FACTORS AFFECTING CREDIT RISK IN INDIA MICROFINANCE INSTITUTIONS

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DECLARATION

We hereby declare that:

(1) This undergraduate FYP is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the FYP.

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CAR	Capital Adequacy Ratio
CSM	Credit Scoring Model
GDP	Gross Domestic Growth
HI	Household Income
INR	Indian Rupee (₹)
JLG	Joint Liability Group
LS	Loan Size
MFB	Microfinance Bank
MFI	Microfinance Institution
NPL	Non-Performing Loan
ODTI	Other Deposit Taking Institutions
PAR	Portfolio At Risk
RBI	Reserve Bank of India
RCS	Registrar of Cooperative Societies
RIR	Real Interest Rate
ROA	Return On Asset
SBLP	Bank Linkage Programme
SHG	Self-Help Group
SME	Small and Medium Enterprise

ABSTRACT

The purpose of this research is to determine the factors that affect the credit risk of microfinance institutions in India. Quantitative research methods had been applied in this study by using the data that was obtained from the World Bank as well as the annual report from the six major microfinance institutions in India. E-views had been used for analyzing the data with descriptive analysis, Diagnostics test, F-statistic, T-statistic, Poolability test and Breusch and Pagan Lagrange Multiplier (BPLM) test.

The results found from E-views indicates that independent variables which are Loan Size (LS) and Household Income (HI) are significantly affect the credit risk of microfinance institutions in India while the other three independent variables which are Gross domestic product growth (GDP growth), Capital Adequacy Ratio (CAR) and Real Interest Rate (RIR) are insignificantly affect the credit risk of microfinance institutions in India. Furthermore, this study provided benefit to the India government to provide guidance and reference for policy implication.

CHAPTER 1: RESEARCH OVERVIEW

1.1 Introduction

The overview of credit risk in Indian Microfinance Institutions (MFIs) is presented in this chapter. Following a short introduction, the problem statement and research background are presented in this chapter. Problem statement is the issue that is discussed by the research team. In addition, research questions and objectives have stated to indicate the purpose of the research. Furthermore, this chapter also contains the significance of study and a short conclusion.

1.2 Background of Study

Bank activities are associated with several risks, including risks arising from internal and external processes. Bank risk refers to the potential loss to a bank due to the occurrence of particular events. However, these risks only can be mitigated but they are unable to be eliminated. Higher risk brings about higher profit in terms of profitability. Okafor and Fadul (2019) revealed that major risks faced by commercial banks comprise of credit risk, liquidity risk, market risk, operational risk, legal risk, capital risk, reputational risk, strategic risk, and off-balance sheet risk. These risks are generally being categorized into financial risk and non-financial risk. Non-financial risk is associated with the risk that is unable to be quantified, while financial risk usually can be measured by figures or ratios. Non-financial risk refers to legal risk, operational risk, counterparty risk, strategic risk and reputational risk, and financial risk consists of credit risk, liquidity risk, market risk and off-balance sheet risk.

Operational risk exists due to the uncertainty in daily operation, such as error made by employees or failure in computer systems. It is wide in range since it could have arisen due to misbehave of any individuals and personnel, systems, or processes, and external events such as natural crisis (Azar & Dolatabad, 2019). Legal risk is the non-financial risk faced by a bank on behalf of government regulations, which a bank failed in complying to the rules and regulations (Usanti, 2020). Bonime-Blanc and Ponzi (2017) stated in their research, reputation risk reflects the potential negative publicity of a company, most of the time, it arises due to the inappropriate or unethical behaviour of its employees. It generally associates with credit risk and operational risk (Hill, 2019). Strategic risk threatens a bank through an unsuccessful business, for instance, inappropriate resource allocation that led to bad decisions (Chockalingam et al., 2018). Off-balance sheet risk arises due to the uncertainty in income caused by unexpected loss due to the business that is not stated in the bank's financial statement, for example letter of credits (Zhang et al., 2020). Liquidity risk indicates the risk that a bank might be incapable of meeting contractual obligations or financial demands in the short-term (Scannella, 2016). The risk can also be defined as the inability of a bank to make a disposal of its asset, for instance, the securities held by the bank or other assets with market price (Papavassiliou, 2013).

Serwadda (2018) claims that credit risk refers to the potential of a bank's customer as well as counterparty unable to meet its financial obligation that has been agreed in the form of agreement. Generally, it was defined as the bank's debtors unable to repay the amount, including principal and interest, that is owed to the bank. Since lending activities are the main business of a bank, the bank always cares about the credit risk evaluation and management in their daily operation. In addition, credit risk is hard to reconcile simultaneously. Thus, credit risk is considered as one of the most essential risks in commercial banks (Jin et al., 2020).

Muralidharn and Sivaraman (2021) viewed from a wider range of perspective, banking is defined as any financial institution that accepts, collects, transfers, pays, exchanges, lends, invests, or safeguards money for its customers. Investment banks, financing companies, and money lenders are a few examples of banking institutions. Banking industry is significant to the economic activities as commercial banks function as the facilitators of cash flow by accepting deposits and conducting lending activities. Most importantly, commercial banks play a role as the major credit center which provides lending opportunities (Oteshova et al., 2020). To ensure the banks are solid in liquidity, commercial banks are usually subjected to minimum capital requirements which comply with the Basel accords that apply to the banking industry globally.

Muralidharn and Sivaraman (2021) found that aside from central banks, there are 11 types of banks in India, to name a few, investment banks, commercial banks, universal banks and offshore banks. In India, the bank functions as a financial institution that accepts deposit, granting of loan and advances, provides agency service in cash flow and provides utility (Muralidharn & Sivaraman, 2021). Although they are slightly different among the functions of various types of banks, the primary functions are accepting deposits and granting of loans and advances. The deposits received from the public will be utilized as loan disbursement to the parties that required funds, such as businesses and individuals to align with their uncertainties. As for the cost, borrowers are charged with a higher interest rate on loan than banks pay for deposits. The discrepancy of interest rate between deposits and loan will be taken by the banks as profit.

Banking system had become more consummate from the development of the industry. According to the World Bank (2023), India is categorized under the low income class. As stated in the study of Mohd (2018), the provision of financial services to the indigent and necessitous person can be essentially aided by microfinance. In a developing country such as India, microfinance is viewed as a helpful tool for socio economic improvement (Bi & Pandey, 2011). However, there is no historical research from the perspective of microfinance currently, even the microfinance industry started over in the 1700s. Moreover, it was first named as “microfinance” for the services in 1990, including microcredit and microsavings, to the poorer sections of the population or for those who are absent from formal employment and considered not eligible to involve in conventional credit lending. Primarily, the microfinance industry is serving poor people and women. Later, it also became popular in microbusiness and nonprofit organizations (Trezza, 2006). Before the formal system of microfinance services, poor people tended to borrow funds from money lenders, even if it was illegal. The microfinance services can be provided by MFIs or commercial banks that support microfinance services (Khan, 2018). As for the beginning, the project started with the concept of providing collateral free microcredit to the poor in the form of group lending. The system operates in the absence of a legal contract and is based on trust, peer monitoring, and collateral substitutes such as credit denial in the event of default (Mohd, 2018). In the study of Bi and Pandey (2011) the loans provided by MFIs serve the low-income population in various ways. MFIs provide working capital loans for small and medium businesses for start-up and operating. Loans for accessing necessities such as food, clothes, shelter and education are also being granted. Furthermore, they serve as alternatives to the loans provided by money lenders, which mitigate the problems caused by illegal borrowing activities.

Nowadays, microfinance does not only provide the service of microcredit, but it also covers microinsurance, housing credits, transfer of funds and remote financial services. It is predominantly product driven (Trezza, 2006). Furthermore, non-financial services which involve support services such as marketing and management, as well as social services that consist of education and healthcare etc. are also provided. Due to the small loan size, MFIs are required to ensure the solvency and financial soundness themselves so as to protect the depositors. Thus, MFIs are subjected to a minimum capital requirement that is above the capital adequacy ratios (CAR) for conventional banks (Tiwari & Fahad, 2004). However, the law imposed tends to be more lenient compared to commercial banks. In addition, the interest rates and fees charged tend to be lower and more flexible as well. BASEL II had announced that the CAR ought to be modified to the nature of microfinance risks for all types of institutions and the amount and sources of capital of institutions involved in microfinance (BCBS, 2010). A country is allowed to regulate specialized microfinance regulation. The same CAR will be applied for both Other Deposit Taking Institutions (ODTI) and banks in countries without specific regulation for microfinance activities. BASEL III required the minimum capital ratio of regular commercial banks to exceed 8% but there is no clear instruction or requirement updated for other institutions of microfinance services providers. Additionally, microfinance organizations could act as a bridge between borrowers and the conventional financial system and lend money secured by a public guarantee (Tiwari & Fahad, 2004). Microfinance services also comply with Basel requirements which restrict MFIs of a certain size or limited operation scope which attempt only to permitted activities, such as lending only to deposit taking. The risk management process of MFIs is less subjected to requirements and tends to be simple compared to commercial banks. However, MFIs require experts who are specialized in the MFIs in order to monitor the operation appropriately. In credit risk management, policies and procedures on microfinance loans only appear little differences with conventional loan, no matter the approval of new credit exposures or the renewal and refinancing of existing exposures (BCBS, 2010).

Since the 1990s, the banking sector in India has been rapidly changing as a result of technological innovation, financial liberalization with the entry of new private and foreign banks, as well as regulatory changes in the corporate sector (Kaveri, 2020). However, due to the cluster that commercial banks are unable to serve, microfinancing was introduced in India during the 1980s as a solution to poverty and to empower women. In India, the Self Help Group (SHG) - Bank Linkage Programme (SBLP), launched by NABARD. as a pilot initiative in 1992, is credited with sparking the microfinance movement with great success (Mohd, 2018). In order to assist the economically disadvantaged and lower income segments of society realise their dreams of owning a home, HDFC Bank has been collaborated with a German Development Bank Kreditanstalt fur Wiederaufbau (KfW) to provide low-cost housing project in India by implementing innovative low-cost technologies and locally available materials for construction (Piyush & Fahad, n.d.). This revealed that the regulatory framework for microfinance is not consolidated in India. Commercial banks, non-bank financial institutions, cooperative societies, and MFIs as well as non-governmental organizations are the providers of microfinance service. To name a few, the Reserve Bank of India

(RBI), which is the central bank of India, takes the responsibility to govern banks and non-bank financial institutions. Self Help Groups are monitored by NABARD, and the cooperatives are monitored by the Registrar of Cooperative Societies (RCS). As an agricultural country, microfinance acts a significant role in rural financing. Additionally, Joint Liability Group (JLG) act an essential role of providing financing activities for an MFI member while the members are guarantors of each other. Grameen Bank Model also offers savings and deposits to the underbanked and unbanked people due to their inability in income. Since it is dealing with small loans, it is able to cater the needs of people in India which is considered as low income. As a result, microfinance in India functions as one of the most effective and warranted Poverty Alleviation Strategies from the government's perspective. By assisting the microbusiness, it provides opportunities in self-employment especially among women who are involved in electronic activities (Mohd, 2018). The research of Abrar et al. (2021). suggested there is less study given on analyzing the impact of MFIs at the macro level although the institutions have changed the financial system of many countries by introducing a dual system in which both microfinance and conventional institutions operate.

According to the research from Nadeem Iqbal and Muhammad Mohsin (2021), they address how to successfully combine credit scoring model (CSM) with corporate risk management and offer guidance for microfinance businesses in evaluating and implementing credit risk management techniques. The study also gives policymakers a framework for measuring credit risk quantitatively, as well as instructions on how to address it, reduce credit risk, and increase loan distribution for their clients in a responsible manner. As a result, it is seen that education, bank credit, old customers, and interest rate have a bigger impact on the discriminatory effect in the study model (Iqbal & Mohsin, 2021). Low-educated and new customers have greater default risk, which requires more attention and this result is steady and consistent with the evaluation of the loan staff's expertise. High lending rates put customers at greater risk of default. Since the loan rate is based on the company's evaluation of the client's credit, this variable suggests that the loan rate affects the client's ability and desire to make repayments. MFIs may lack the professional knowledge, risk management tools, and experienced personnel in credit risk management to effectively compete with major commercial banks and other financial institutions such as international banks. The capacity of MFIs to manage credit risk and maintain their competitiveness depends on a variety of data processing technologies, including financial control, risk management, accounting, Internet banking, credit card service, customer care, and other systems. In order to effectively manage credit risk, it is essential to establish a clear structure, assign roles and responsibilities, priorities and discipline procedures, and assign accountability. In conclusion, MFIs operate in a distinctive business environment and confront distinctive risks, demanding a specific credit risk management strategy that takes quantitative factors into account.

