types of poverty. Increases in per capita income only significantly reduce poverty in the categories of poverty headcount and poverty gap, but not in the category of poverty severity. This suggests that income and education policies can supplement microfinance policies in Indonesia's fight against poverty.

It is critical to note that this study only considers credit as a representation of BPR and does not consider other variables such as savings and smooth payments. In terms of poverty alleviation, BPRs' mobilisation of savings and provision of payment systems in the economy have significant potential. As a result, it is suggested that the study's limitations be considered as a topic for future research. Furthermore, given the variety of microfinance service providers in Indonesia and other countries, more research into the impact of each MFI on poverty should be considered.

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Author contributions

MI and DBS conceived the study and were responsible for the design and development of the data analysis. MI, DBS, and DS were responsible for data collection and analysis. DB and DS were responsible for data interpretation. MI and DBS wrote the first draft of the article.

Disclosure statement

The authors declare that there are no potential conflicts of interest in the writing of this manuscript.

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