Moreover, another research found that 99.8% of firms that fall under the category of small and medium-sized enterprises in the Czech Republic are heavily relying on banks for their access to external financing (Belas et al., 2017). Finding the elements that influence credit risk for SMEs may thus be an important contribution to the literature on SME financing since it can help entrepreneurs become more aware of these variables and show them how to easily acquire bank funding. The results of this study make it abundantly evident that banks place a heavy focus on important accounting indicators and characteristics that transfer risk from the bank to the borrower when making loans to SME (Belas et al., 2017). The results of the study demonstrate that the structural model's element representing education was its most important connection. This is further explained by the fact that information gained by the entrepreneur through a learning process focused on the wise use of money in life has a significant impact on their capacity to manage credit risk in a company. Entrepreneurs' financial literacy is directly correlated with their understanding of finance. The family environment is the second most crucial element in establishing an entrepreneur's capacity to effectively handle credit risk in a business. This environment offers a platform for obtaining helpful guidance on one's life, such as how to manage money and raise money.

Referring to the study from Isah Serwadda (2018), the report makes the suggestion that Ugandan banks create sensible solutions to address problems with credit risk management. The research aims to analyze the effect of credit risk management on the performance of banks with the use of credit risk management elements and financial performance metrics or measures. According to the empirical findings, the profitability of Ugandan commercial banks which was measured by Return on asset (ROA) is influenced by a number of critical credit risk characteristics, including growth in interest profits, non-performing loans, and the ratio of loan loss provisions to total loans. This is due to the negative impact inadequate credit risk management practices have on asset quality, which ultimately leads to a rise in loan losses and non-performing loans, exposing banks to financial difficulty (Belas et al., 2017). To be able to compete favorably, banks must develop effective management systems by working in environments that are favorable to credit, with strong loan evaluations, loan-granting procedures, and efficient credit administration control systems for ongoing monitoring and flow of the entire loan process.

Last but not least, according to the study from Kanak Pervez, overlapping credit issues between MFIs and their consumers have become a major challenge. As MFI branch offices don't have connected databases regarding their clients, overlapping occurs when one customer uses credit from multiple institutions simultaneously for the same purpose. It may increase systemic risk among MFIs and weaken the foundation of Bangladesh's microfinance industry as a whole. These clients who overlapped are having extremely difficult times paying back the credit balance to lending organizations. The fact that a quarter of MFIs customers accept loans from six or more different financial institutions leads to a severe repayment scenario in the microfinance industry (Pervez, 2018). A cash crunch brought on by the repayment problem has a negative impact on MFIs' normal performance. This critical problem may be solved by effective credit risk management, ensuring the long-term viability of MFIs. Credit risk management requires special attention since it is a crucial element and a pressing issue among the problems the microfinance business faces. The problem of credit risk management is crucial for sustainability as well as the expansion of the microfinance sector. The national economy can experience financial stability thanks to the MFIs sector's steady expansion and development. A lack of cash might result from poor credit risk management, which would bankrupt MFIs. If loan quality somewhat declines, the microfinance sector may experience a standstill. Credit risk management has become increasingly important in recent years as a result of the significant financial losses suffered by major international financial institutions.

However, only a few studies have been conducted to assess the impact of credit risk factors on credit performance, and no precise findings concerning the elements of credit risk management that can minimize credit risk have been made. There is not much research that has addressed how credit risk factors influence the credit performance of microfinance in India. Therefore, it is crucial to determine how credit risk factors affect MFIs' credit performance in India.

1.3 Problem Statement

Although India's GDP is among the top 15 in the world, the distribution of GDP (Figure 1.3.1) reaching USD 3.17 trillion in 2021, and GDP Per Capita (Figure 1.3.2) is not balanced, where only USD 2277.43 is captured. It means that the higher contribution of India's GDP has failed to improve its GDP per capita, thus resulting in poverty of about 300 million people and 60 million households are under the poverty line. There are about 20% who can get credit from formal institutions, and rural people are above the poverty line but not wealthy and do not have easy access to financial services, including savings services.

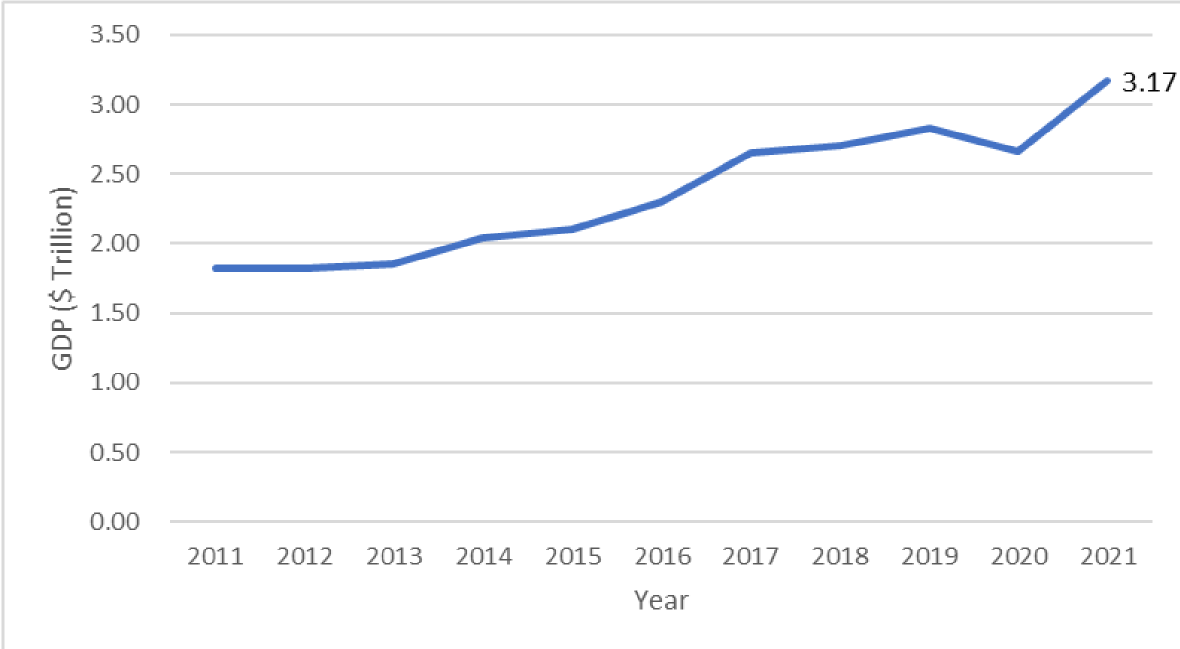

Figure 1.3.1. Gross Domestic Product (GDP) in India 2011-2021

Source: World Bank

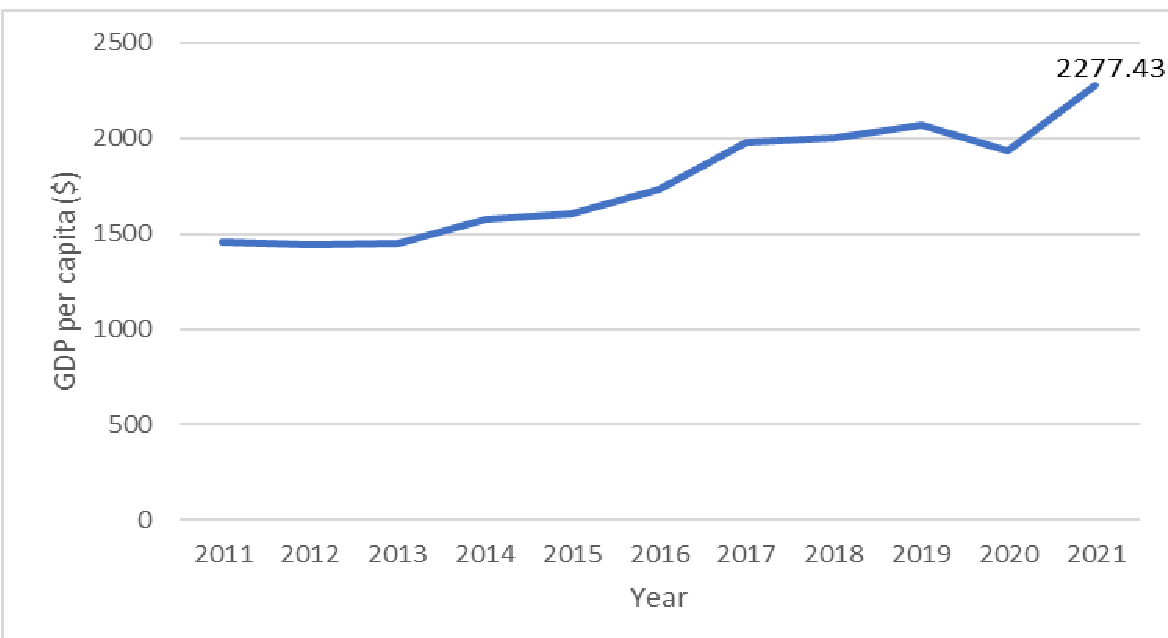

Figure 1.3.2. GDP Per Capita in India 2011-2021

Source: World Bank

In the past 20 years, the development of microfinance institutions in India has been remarkable and the loan growth increased constantly as the gross loan portfolio increased by 10% (Microfinance Institutions Network, 2022). Increase in the loan portfolio shows a good trend in MFIs lending activities, larger amounts of loan portfolio lending, with 113 million loan accounts, but it also gives a sign that Indian MFIs have a higher probability of facing credit risk. Following an increment in portfolio at risk (PAR>30) by 0.5% from 2021 to 2022, it means an increase in investment risk leads to higher chance of loss, subsequently, it will affect the borrower's repayment capacity and raise credit risk indirectly. The historical case of Andhra Pradesh (State of India) in 2010 shows that many microfinance institutions in Andhra Pradesh have suffered financial losses due to large size of loans, and are extremely fragile in their operation, including restructured microfinance institutions. As the result of numerous foreign invested money moving to few MFIs because the cost of lending in India MFIs is relatively lower, borrowers apply for loans from different MFIs, and they are therefore unable to repay the outstanding loans as well as repay the banks, leading to higher credit risks.

In India, microfinance institutions offer a variety of microfinance services as well as credit schemes. Microfinance in India targets a low-income clientele that has been overlooked by the mainstream banking system. The borrower's loan delinquency is heavily influenced by the socioeconomic features of the household. The lower a household's income, the more it needs a loan to raise their income. While India's fast expansion in the microfinance industry has drawn considerable foreign financial investment. However, several microfinance organizations charged customers exorbitant interest rates for loans, resulting in a "wave of late payments." The decision by the Reserve Bank of India in eliminating interest rate limitations on microfinance loans meant that there was no limit to the growth in interest rates on floating rate debt, including risk premiums, cost of funds, and other variables that complicate loan pricing.

As a result, the credit risk concern persists. It compels debtors to apply for another loan to cover the existing one, which can lead to a downward spiral of debt.

Since these problems may influence credit risk in Indian MFIs, it is critical to investigate the relationship from various aspects and offer solutions that would allow India's economic growth to progress.

1.4 Research Objectives

General Objective

I. To examine the factors that affect credit risk in India MFIs by NPLs.

Specific Objectives

I. To examine the impact of GDP growth on NPLs and credit risk in India MFIs.
II. To examine the impact of real interest rate on NPLs and credit risk in India MFIs.
III. To examine the impact of capital adequacy ratio on NPLs and credit risk in India MFIs.
IV. To examine the impact of loan size on NPLs and credit risk in India MFIs.
V. To examine the impact of household income on NPLs and credit risk in India MFIs.

1.5 Research Questions

I. What is the impact of GDP growth on NPLs and credit risk in India MFIs?

II. What is the impact of real interest rate to NPLs and credit risk in India MFIs?
III. What is the impact of capital adequacy ratio to NPLs and credit risk in India MFIs?
IV. What is the impact of loan size on NPLs and credit risk in India MFIs?
V. What is the impact of household income on NPLs and credit risk in India MFIs?

1.6 Significance of Study

India is the largest microfinance marketplaces in the world. In India, women's groups make small loans to borrowers who live far away or are too poor to borrow from banks. India's microfinance sector is a crucial enabler of financial inclusion. In academia, there will be a new discovery, the study of the credit risk of Indian MFIs. Therefore, findings from this study may give a clearer picture on factors influencing the MFIs credit risk in India and lead to NPLs. Annual interest rates on NPLs in India range from 25% to 100%.

Over the years, microfinance has spread across Indian states, infiltrated vast rural areas, and achieved great success in tackling poverty. Furthermore, this study is going to contribute a better comprehension of the MFIs credit risk in India and the factors of NPLs including GDP growth, real interest rate, funds, loan size, and household income to improve the credit of MFIs in India. The change in these factors will directly affect the credit risk of MFIs. A country's economic size and health are measured by the GDP growth of that country. Although India's GDP growth is not low, there is still a deviation phenomenon due to its large population.

With the development of the microfinance business, international capital gradually influx, and the scale of the microfinance industry is expanding. On the industrial side, many entrepreneurs have been able to tap into microfinance, which has greatly boosted the success of Indian SMEs and other businesses. A thriving SMEs sector is essential in creating new jobs and achieving high economic growth and has the greatest potential to provide employment to the 70 percent of the workforce still engaged in agricultural production. So, the growth of industry and services was spurred by the expansion of small and medium-sized businesses that were given loans after applying.

In addition, microfinance has expanded from simple credit for daily life to housing loans and loans for small and micro businesses, from simply meeting household consumption needs to increasing income through productivity improvement. This study will accord with an international understanding of the improvement of poverty alleviation efficiency and enhance the measurement of credit risk in the risk assessment process that influences the decision-making of loan providers. At the same time, the study will catch the attention of Indian politicians, regulators, and some in the microfinance industry amid concerns that unfettered expansion will lead to irresponsible lending, the concentration of loans to the same borrowers, and widespread delays in loan repayment. As a result, those involved can have a clearer understanding of the credit risk of MFIs in India and in some ways contribute to their policies to achieve more effective governance.

1.7 Conclusion

Chapter one gives a broad overview of this research by discussing the background, problem statement, research objectives, research question, significance and layout of study. The selected variables will receive more focus in the following chapter. The next chapter will go into more detail on prior research studies carried out by other researchers, theoretical frameworks, conceptual frameworks, and hypothesis development. The topic of research methodology is covered in chapter three. It is split into many categories, that is data collection, sampling design, research instrument, construct measurement, data processing, and data analysis. In contrast, chapter four will discuss the result of the analysis, and chapter five will examine the research's limits as well as recommendations.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

Macroeconomic variables, microeconomic variables and bank-specific variables are included because they are used as indicators of credit risk level. Macroeconomic variables are indicated by GDP growth and real interest rate; Microeconomic variables include household income; while bank-specific variables are indicated by capital adequacy ratio and loan size. Therefore, they become independent factors in explaining NPLs in this study.

The aim of this chapter is to provide, through selective reference to some of the literature. From the relevant past studies, business cycle theory, theory of loan, information asymmetry theory, and life-cycle consumption theory were selected that could further answer the above research question. A conceptual framework developed to elucidate the relationship between the dependent variable of NPLs and independent variables of GDP growth, real interest rate, household income, capital adequacy and loan size. Lastly, it is followed by the hypothesis development for further investigation.

2.1 Theoretical review

2.1.1 Business Cycle Theory

Barseghyan, L., Battaglini, M., and Coate, S. (2013) defined that a business cycle comprises stages of economic expansion, recession, trough, and recovery as well as the period of each of these stages will differ depending on the circumstances. The fundamental premise underlying the theory of business cycles is that an economy observes all the stages of the business cycle as a consequence of technological shocks. The literature review suggests that there is a strong relationship between NPLs and annual GDP growth. The explanation offered in empirical studies for this relationship is that higher levels of GDP growth typically correspond to higher levels of income. This enhances the capacity of borrowers to repay their debts and facilitates a reduction in bad debt. Conversely, when the economy is performing poorly, with slowing or negative GDP growth, the level of bad debt tends to rise.

Although the majority of the extensive empirical research supports the notion of an inverse correlation between GDP growth and NPLs, the evidence regarding the sensitivity of credit quality to growth performance is highly inconsistent and constrained by several limitations. According to Vazquez, F., Tabak, B. M., and Souto, M. (2012), loan portfolios across various categories exhibit varying degrees of responsiveness to macroeconomic conditions. Louzis, Vouldis, and Metaxas (2012) demonstrate that the quantitative influence of GDP growth on non-performing loans is more noticeable for corporate NPLs than for mortgage and consumer NPLs.

Furthermore, the relationship between NPLs and capital is considerable. The Business Cycle Theory, Barro (1979) introduces an economy-wide capital market with the Business Cycle as the model. A facet of this modification is that the relative prices appearing in the local product market supply and demand function is now the expected real rate of return on the earning asset, as opposed to the ratio of the actual price to the expected price. The capital adequacy ratio (CAR) may be seen as countercyclical in nature since it restricts the capacity of banks to leverage up their financial position (BCBS, 2010), this tends to increase the credit risk of banks. Since there is a positive correlation between capital and total income, which means that as capital increases, so does total income. Next, when the company's overall income increased, the non-performing loan element decreased in value. This will indirectly have a negative effect on stock price variables when it comes to NPLs. According to Eka Yulianti (2018), the

CAR value of Indonesian commercial banks has a substantial impact and can decrease the level of non-performing. This indicates that when a bank is able to enhance its capital adequacy ratio, it will minimize bad debts. According to the large majority of academic research, NPLs have a negative effect on the capital adequacy ratio. Bengawan (2019) also discovered that banks with a larger capital base tended to follow lax credit standards, resulting in a high proportion of NPLs.

2.1.2 Theory of Loan

The interest rate is a macroeconomic variable that is usually expressed as a percentage in a certain period, and it could directly affect the economic situation. According to Knut Wicksell's (1936) theory of loan, interest rates are distinguished from two angles, one is the natural interest rate and the other is loan rate. In this study, interest rate is the dependence on borrowing, which refers to borrowing rate or lending rate, which can be fixed rate or floating rate. The real market rate is the ratio of the loan market determined by the relationship between money supply and demand (Spahija, 2016).

According to this theory, the high interest rates come from huge demand for borrowing. The more efficient financial market is, the more choices borrowers have in terms of return, risk and liquidity. Instead, it would have the opposite result, with inefficiencies in financial markets allowing borrowers to make limited choices from returns, risk and liquidity. It pointed out an idea that there is a large demand for loans, and higher loan interest rates will force borrowers to bear higher loan interest rates. If the borrower fails to pay the principal plus interest on time, it is deemed as default of contract and increases the NPLs. From this perspective, a positive relationship between interest rate and NPLs is highlighted.

Several studies have shown that interest rates are positively related with NPLs while holding other variables constant. So, the decisions of determining NPLs toward the credit risk will be affected through the interest rate movement. However, the effect of interest rate on NPLs is not directly captured from short-term observation. It requires a long time to discover a fluctuation of interest according to the market movement, therefore interest rates have a long-term effect on NPLs.

2.1.3 Information Asymmetry Theory

The information asymmetry theory's component, which causes the problems of unfavourable assortment and moral hazard, is based on the idea that the borrower is more likely to know statistics regarding the dangers of the business for which they get funding than the lender. These challenges reduce the efficiency of financial transfers from surplus to deficit units.

Before a debt defaults, it goes into delinquency, which indicates that its chances of recovery are very slim. Loan default is the inability of a borrower to fulfil their loan obligations while they are still due (Balogun & Alimi, 1990). Additionally, a microfinance bank's (MFBs) potential inability to obtain its loan plus interest from borrowers is a coincidence (Warue, 2012). Because the majority of microloans are not secured, which might deteriorate the credit portfolio, MFIs throughout the world face the challenge of loan defaults. Furthermore, Loan default was described by Adedapo (2007) as the borrower's inability to defend his loan responsibility at the time it became due. Due to defaulting on a loan results in a loss of capital for the lender and renders banking operations unmaintainable, microfinance banks work to prevent delinquency and default. Besides that, Okorie (1996) found that in Ondo State, Nigeria, loan type, loan term, lending rate, borrower's poor credit history, borrower's income level, and loan transaction cost are factors associated with loan delinquencies, whereas loan size, repayment period, regulation, and enterprise productivity are contributory factors to the repayment capability, and consequently high default rates. In Uganda, inadequate loan provisions, illiteracy, and a lack of cash are the main reasons for loan default, making it crucial for loan officers to decide together whether to grant a borrower's request for a loan or not. However, an insufficient loan puts the business at risk, which causes default (Sheila, 2011) and makes the loan size become an important factor to be determined before the loan is approved.

2.1.4 Life-cycle Consumption Theory

Besanko and Braeutigam (2020) stated that individual household income is a behaviour studied by microeconomics. Incorporates income before tax pay of the householder and any remaining individuals 15 years and more established in the family, whether they are connected with the householder (Varlamova & Larionova, 2015). The life-cycle consumption theory describes the spending behaviour of individuals throughout their lifetime, taking into considerations of future income. The theory proposed that individuals attempt to streamline utilization of consumption over the lifetime, which is to borrow in the low-income period and increase saving during the high income period. People tend to engage in commitment during lower income time since they assume that their future income enables them to pay off the debts. However, the possibility of a borrower unable to make repayment on loan principal and interest is known as credit risk. Cash flow is an essential guarantee of the repayment schedule.

The valuation of existing assets has an effect on consumption in accordance with the life cycle model. In the long run, the proportion of consumption and income is consistent with cross-sectional facts, since higher income led to a higher saving ratio. The hypothesis also suggested the implication of the current income falling below the highest previous income, saving may become negative and stay negative. In this case, it is vague in the way in which low-income families could borrow to maintain level of consumption after depleting their assets. Furthermore, the yearly consumption propensity fluctuates with current income since a substantial part of the movement in income is transitory and therefore does not affect consumption.

Moldigliani and Brumberg (1954) proposed the hypothesis that everyone is a capitalist regardless of income level as all individuals save for retirement in a form or more in this paper. The theory assumes everyone started with zero monetary abundance, the distinction in long-lasting lifetime pays toward the start of the grown-up life cycle reflects contrast in natural capacity, contrast in human resources procured through training and family childhood and difference in admittance to the capital market. Uncertainty brings effect to the spending structure of an individual. In the research of Merton (1969), if risk is confined to financial assets, the fundamental rule for life-cycle customers of setting utilization relative to resources, stays genuine when utility augmentation was supplanted by anticipated utility expansion. From the assumption above, rich people are more likely to get loan approval.

This theory claims that consumption will be a function of wealth over the duration of life.

$C = (W+RY)/T$

C = Consumption

W = Wealth

R = Years until retirement

T = Remaining years of life

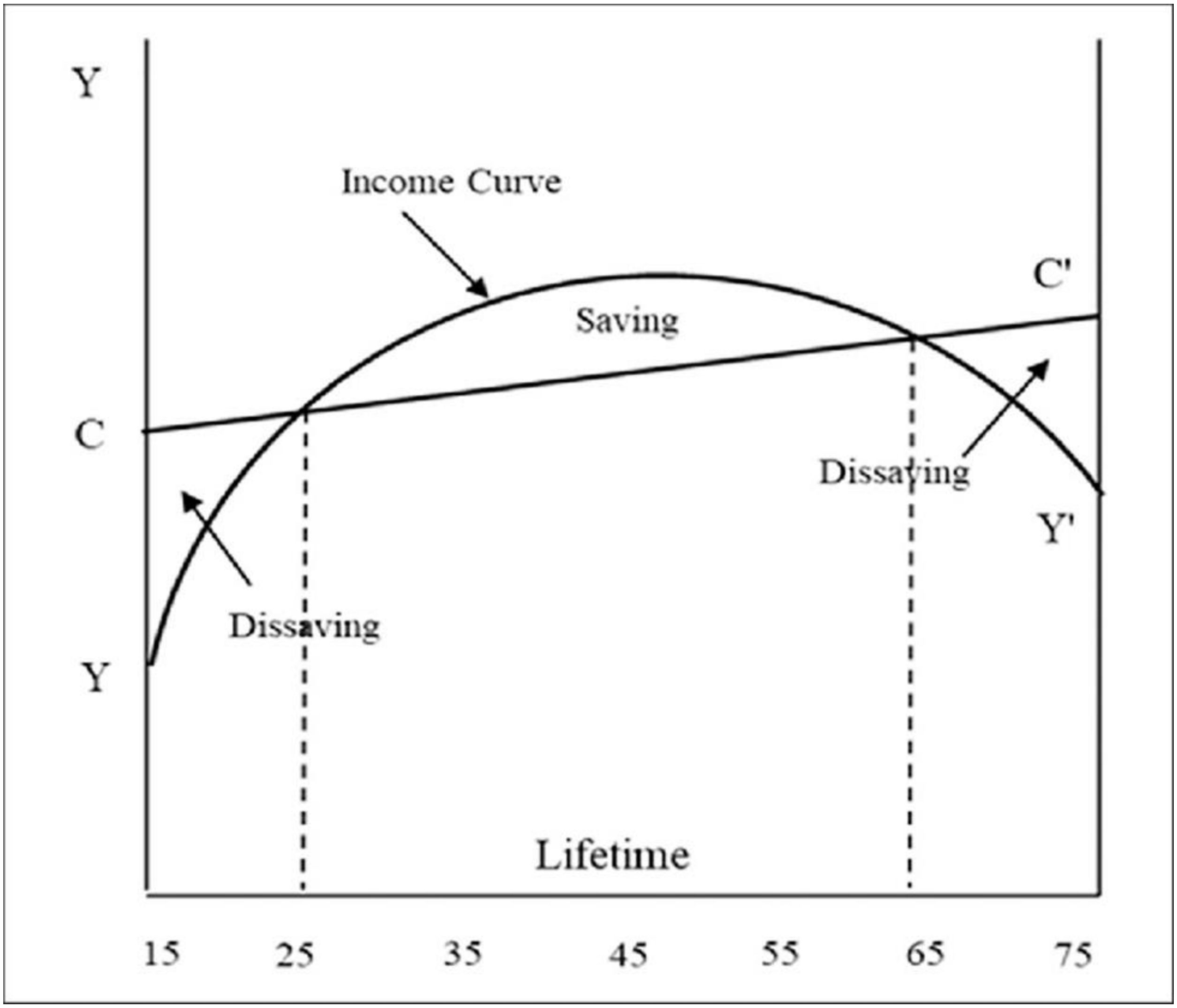

Figure 2.1.4. The Life-cycle Consumption Theory. From "The effect of expected income on wealth accumulation and retirement contribution of Thai wageworkers," by Ketkaew, C., Van Wouwe, M., Vichitthamaros, P., & Teerawanviwat, D., 2019, 9(4), 2158244019898247. Copyright 2019 by SAGE Open.

An empirical investigation on the likelihood of becoming in arrears is conducted utilizing a cross-sectional and time series approach, which is derived from a life-cycle model (Rinaldi & Sanchis-Arellano, 2006). The outcome revealed that the households might face greater exposure in financial standing under unfavourable shocks in their revenue and possession. Due to uncertainty in future income, the default risk of a borrower tends to increase. Lower income represents lower repayment capability, when the borrowers unable to meet their financial obligation with their future income are considered as default. Murthy et al., (2017) mentioned that borrowers inevitably require a loan to purchase an asset, the loans are more likely to default since the income of a borrower might be lower than the consumption.

2.2 Literature review

2.2.1 Gross domestic product growth (GDP growth)

GDP growth is typically defined as a steady increase in a country's output. The level of GDP growth rate indicates the rate at which a country or region's total economic output increases over a specific period and is also a measure of its overall economic vitality. Generally, GDP growth is one of the primary factors that impact the growth of NPLs.

There is an anticipated negative correlation between GDP growth and NPLs, meaning that higher GDP growth rates are likely to correspond to lower NPL levels. According to Singh, Basuki and Setiawan (2021), the findings indicate that NPLs are negatively affected by GDP growth. Additionally, the studies conducted by Mazreku (2018) revealed that a decline in GDP growth is likely to lead to an increase in NPLs. In another study utilizing panel data analysis, Kuzucu (2019) discovered that NPLs remained a statistically significant even during the post-crisis period. Demonstrating a negative correlation, the research of Al Masud and Hossain (2021) showed that there is an inverse relationship between GDP growth rate and NPLs, it can be justified that high demand for loans due to economic expansion caused banks to make more loans without properly credit rating the customers. In the long run, GDP has a negligible impact on property NPLs (Tham, Said, & Adnan, 2021).

Most previous empirical studies investigating the correlation between the macroeconomic environment and asset quality have found a significant negative relationship between GDP growth and NPLs. During an economic upturn, firms and households generally have adequate income streams to fulfill their debt obligations, whereas borrowers' ability to service their debts is reduced during a downturn. According to Naibaho and Rahayu (2018) and Szarowska (2018), NPLs tend to decrease or remain low during economic booms but increase during economic downturns or busts, as a result GDP growth has a negative and significant relationship with NPLs which NPLs will decrease as the GDP growth rises. When there is a decline in society's income, NPLs are likely to increase as customers may experience difficulty in repaying loans. This situation is commonly observed during a recession when a reduction in income can directly impact the ability of banking customers to make timely payments, leading to a rise in the NPLs ratio. When the economy is weak and under pressure, businesses face production and operational challenges, liquidity constraints, and financial difficulties, which can often result in an increase in NPLs for banks. Umar and Sun (2018) have provided evidence that among external macroeconomic factors, GDP growth has a significant impact on NPLs. Specifically, their study found an inverse relationship between GDP growth and NPLs, meaning that higher economic growth is associated with a reduction in the NPLs ratio in the country.

On the other hand, Shingjergji (2013) discovered a positive relationship between GDP growth and NPLs. According to this study, society's prosperity is improving. It indicates that people prefer to defer repayment of bank loans in order to prioritize saving, asset acquisition, investment, or consumption (Lubis and Mulyana, 2021). The results of this research align with the conclusions drawn from earlier investigations carried out by Agi and Jeremi (2018), which revealed a positive correlation between GDP growth and NPLs, though the impact was deemed insignificant.

Since previous studies produced conflicting results regarding the relationship between GDP growth and NPLs, this study aims to clarify this relationship; thus, GDP growth is chosen as the independent variable to explain NPLs, assuming a negative relationship between GDP growth and NPLs.

H1: There is a negative relationship between gross domestic product growth and non-performing loans.

2.2.2 Real Interest rate

The real interest rate is the loan interest rate adjusted for inflation. There is positive relation and significantly related to NPLs (Riantania et al., 2019). Raising real interest rates increases the cost of credit, leading to an increase in NPLs, because borrowers are unwilling to pay higher principal interest. Instead, they tend to repay on time with lower interest rates (Arham et al., 2020).

Iqbal (2022) pointed out that MFIs provide loans to borrowers on unfavorable conditions, such as offering small loans at higher interest rates for a limited time, which lead to the repayment performance of loan. The borrower might be unable to pay the high interest rate, thus causing a heavy burden on the debtor. Borrowers face high borrowing costs due to the practice of profit-making, charging higher interest rates on performance loans (Shonhadji, 2020). The finding is consistent with Arham et al. (2020) that rising interest rates affect higher credit costs and increased NPLs risk as borrowers default on their repayments. Hence, rising interest rates can worsen the loan quality. Panta (2018) stated that when interest rates increase, the borrowers' debt level rises. It said that borrowers were not informed about the interest rate changes and their consequences for them to pay interest plus principal on their loans when they reached maturity. The higher the debt cost, the harder it is for debtors to realize the loan term, thus reducing the repayment ability (Jote, 2018). Therefore, the probability of loan delinquency and default will increase with the increase of interest rates, which will bring great risks to the debtors (Ngonyani & Mapesa, 2018).

On the other hand, according to Ahmadi et al. (2019), the variable lending interest rate is significant, positive impact on NPLs. Atoi (2018) stated that interest rates limit borrowers' ability to repay debt, and rising interest rate repayment may increase the incidence of bad loans. It was also supported by Bredl (2018) that the likelihood of default occurs by charging higher interest rates on existing risky loans. There is a significant relationship among interest rates and debt payment. When interest rate increases, debtors find it difficult to repay their debts, thus affecting bad credit (Bellotti et al., 2020). In short, loans with higher interest rates are more likely to default. It is suggested that loans with lower interest rates should be provided and loans with higher interest rates should be reduced to maintain the positive relationship of real interest rate to NPLs (Gebeyehu, 2020). Nadeem Iqbal and Mohsin (2021) concluded that the loan interest rate depends on customers' credit evaluation. It reflects the accuracy of the company's credit evaluation of customers, and the loan interest rate itself will also influence the customers’ repayment ability and willingness.

In contrast, Rono (2020) found a negative relationship with interest rates and NPLs. Msomi (2022) stated lending interest rate negatively impacts NPLs, because interest rate is an unconstructive reason for NPLs. This implies that raising interest rates result in reducing NPLs. It is with Om’mbongo (2020) justification: lending interest rates negatively affect NPLs. It said that the reduction of bad debt depends on the adverse incentives of lending strategies to its related risks, such as repayment delay and default when lending to unreliable customers. It believed that preference for interest rate can cushion loan default and its subsequent impact on profitability. Wood and Skinner (2018) stated that real interest rate is significantly and negatively effect on NPLs, as higher lending rates can lead to slower loan growth, which reduces the NPLs level. Another interesting finding from Gebeyehu (2020) showed that real interest rates negatively affected NPLs in the short-term period; it said that real interest rate was only significant in the long term. Bahruddin and Masih (2018) justified that loan interest rates are asymmetric with NPLs in a short period, but symmetric with NPLs in the long term.

However, Mubin (2019) indicated that interest rate is insignificant on credit risk, because borrowers will continue to make loans to meet their day-to-day needs even if interest rates rise, it said current interest rates are not being overly concerned by customers. Purnamasari and Achyani (2022) shows that loan interest rates have no significant influence on NPLs. This illustrates that NPLs are not affected regardless of whether the loan provider raises or lowers the interest rate, because banks can implement some policies, such as raising the interest rate of new customers' loan. The study has proved that if loan providers recalculate the risk level of each borrower's credit evaluation when loan interest rate rises and sets aside some capital for the non-performing loan reserve, the formulation of policies is feasible, which can prevent the risk of NPLs. Additionally, Arham et al. (2022) found there is an interaction between real interest rates and state governance has an insignificant relationship on NPLs. It suggested real interest rate was not considered as an element to reduce NPLs from macroeconomic factors.

Since previous studies showed different outcomes of interest rate and NPLs relation, this study intends to clarify this relationship and hence, real interest rate is chosen as an independent variable to explain NPLs, with the hypothesis of positive relationship of real interest rates and NPLs.

H2: There is a positive relationship between real interest rates and NPLs.

2.2.3 Capital Adequacy Ratio (CAR)

The capital adequacy ratio, or CAR, demonstrates bank capacity in maintaining sufficient capital and the management capacity of identify, evaluate, and manage risks which might have an influence on a bank's capital size. CAR accounts for the risk of losses that a bank may experience (Eka Yulianti, 2018). Banks are better able to withstand the risk of any credit or high-yielding asset with high credit risk the higher the CAR. If the data of CAR is increased, the bank can finance its operations as well as greatly increase its revenue. As a result, there is an unfavorable relationship between capital and subprime loans. Significant effects can be seen and non-performing loans can be decreased by Indonesian commercial banks' CAR values. (Eka Yulianti, 2018). This suggests that a bank will reduce bad debts when it is able to improve its capital adequacy ratio. An appropriate CAR ratio calculation of listed firm bank capital should also be adept at preventing all business risks from happening, such as non-performing loans (Reyhan Farras Brastama, 2020). These investigations confirmed the research's finding that CAR and NPL have an inverse relationship. The bank will have fewer non-performing loans and a stronger flexibility to minimize credit risk as the CAR increases. Then, in EL-Maude (2017)'s journal, Djiogap and Ngomsi examined factors influencing long-term bank lending in the Economic and Monetary Community of Central Africa (CEMAC). Panel data is used from 35 commercial banks in six different African countries for years 2001 to 2010. Fixed-effects model is used in examining bank size. According to the report, CAR significantly slows down the number of NPLs. It shows that well-capitalized and more diversified banks are better prepared to sustain potential credit.

The connection between the opposite NPLs and CAR is positive, this is what Bengawan (2019) research suggests. Banks with a larger capital base are more likely to pursue liberal credit policies, resulting in a greater number of non-performing loans. According to Muhammad Asif Khan's (2016) empirical study, NPLs in Indonesian state banks are reduced due to the capital adequacy ratio (CAR).

However, Bengawan (2019) stated CAR does not affect NPLs in Indonesia traditional commercial banks. Additionally, Eka Yulianti (2018) supports this claim by showing that NPLs have a slight negative impact on financial performance. Few banks are anticipated to have substandard loans outside of their regulatory jurisdiction, so the effect is negligible.

Capital adequacy ratio is selected as the independent variable for explaining non-performing loans. Given the divergent opinions and conflicts of researchers, the hypothesis is suggested:

H3: There is a negative relationship between capital adequacy ratio and NPLs.

2.2.4 Loan size

Borrowers may receive loans in the form of small, medium, or large loan amounts. The majority of MFIs create small and medium-sized loan products to meet the needs of low-income and underprivileged household clients (Adurayemi et al., 2019). Assuming that the loan size equals the money that the borrower has asked for, this loan amount represents the degree of risk tolerance and estimation of repayment capacity of the intended borrower. The loan size that borrowers get from the microfinance should be effective and matches their repayment capacity as the loan size has an impact on the ability of the MFIs to collect the repayments (Lubis et al., 2021).

According to the research from Adurayemi (2019), there is a positive relationship between loan size and risk of default, the higher the amount of the loan size, the higher the risk involved throughout the default period. This indicates that a client's capacity to pay installments for the duration of a loan repayment depends significantly on the size of the loan they borrow from the microfinance bank. The study shows that the risk connected with the client's non-repayment of the loan might grow dramatically as a result of the loan amount and demonstrates how important loan size is when a loan is in default. It could be explained by the fact that a borrower may feel it more challenging to return a big loan amount with cumulative monthly payments than a borrower with a smaller loan amount and fewer monthly payments in the period of loan default. Moreover, the study from Oluwaseyi and Adegoke (2021) shows that the loan size is having significant and negative impact on the loan repayments which means the loan payback rate decreases as loan size increases and it will cause the default during the payment period. In other words, the possibility that the borrowers will be capable of repaying their loans is higher and the default probability is lower when the loan size is lower. Furthermore, the research conducted by Olivaresa et al (2021) also points out that loan size is positive in explaining both individual and group loan failures significantly which indicates that the default rate is rising as a result of increased loan size. These findings are aligned with the research conducted by Sanchez et al. (2021) as the study mentioned that average loan had a consistently positive and significant effect on NPLs behavior.

In the other way, Lubis et al. (2021) has a different result compared to the previous studies, their study found that loan size is having a negative relationship with the probability of default. This might be as a result of the staging that the Indonesian microfinance system uses in which clients are given the option to acquire loans with larger amounts by having a record of on-time repayment. Another idea to explain the negative relationship is larger loan size will cause larger investments with possibly greater returns and thus decrease the probability of default (Lubis et al., 2021). Moreover, the study from Ashhari and Nassir (2015) also mentioned that the amount of loan has a significant and positive relationship towards loan repayment performance which eventually decreases the NPLs due to the strict monitors and frequent visits conducted by the institutions to the large loan amount borrowers.

However, a study from Haile (2015) and Nelson (2020) showed that borrower's MFIs' loan repayment performance was not significantly influenced by loan size or loan amount. In other words, both studies point out that the loan size does not influence the loan repayment performance and yet has no impact on the credit or default risk of the MFIs which will not cause any problem related to the non-performing loan.

Neither the relevant study nor the previous research is having the same result or same significant level of loan size on the NPLs. Hence, this study includes loan size as one of the independent variables and assumes there is a positive relationship between loan size and NPLs to determine the relationship among them.

H4: There is a positive relationship between loan size and NPLs.

2.2.5 Household Income

Microfinance industry mainly serves the customers who are low income that are not eligible to enjoy conventional banking services. In this research, income distribution is measured by the income per capita since it automatically adjusted the household size. Kuznets (1976) claims that it is necessary to convert size distribution per household into household income per capita. This eliminates the inequalities of household income distributions since the numbers of members in families vary. By using income per capita, the impact of the life cycle on household size, and individual welfare within a household can be corrected (Datta & Meerman, 1980). Since the effects of the life cycle are not taken into account, a measure that spontaneously revises for household size also decreases some of the inaccuracy in the measurement of income.

Household income is expected to be negatively related to NPLs. The repayment hypothesis had been proven in different past studies regarding loans to different industries. In a study of home mortgage default, household income is important in explaining credit default since it affects the probability of default (Rachmansyah et al, 2021). Antoniou et al. (2022) stated in their study, low income increases the debt carried by households and increases the possibility of a household's default. In their study concluded a positively significant relationship between the debt service to income ratio and household's default likelihood. By comparing households with the lowest debt service to income ratio percentile, their study concluded that households which carried 37% and above can have up to 44% higher likelihood to default. A better management of funds resulting in higher income in the agriculture industry, allows higher ability of loan repayment (Oladeebo et al., 2008). Borrowers with low income become risky due to the restriction of their repayment capacity (Naili & Lahrichi, 2022). In their research, banks might charge 'risky clients' with higher loan interest rates that lead to a worsening repayment ability of low-income individuals.

Moreover, a high level of income enhances the capacity of borrower repayment, which contributes to lower default risk (Messai and Jouini, 2013; Kjosevski et al., 2019).

Hence, low household income leads to high NPLs. An empirical study on mortgage loans shows that low-income and moderate-income borrowers carry higher defaulting likelihood, compared with higher income borrowers (Fout et al., 2020). In their research, if the income of borrowers relative to median income increases, the rate of default tends to decrease. However, low-income households are highly vulnerable to credit risk, since they are severely affected by the property, death, health and disability risk (Lassoued, 2017). Low-income customers are encouraged to be protected by insurance to mitigate the losses suffered due to specific events. In order to mitigate credit risk, MFIs charged lower rates through diversification, predominantly non-interest income as an alternative to prevent the default of a low-income borrower. During the economic expansion period, the repayment capacity of the borrowers have improved, supported by the favourable movement of income (Lassoued, 2017). The outcome generated by the research of Lassoued (2017) stated that higher income flows create better solvency of small borrowers, resulting in an increase in the profitability of MFIs. Furthermore, a study of student loans reveals that the default risk of students from lower family income is higher than students from wealthy families (Ionescu & Simpson, 2016). Low-income borrowers are assumed to be risky in credit, the study of Priyankara and Sumanasiri (2019) confirmed that most microfinance borrowers obtain loans for other purposes such as settling other loans and daily consumption purposes, which places their repayment ability jeopardized.

In contrast, arguments of high household income associated with high credit risk also exist. This is proposed by the research of Blanco and Gimeno (2012), in which high level of household income distribution leads to higher level of indebtedness by DRSL and DRNB model. In the empirical study of Zainol et al. (2018), household income distribution is proven to be positively affecting the NPLs in both long run and short run in Malaysia by using ADRL approach. Since their study focused on housing loans, the assets might be purchased for an increase in high disposable income in the long-term, rather than becoming shelters for primary holders.

According to Rinaldi and Sanchis-Arellano (2006), income is insignificant in explaining the relationship between income and NPLs. This could imply that these households do not possess most of the financial assets or do not own investment portfolios. In addition, household income is claimed to be insignificant to NPLs since it is incompatible with the life cycle hypothesis (Theong et al., 2022). They assumed rational consumption behaviour is the predominant factor of NPLs instead of household income distribution. The insignificance of household income revealed that the default of loans is not mandatory driven by source of revenue but depends on the household rational consumption behaviour that is able to wisely manage their limited income. Moreover, household income is possibly not significant to the loan default due to the use of consumer credit facilities to substitute wages.

Previous studies show inconclusive results between the relationship of household income and NPLs. It had aroused the interest in examining the actual relationship between the household income and NPLs in this study with the hypothesis below:

H5: There is a negative relationship between household income and NPLs.

2.3 Conceptual framework

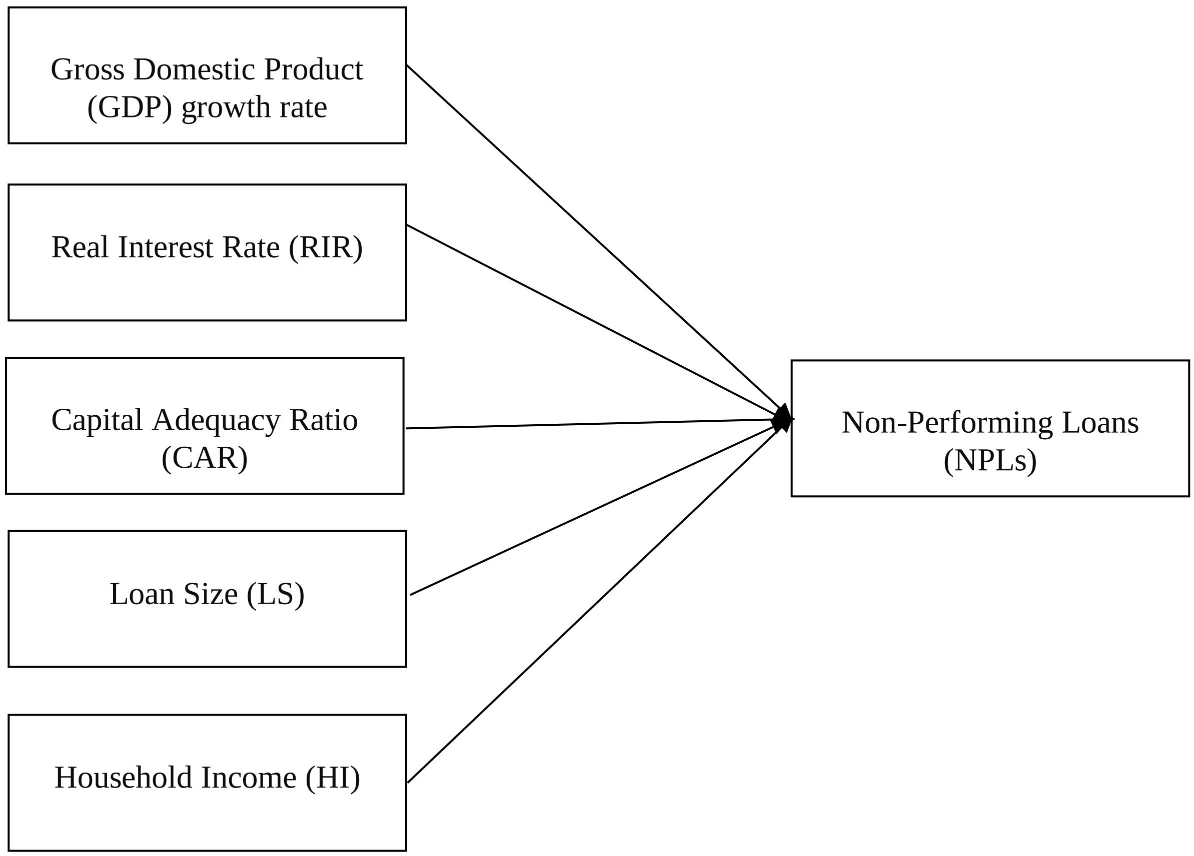

Figure 2.3: Proposed Research Framework

CHAPTER 3 METHODOLOGY

3.0 Introduction

This chapter provides an overview of research methods, consisting of research design, data collection methods, and data analyzing that include descriptive analysis, inferential analysis and diagnosis analyzing. The objective of this chapter is determining the explicit methods that would be conducted in chapter four.

3.1 Research Design

The "blueprint" for empirical research, which tries to address certain research questions or test particular research hypotheses, is called the research design, and it must include at least the following three procedures: First, the process of the data collection, second, the process of scale development, and third, the process of sampling (Akhtar, 2016). In the first phase of the literature evaluation, this paper uses the content analysis method to obtain the data of credit risk of microfinance institutions in India and reduce the factors of non-performing loans. Thus, this research has used quantitative research to process. (Richard A. Swanson, 2009) The process of quantitative research includes the collection and analysis of numerical data, which is the systematic investigation of data and the relationship between the data collected. In addition, the content of this study is the use of secondary data to conduct research questions. The data are analyzed using descriptive and inferential techniques. In addition, the inferential analysis also mentions proposed analysis tools to support the analysis.

3.2 Data Collection

This research is using secondary data to answer the research questions. Since this research is composed of both cross-sectional and time series data, the panel data are obtained from the World Bank and annual report of six different MFIs in India within the time period of 2012 to 2021. The microeconomic factors which are GDP and interest rate, as well as microeconomic factors, which is household income, are collected from the World Bank. Meanwhile, bank specific variables which consist of CAR and loan size are obtained from the annual report. Other data sources such as official websites, news and journals were also included in this research.

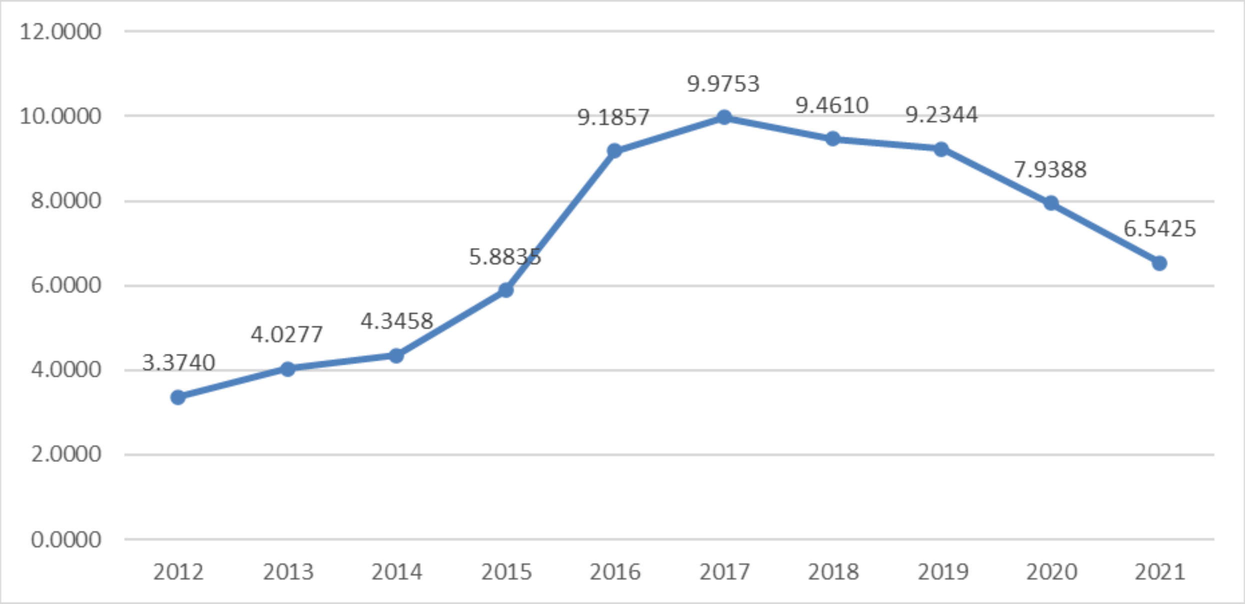

Figure 3.2 Bank NPLs to Total Gross Loans (%) in India

Source: World Bank

By looking at Figure 3.2, it is indicated that the percentage of bank NPLs to total gross loans in India is fluctuating across 2012 to 2021. There is a significant gap between 2015 and 2016 of the default risk. Also, a global financial crisis occurred during the COVID-19 pandemic but the percentage of NPLs in India's banking sector showcased a reduction value. Thus, it is meaningful to study the impact of macroeconomic, microeconomic and bank specific factors to NPLs.

Additionally, six MFIs in India are selected in this research includes National Bank For Agriculture And Rural Development (NABARD), CreditAccess Grameen Limited (CreditAccess), Small Industries Development Bank of India (SIDBI), ESAF Small Finance Bank (ESAF), Housing Development Finance Corporation Limited (HDFC) and AU Small Finance Bank (AU SFB). The data of these MFIs are meaningful to be studied since they are targeting to provide financial services for different purposes or serving different targeted customer segments. NABARD is predominantly focusing on promoting sustainability and equitability in agricultural as well as rural development. CreditAccess and ESAF mainly serve the low income household by fulfilling basic needs of its customers, for instance health care, education, appropriate shelter, water, and sanitation. Additionally, SIBDI and HDFC are providing banking services to the business sector. However, AU Bank targeted to provide financing for both Micro, Small and Medium Enterprise (MSME) and the unreached and unbanked population of India.

3.2.1 Secondary Data

The data utilized for the analysis is panel data. The data included six MFIs in India as observations with 10 years ranging from 2012 to 2021. The details are stated in the table below:

Table 3.2.1

Source of Data

Variables	Proxy	Units	Explanation	Data Sources
Non-performing Loan	NPLs	INR (₹)	Amount of loan more than 90 days passed without the payment of agreed installment and interest by the borrowers.	Annual report of MFIs

Gross Domestic Product growth	GDP	Percentage (%)	Annual percentage growth rate of GDP at market prices based on constant local currency.	World Bank
Real Interest Rate	RIR	Percentage (%)	The lending interest rate adjusted according to the inflation rate as measured by the GDP deflator.	World Bank
Capital Adequacy Ratio	CAR	Percentage (%)	Sum of Tier 1 and Tier 2 capital divided by Risk Weighted Assets (RWA).	Annual report of MFIs
Loan Size	LS	INR (₹)	The amount agreed by the borrower and the lender.	Annual report of MFIs, official website, news and journals
Household Income	HI	INR (₹)	Gross Disposable Income (GDI) of India household.	CEIC, World Bank

Note: INR refers to Indian Rupee (₹)

3.3 Descriptive Analysis

Descriptive analysis is a fundamental method for analyzing data that involves statistical summaries of data pertaining to all variables in the survey. This method incorporates several fundamental statistical tools, including frequency analysis, concentration trend analysis, dispersion analysis, distribution analysis, and straightforward graphical representations of the data (Kemp, Hort, & Hollowood, 2018). Mean tables by subgroups are used to demonstrate significant differences between subgroups, resulting in inferences and conclusions. Random variation can often result in differences in means or other statistical measures when comparing different groups or samples. Nonetheless, it is crucial to ascertain whether or not these variations are statistically significant. This research used Eviews to analyze descriptive data. The coefficient in a regression model in Eviews stands in for the predicted effect size of the independent variable on the dependent variable. In contrast, the dependent variable is explained by the model. The standard error of the regression coefficient is a measure of the uncertainty of the coefficient estimate, with larger standard errors indicating less precise estimates. The t-statistic is used to test whether a coefficient is statistically significant or different from zero, with larger absolute t-values indicating greater evidence against the null hypothesis of no effect; Prob represents the likelihood that the regression coefficient's t-statistic value falls inside a certain range in the regression result, if Prob is less than the test level, it means that the corresponding coefficient estimate is significantly different from zero; otherwise, the coefficient is not significant; R-squared is the sample decidable coefficient; the adjusted R-squared of the model estimate, which is the corrected sample decidable coefficient. A higher value of the R-squared statistic signifies that the regression model is a good fit for the dependent variable, and the independent variables included in the model can account for a significant proportion of the variation observed in the dependent variable. Besides, the result also showed Log likelihood which is a statistic based on the maximum likelihood estimation as well as the F-statistic are the F-test statistics and their corresponding probabilities, respectively, used to test the overall significance of the equation. This research will run the data through Eviews and interpret the generating data results.

3.4 Research Framework

The research framework is an econometric regression model to examine the significance of Non-Performing Loan (NPL) with variables of Gross Domestic Product Growth (GDP), Real Interest Rate (RIR), Capital Adequacy Ratio (CAR), Loan Size (Loan Size), Household Income (HI) in six MFIs in India from 2012 to 2021, as estimated in equation 1.

$$\log \widehat{NPL}_{it} = \beta_0 + \beta_1 \log (GDP)_{it} + \beta_2 \log (RIR)_{it} + \beta_3 \log (CAR)_{it} + \beta_4 \log (LS)_{it} + \beta_5 \log (HI)_{it} + \varepsilon_{it} \quad \text{(Equation 1)}$$

where log_NPL = Non-Performing Loan (in INR)

log_GDP = Gross Domestic Product Growth (in percentage)

log_RIR = Real Interest Rate (in percentage)

log_CAR = Capital Adequacy Ratio (in percentage)

log_LS = Loan Size (in INR)

log_HI = Household Income (in INR)

ε = error term

i = MFIs in India (NABARD, CreditAccess, SIDBI, ESAF, HDFC, AU SFB)

t = time (annual observation from 2012 to 2021)

3.5 Inferential Analysis

3.5.1 Propose Analysis Tools

Throughout the study, there are numerous independent factors and one dependent variable. Following the determination of the regression analysis, the following step will be to select the type of data to be used. It is preferable to utilize panel data in this scenario, which combines time series and cross section components. The rationale for utilizing panel data is to detect and measure effects from a larger data set than merely pure time series or cross-sectional data, hence the more accurate the result is. This research uses quantitative data. The reason for using panel data is to consider different characteristics (heterogeneity explicitly) by allowing subject-specific variables and to minimize bias in the model. Besides, it provides more information and data, more variability, less linearity and more degree of freedom, hence, it is more effective than using only one direction of data. There are three types of panel regression model, which is (1) pooled ordinary least-squares model (POLS), (2) fixed effects model (FEM), (3) random effect model (REM); and its effectiveness and consistency is further investigated by (1) Poolibility hypothesis test, (2) Hausman test, (3) Breusch and Pagan Lagrange Multiplier (BPLM) test respectively.

3.5.1.1 Pooled Ordinary Least-Squares Model (POLS)

POLS or constant coefficient model, the intercept and slopes of coefficient are constant due to its nature of intercept and regression coefficients are the same for all cross-sectional variables, with no time effect. In other words, POLS can also be said as a homogeneous model. It is assumed that the regressor is exogenous, whereby independent variables are independent from the past, present and future values error term. It is normally distributed between independent variables and error term, which means that there is uncorrelation between independent variables and error term, therefore hypothesis testing result is valid. Hence, OLS estimation can be used with all conditions met, which is BLUE (unbiased, linear, have the least variance in the estimators). However, POLS raises some problems, as the model does not distinguish between the effect and characteristics, it causes the estimated parameter value to be biased and inefficient, and there is heterogeneity in the observed values in different periods.

3.5.1.2 Fixed Effects Model (FEM)

FEM or fixed effect least-squares dummy variable (LSDV) model, in which unobserved effects are allowed to be arbitrarily related to explanatory variables within a time period (Wooldridge, 2015), with its unique features of cross-sectional data that allow the use of dummy variables that result in different intercept, each variable have its own special character. Slope of coefficient remained constant and had no time effect. However, it is recommended not to include many dummy variables in the model because FEM fail to determine time invariant impact, due to nuisance variable of unable detect the impact of unwanted factor such as environmental conditions, and lurking variables (fail to measure the variables that will affect dependent and independent variables exist in the model). FEM can be used when an individual-specific intercept is correlated with one or more regressors with its possibility of causing unobserved heterogeneity and multicollinearity problem in the model.

3.5.1.3 Random Effect Model (REM)

REM or Error Components Model (ECM) assumes that intercepts are randomly selected from a huge population with a constant average. The single intercept is expressed as a deviation from the average value of the constant. The slope of coefficient remained constant and had no time effect. This is appropriate when the random intercept of each cross-sectional element is irrelevant to the regressors. Since independent variables are less than FEM, there is less probability of occurrence of multicollinearity problems in the model. In order to obtain BLUE estimation in REM, Generalized Least Square (GLS) is used in estimation instead of using Ordinary Least Square to avoid the error term being found not constant which leads to autocorrelation problems due to the random variables generated.

3.5.1.4 Poolibility Hypothesis Test

Poolibility test is used to test whether there is a common intercept exist in all the variables (null hypothesis with POLS) and there is no common intercept exist in all variables (alternative hypothesis with FEM), that is determined by the F-test statistic or P-value. If the test statistics are less than the critical value, it is concluded that the POLS model is best to use; If the experimental statistic exceeds the critical value, it is considered that the FEM is best (Wooldridge, 2015).

H_0 : There is a common intercept in the model (POLS is preferred).

H_1 : There is no common intercept in the model (FEM is preferred).

3.5.1.5 Hausman Test

Hausman test proposed by Hausman (1978) is used to determine the REM (null hypothesis) and FEM (alternative hypothesis). Hausman test shows that fixed effect is the best fit model in the study by using the H-test statistic or P-value. If the test statistic is greater than the critical value, FEM is preferable because FEM is more consistent to be used; If the significant level is more than the P-value, REM is preferable and more consistent to be used than FEM.

H_0 : There is a common intercept in the model (REM is preferable).

H_1 : There is no common intercept in the model (FEM is preferable).

3.5.1.6 Breusch and Pagan Lagrange Multiplier (BPLM) Test

The BPLM proposed by Breusch and Pagan (1979) is used in heteroscedasticity testing with assumption of normal distribution of error terms. BPLM tests the hypothesis in random effect occurring in the model. If the P-value is more than significance level, this can be concluded that homogeneity exists in POLS assumption, hence POLS is preferable; If the P-value is less than significance level, it can be concluded that heterogeneity exists and there is random effect, hence REM is more preferable.

H_0 : There is a common intercept on bank performance in the banking system. (POLS is preferable).

H_1 : There is no common intercept on bank performance in the banking system. (REM is preferable).

3.5.2 Diagnostic Test

3.5.2.1 Normality test

A common initial step in data analysis is to test the data for normality. The normality test determines whether data conforms to the normal distribution which is a particular type of statistical distribution. The mean and standard deviation of the data serve as the parameters for the symmetrical continuous distribution known as the normal distribution. The data being studied must roughly conform to normality for many statistical analysis methods to perform. The normality test assists in determining whether the data meets that requirement. There are several benefits to doing a normalcy test, including compliance with the fundamental premise of statistical tools and the ability to move forward with research while appropriately responding to the p-value. Jarque-Bera (JB) test can be implemented to determine the normality. Set the null hypothesis (H0) as the data are normally distributed and set the alternative hypothesis (H1) as the data are not normally distributed. The decision will be made based on the p-value, we reject H0 when the p-value is lower than the alpha and conclude that the data is normally distributed. The equation for the JB test is shown as follow:

$$JB = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right]$$

3.5.2.2 Multicollinearity test

High intercorrelations between two or more independent variables in a multiple regression model are referred to as multicollinearity. When a researcher tries to figure out how well each independent variable can be utilized to predict or comprehend the dependent variable, multicollinearity can result in skewed or misleading conclusions. When two independent variables are significantly correlated, multicollinearity may be present. It may also occur if two independent variables generate identical and repeated findings or if an independent variable is calculated using data from other variables in the data set. Multicollinearity may result in less accurate regression model findings, causes the coefficient estimators to swing wildly, and makes them susceptible to minor changes in the model. To identify the multicollinearity problem, there are few indicators to detect such as pairwise correlation; multicollinearity might occur when the pairwise correlation between two independent variables is higher than 0.8. The most accurate indicators to determine multicollinearity is Variance inflation factor (VIF) as it identifies correlation and also the strength for this particular correlation among the independent variables, the equation and value of VIF represent the results as follow:

$$\text{VIF} = \frac{1}{(1-R)^2}$$

Table 3.5.2.2

Rules of Thumb of VIF

Values of VIF	**Results**
1	No correlation between independent variables

1 - 5	Moderate correlation between independent variables (do not need any corrective measures)
5 - 10	Critical levels of multicollinearity between independent variables where the coefficients are poorly estimated
> 10	Signs of serious multicollinearity between independent variables which require immediate correction.

3.5.2.3 Heteroscedasticity

Heteroscedasticity refers to the unequal scatter and the variance of the error term are non-constant. These variations give a measure of the deviation of data points from the average value and may be used to quantify the error range between data sets, that are predicted results and actual results. Generally, heteroscedasticity might cause the variance of the estimators to become inefficient and less accurate as there is less chance to reject the null hypothesis when the confidence interval has become larger. White test can be implemented to determine heteroskedasticity errors in regression analysis.

The estimated linear regression model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_p X_p + \mu$$

The auxiliary regression equation:

$$\hat{\mu}^2 = \alpha_0 + \alpha_1 X_1 + \alpha_p X_p + \alpha_{11} {X_1}^2 + \alpha_p {X_p}^2 + \alpha_{21} X_1 X_p + \nu$$

The test statistic formula for white test is shown as follow:

$$n*R^2$$

Set the null hypothesis (H0) as the variances for the error are equal (homoscedasticity) and set the alternative hypothesis (H1) as the variances for the error are not equal (heteroscedasticity). The decision will be made based on the test statistic value or p-value, we reject H0 when the test statistic is higher than critical value or the p-value is lower than the alpha and conclude that the data is having heteroscedasticity.

3.5.2.4 Autocorrelation

Autocorrelation refers to the degree of similarity of the same variable two successive time intervals which can cause the underestimation of the standard deviation from the predicted variable. The Durbin Watson Test can be implemented to determine autocorrelation problems in regression analysis. The decision will be made based on the test statistic, setting the null hypothesis (H0) as there is autocorrelation problem exist in the model and set the alternative hypothesis (H1) as there is autocorrelation problem exist in the model, concluding that autocorrelation exists when the test statistic value is less than lower critical value (dL) or the value is more than the value from (4-dL), autocorrelation does not exist when the test statistic value fall between upper critical value (dU) and the value from (4-dU). Otherwise, the result is inclusive.

Table 3.5.2.4

Decision rule of Autocorrelation

Durbin Watson test statistic	**Decision Rule**
$0 \sim d_L$	Reject H0, there is autocorrelation problem exist in the model

d_L ~ d_U	Inconclusive
d_U ~ (4-d_{U-})	Do not reject h0, there is no autocorrelation model exist in the model
(4-d_{U-}) ~ (4-d_L)	Inconclusive
(4-d_L) ~ 4	Reject H0, there is autocorrelation problem exist in the model

CHAPTER 4: DATA ANALYSIS AND RESULT

4.0 Introduction

In chapter four, it discusses factors affecting NPLs in India MFIs will be conducted based on the research framework. The factors influencing the NPLs of MFIs in India consist of GDP, real interest rate, loan size, CAR, and household income. Pooled Ordinary Least Square (POLS), Fixed Effect Model (FEM) and Random Effect Model (REM) will be carried out accordingly, followed by Poolibility Test and Breusch and Pagan Lagrange Multiplier (BPLM) Test to determine the appropriate model in the research. Diagnostic testing will be conducted in order to investigate issues on normality, multicollinearity, heteroscedasticity and autocorrelation.

4.1 Descriptive Analysis

This research consists of 60 observations from India MFIs and World Bank, and CEIC. The six different MFIs in India included NABARD, CreditAccess, SIDBI, ESAF, HDFC and AU SFB. Additionally, the data are being retrieved between 2012 to 2021 from the annual report.

Table 4.1

Descriptive Analysis Result from E-views Output

	log NPLs	log GDP Growth	log RIR	log CAR	log LS	log HI

Mean	21.19202	1.700434	1.450885	3.072208	26.22234	12.87755
Median	21.29425	1.890460	1.676089	3.020422	26.79040	18.25580
Maximum	25.73386	2.161163	2.022407	3.602504	31.73035	18.69471
Minimum	15.40475	0.000000	0.000000	2.681022	19.36143	0.000000
Std. Dev	2.595683	0.617547	0.594564	0.247910	3.554597	8.503236
Skewness	-0.234921	-2.048992	-1.348344	0.347940	-0.234278	-0.871518
Kurtosis	2.138695	6.035446	3.931550	1.939196	2.035126	1.767507
Jargue Bera	2.406498	65.01851	20.34979	4.023888	2.876320	11.43010
Probability	0.300217	0.000000	0.000038	0.133728	0.237364	0.003296

Observation	60	60	60	60	60	60

Source: E-views 12 output generation

Table 4.1 summarized the outcome of descriptive analysis of NPLs as dependent variable in this research, with the independent variables of GDP growth, RIR, CAR, LS and HI. Referring to the table above, the mean value of log NPLs, log GDP growth, log RIR, log CAR, log LS and log HI stated 21.19202, 1.700434, 1.450885, 3.072208, 26.22234, 12.87755 respectively. The median recorded accordingly by 21.29425, 1.890460, 1.676089, 3.020422, 26.79040 and 18.25580 for log NPLs, log GDP growth, log RIR, log CAR, log LS and log HI. The maximum value existed in log LS, which is 31.73035, while the minimum value recorded 0.000000 in log GDP growth, log RIR and log HI. In addition, the highest standard deviation appeared in log HI by 8.503236, indicating the highest volatility in the sample. It followed by log GDP growth 0.617547, log RIR 0.594564, log LS 3.554597 and log CAR 0.247910. The lowest standard deviation recorded in log CAR, showing that there is not much discrepancy of CAR in six different MFIs across 10 years. However, the fluctuating value represented that bank specific factors, microeconomics factors and microeconomic factors might bring impacts on the NPLs.

4.2 Diagnostics Test

Diagnostic testing will be conducted in order to investigate issues in error terms of the model, by including normality testing, multicollinearity testing, heteroscedasticity testing and autocorrelation testing.

4.2.1 Normality Test

Normality tests identify the normal distribution of error terms in the FEM within this research. The Jarque-Bera test has been conducted to investigate the error term on its normality distribution.

Table 4.2.1

Jarque-Bera test

Jarque-Bera	6.248547
Probability	0.043969*

Note. ***,**,* denote significant levels at 1%, 5% and 10% respectively.

Source: E-views 12 output generation

By referring to the result from Table 4.2.1, statistics of the histogram showcased a normal distribution in error term. The null hypothesis stated that there is a normal distribution. At the significance level of 0.10, the null hypothesis is rejected since the probability stated 0.043969 which is smaller than the significance level. Thus, this research does not reject the null hypothesis with normally distributed error terms at significant level 10%.

4.2.2 Multicollinearity

Multicollinearity problems may arise due to highly correlated between two independent variables. In this research, Variance Inflation Factors (VIF) are applied to identify the existence of multicollinearity issues.

Table 4.2.2

Result of VIF

Independent Variables	**VIF value**
GDP	1.675685
RIR	1.398754
LS	7.443688
CAR	2.831449
HI	2.594061

Source: E-views 12 output generation

According to the rules of thumb of VIF, there is no critical multicollinearity issue in GDP, RIR, LS, CAR and HI whereby the value of VIF from the calculation is less than the max value of 10. Therefore, it is believed that immediate correction on the model is not necessary. However, LS should be paid attention in this research with a VIF value of 7.443688, which might be due to the poor estimation between independent variables. In conclusion, the multicollinearity issue does not exist in the model since no compulsory adjustment is required.

4.2.3 Heteroscedasticity

Heteroscedasticity problems tend to exist when the error term is not constant. This research carried out a Likelihood Ratio Test to identify heteroscedasticity problems of the model. Moreover, panel data are assessed with Panel EGLS to examine the existence of heteroscedasticity problems of independent variables.

H0: There is homoscedasticity in the model.

H1: There is heteroscedasticity in the model.

Table 4.2.3

Result of Heteroscedasticity

Likelihood Ratio	40.08481
Probability	0.0000***

Note. ***,**,* denote significant levels at 1%, 5% and 10% respectively.

Source: E-views 12 output generation

From the result above, the model contains heteroscedasticity problems since the null hypothesis is rejected at 1%, 5% and 10% level of significance.

Independent Variables	**t-statistic**	**Prob**
Log GDP growth	-1.161112	0.2507
Log RIR	5.945568	0.0000***

Log CAR	-2.056977	0.0445**
Log LS	9.763920	0.0000***
Log HI	1.881897	0.0652*

Note. ***,**,* denote significant levels at 1%, 5% and 10% respectively.

Source: E-views 12 output generation

By looking at the independent variables individually heteroscedasticity issue exists in RIR and LS at levels of 1%, 5% and 10%. The heteroscedasticity problem does not exist in CAR at 1% significance level. HI is considered to be heteroscedasticity at level 10% but the problem does not exist at level of 1% and 5%. GDP is homoscedasticity in error terms at 1%, 5% and 10% level of significance. In conclusion, LS and RIR are facing heteroscedasticity problems.

According to the BPLM Test, REM is a better model than POLS that fits the data set. BPLM Test is a test to identify the heteroscedasticity in the data set. The result suggested that a random effect existed in the data. Thus, REM should be applied when analyzing the panel data. However, the Hausman Test was unable to decide the better model between FEM and REM. Due to the inconsistent result generated from the Poolability Test and BPLM Test, the best model are selected based on the value of adjusted R-square. This is because higher adjusted R-square represents that the percentage of dependent variable can be explained by the independent variables in the model after taking into account the degree of freedom. FEM is selected as the best model due to a higher adjusted R-square than REM that carried an adjusted R-square of 38.82%.

4.2.4 Autocorrelation

Autocorrelation exists since observations of a sample are significantly related to each other across in the panel data. This research is using the Durbin Watson test to identify the issue of autocorrelation in the model.

Table 4.2.4

Result of Durbin Watson Test

Durbin Watson test Statistics value	0.835159
d_L	1.248
d_u	1.598

Source: E-views 12 output generation

Decision Rule of Durbin Watson Test

H0: There is no autocorrelation problem in the model.

H1: There is an autocorrelation problem in the model.

Durbin Watson test statistic	**Decision Rule**
0 ~ 1.248	***Reject H0, there is autocorrelation problem exist in the model***
1.248 ~ 1.598	Inconclusive
1.598 ~ 2.402-	Do not reject h0, there is no autocorrelation model exist in the model

2.402-- ~ 2.752	Inconclusive
2.752 ~ 4	Reject H0, there is autocorrelation problem exist in the model

Since the Durbin Watson test value is 0.835159 which falls between 0 and lower critical value, the result is showing that there is an autocorrelation problem in the model.

Alternatively, if the fixed effect model is having autocorrelation problem, the random effect model and pooled ordinary least square model should be considered to replace the fixed effect model. However, since the random effect model and pooled ordinary least square model have the same autocorrelation result with fixed effect model (Durbin Watson test statistics fall between 0 and lower critical value) with lower adjusted R square, fixed effect model is still preferred in this research.

The fixed effect model may still be the most appropriate model for the data at hand, even if there is some degree of autocorrelation in the residuals. This is because the fixed effect model may still provide useful insights into the relationship between the independent variables and the dependent variable, even if it does not fully capture all of the relevant factors that affect the dependent variable.

4.3 Selection for Best Model

Poolability Test, Hausman Test and Breusch Pagan Lagrange Multiplier (BPLM) Tests are utilized to identify the best model among POLS, FEM and REM.

4.3.1 Poolability Test

Poolability test is used to identify the existence of a common intercept in all the variables. In this research, a p-value approach is applied to identify the better model between POLS and FEM.

Table 4.3.1

Result of Poolability Test

Effects Test	Statistic	d.f.	Prob.
Cross-section F	27.280321	5, 49	0.0000*
Cross-section Chi-square	79.842241	5	0.0000*

Note. ***,**,* denote significant levels at 1%, 5% and 10% respectively.

Source: E-views 12 output generation

The result in Table 4.3.1 showed that FEM is better than POLS in explaining the relationship between NPLs with GDP, RIR, LS, CAR and HI. H0 stated that there is no fixed effect in the model. The null hypothesis is rejected at significant level 0.01, 0.05 and 0.10, since p-value is below alpha.

4.3.2 BPLM Test

BPLM test is used to identify the existence of an inconstant variance in all the variables. In this research, the p-value approach is applied to identify the better model between POLS and REM.

Table 4.3.2

Result of BPLM Test

	Test Hypothesis		
Breusch-Pagan	Cross-section	Time	Both
	124.7848 (0.0000)*	4.824728 (0.0281)**	129.6095 (0.0000)*

Note. ***,**,* denote significant levels at 1%, 5% and 10% respectively.

Source: E-views 12 output generation

The result in Table 4.3.2 showed that REM is better than FEM in explaining the relationships between NPLs with GDP, RIR, LS, CAR and HI. H0 stated that there is no random effect in the model. The null hypothesis is rejected and there is random effect at significant level 0.01, 0.05 and 0.10, since p-value is below alpha.

4.3.3 Fixed Effect Model (FEM)

Since the Hausman Test is unable to be generated in this research, the best model will be decided based on the results of the Poolability Test and BPLM Test.

Table 4.3.3

Result of POLS Test and BPLM Test

Test	**Result**
Poolability Test	FEM is the better model.
BPLM Test	REM is the better model.

Source: E-views 12 output generation

However, the results from the POLS Test and BPLM Test drive into an inconsistent result in selecting the best model, this research is considering FEM as the better model which carried a higher adjusted R-square at 83.17% while REM is having 38.82% of adjusted R-square. Therefore, the FEM is the best model in terms of consistency and efficiency to the performance.

4.4 Inferential Analysis

By using inferential analysis, the population is being assessed depending on the sample data acquired from six MFIs in India, over 10 years of time. There will be some degree of uncertainty in the result of inferential analysis since the data obtained in research does not sample the entire population.

Table 4.4

Result of FEM

Variables	Coefficient	Standard Error	t-statistic	Prob.
C	17.91300	4.236654	4.228100	0.0001
Log GDP growth	0.030525	0.290575	0.105050	0.9168***
Log RIR	-0.137567	0.275743	-0.498897	0.6201***
Log CAR	-0.423525	0.940897	-0.450129	0.6546***
Log LS	0.218090	0.106398	2.049747	0.0458**
Log HI	-0.076953	0.026257	-2.930803	0.0051*
R-squared = 0.860248 Adjusted R-square = 0.831728 Prob (F-statistic) = 0.000000*				

Note. ***,**,* denote significant levels at 1%, 5% and 10% respectively.

Source: E-views 12 output generation

$\log \widehat{NPL}_{it}$ = 17.91300 + 0.030525 log $(GDP)_{it}$ - 0.137567 log $(RIR)_{it}$ - 0.423525 log $(CAR)_{it}$ + 0.4218090 log $(LS)_{it}$ - 0.076953 log $(HI)_{it}$ (Equation 2)

where log_NPL = Non-Performing Loan (in INR)

log_GDP = Gross Domestic Product Growth (in percentage)

log_RIR = Real Interest Rate (in percentage)

log_CAR = Capital Adequacy Ratio (in percentage)

log_LS = Loan Size (in INR)

ε = error term

i = MFIs in India (NABARD, CreditAccess, SIDBI, ESAF, HDFC, AU SFB)

t = time (annual observation from 2012 to 2021)

4.4.1 F-statistic

F-test is applicable for the fitness of data set in the model. The test reflects the equality of variances in the model. The table below is a summary from Fixed Effect Model (FEM) output.

Table 4.4.1

F-statistic of FEM

F-statistic	30.16219

Prob (F-statistic)	0.000000*

Note. ***,**,* denote significant levels at 1%, 5% and 10% respectively.

Source: E-views 12 output generation

The null hypothesis that stated no interrelationship between the NPLs and the independent variables, is rejected in this research. The decision is made based on the p-value generated, recorded a value below significant level 1%, 5% and 10%. There is sufficient evidence to conclude that at least one independent variable in the model is significant to explain NPLs of MFIs in India.

In the log FEM, the coefficient of determination of R-square denoted 0.8602, which is 86.02% of the variation in NPLs can be explained by GDP, RIR, CAR, LS and HI. The result of F-statistic concludes that the model has enough evidence to be significant at 1% level of significance.

4.4.2 T-statistic

By looking into the independent variables, the correlation coefficient of GDP growth denotes a positive relationship with NPLs. The amount of NPLs tends to increase when GDP growth increases. However, the p-value (0.9168) from t-test of GDP growth is greater than the significant level of 1%, 5% and 10%. Thus, GDP growth is insignificant in explaining the NPLs. Ahmadi et al., (2019) concluded the relationship between GDP growth and NPLs is positively insignificant.

According to the result of the FEM model, RIR is negatively related to NPLs. This reflects the decrease of NPLs when RIR increases. The null hypothesis does not be rejected by using the p-value approach at alpha 0.10, with p-value of 0.6201. RIR is concluded to be insignificant to explain NPLs. It is similar to Mubin (2019) indicating that interest rate is insignificant on credit risk, because borrowers still make loans to meet their needs regardless of rising interest rates, where the current interest rates are not concerned mostly by borrowers.

CAR denotes an inverse relationship with NPLs. An increase in CAR contributes to a lesser amount of NPLs. However, the p-value (0.6546) from t-test of CAR is greater than the significant level of 1%, 5% and 10%. Thus, there is sufficient evidence to conclude CAR is insignificant in explaining the NPLs. The research of Ruslim and Bengawan (2019) concluded in their research that CAR does not significantly affect NPLs.

Refers to the result of FEM, LS is positively related to NPLs. NPLs will move in the same direction with LS when it increases. The null hypothesis is rejected by using the p-value approach at alpha 0.01 and alpha 0.5, with p-value of 0.0458. However, LS tends to be individually insignificant at alpha 0.10. Thus, LS is concluded to be significant to explain NPLs at 1% and 5% level of significance. The positively significant relationship of LS to NPLs has been supported by the previous studies (Adu et al., 2019; Abimbola, 2021; Medina-Olivares et al., 2022).

Lastly, HI denotes a negative relationship with NPLs. An increase in HI contributes to a lesser amount of NPLs. The p-value (0.0051) of HI falls below the significant level of 1%, 5% and 10%. Thus, there is sufficient evidence to conclude HI is significant in explaining the NPLs. The result is similar to several previous studies which concluded that HI is negatively significant to NPLs (Rachmansyah et al, 2021). However, Rachman et al., (2018) has an adverse opinion on the significance of income distribution to NPLs.

In conclusion, this research provides that GDP, RIR and CAR are not meaningful in explaining NPLs of MFIs in India. GDP is positively insignificant to NPLs. RIR and CAR are negatively insignificant in the relationship between NPLs. LS and HI are individually significant to the model. Besides, LS is positively related to NPLs, while HI is negatively related to NPLs.

CHAPTER 5: CONCLUSION AND DISCUSSION

5.0 Introduction

This chapter is examining findings from chapter four of the relationship of the selected variables that affect credit risk in India MFIs by NPLs, in order to fulfill this research's main objective.

After studying the journal research and analyzing the variables affecting credit risk in India, there are few gaps that have been identified to address these issues, there is still a lack of successful cases of improving the non-performing loan in practical terms. Recommendation and policy implication is suggested for future research on credit risk in India, which is necessary to find solutions that can be applied to the microfinance institution and promote the financial system growth.

5.1 Major findings

Despite India having a higher GDP, the disparity between the affluent and destitute populations has contributed to an increase in NPLs in the country. The decline in GDP can lead to a deterioration in the economic conditions of both businesses and individuals, resulting in their inability to repay their loans promptly and increasing the likelihood of NPLs. Previous studies have noted there was an influential relationship between GDP and NPLs. However, GDP and NPLs are two distinct economic indicators that measure different aspects of an economy. Based on the aforementioned findings, while GDP may have an indirect effect on NPLs, it is not a significant determinant of NPLs in India. The theory proposed by Kjosevski (2019) confirms that GDP was a negative influence on NPLs. Moreover, Dimitrios et al. (2016) found a negatively insignificant correlation between GDP and NPLs. Factors such as non-performing lending practices, economic conditions, and the quality of the banking system have a greater impact on

NPLs in India. The government and Reserve Bank of India (RBI) implemented various measures to address the high levels of NPLs, such as enforcing stricter lending norms, increasing provisioning requirements for banks, and establishing a framework to address stressed assets (Nargis et al., 2019). In conclusion, GDP will not have a significant impact on NPLs in India.

It is mentioned in the problem statement that there is no limit on the interest rate of microfinance loans in India at present, which is the reason RIR has chosen inflation adjustment to reflect the actual cost of borrowing and the real rate of return on the lender. Past studies have supported rising RIR leads to an increase of NPLs by assuming that borrowers cannot repay their debt at a higher interest rate. Nevertheless, the result of RIR has had an insignificant negative impact on India's NPLs, which shows that it is meaningless for the Indian government and banks to eliminate this gap by raising interest rates. This study provides that higher RIR can slow down loan growth, which decreases newly applied loans. Transferring the cost of borrowing from banks to customers made SMEs get rid of institutional loans due to the minimum loan rate increases (Srijonee, 2022). It will eventually reduce NPLs level, which is proven by the positive relationship of loan size and NPLs. It is consistent with Muriithi (2013) that RIR is negatively related to NPLs. Arham et al. (2022) stated changing RIR by national governance has no obvious influence on NPLs. It could be concluded that RIR might not provide a meaningful impact to NPLs statistically.

The capital adequacy ratio (CAR) measures ability in a financial institution to withstand potential losses. To make sure banks and other financial organizations have enough capital to handle any unplanned situations, CAR has some sway in the microfinance world. However, due to a lack of access to capital and high operational costs, many smaller MFIs in India have found it difficult to sustain this level of capital adequacy. Nonetheless, according to Ijaz Hussain Bokhari and Ather Azim Khan., (2019), it should be highlighted that MFIs are not always at risk of failing if their capital adequacy ratio is low. Setting the proper CAR criteria, however, is essential for the industry's development and stability and calls for striking a delicate balance between defending financial institutions and advancing financial inclusion. Other elements including loan portfolio quality, asset and liability management, and liquidity management, have some significance to an institution's financial health. In conclusion, CAR is insignificant to NPLs in India.

Household income affects the size of NPLs negatively since higher household income affects financial stability and ability of households to repay loans with a support of Life Consumption Theory. Nathan et al., (2020) mentioned that income per capita is significant to affect NPLs across all bank types and bank size. This might be due to higher general income reducing the financial stress of borrowers (Kjosevski & Petkovski, 2021). However, a controversy on income distribution positively affects the NPLs due to the ability to carry indebtedness of a borrower becoming higher as income increases (Zainol et al., 2018). The result in this research proved that higher income is able to mitigate the amount of NPLs. By comparing this research with studies conducted by Zainol et al. (2018) and Theong et al. (2022), they studied the impact of household income in Malaysia and other Asian countries. In their studies, household income denoted higher credit risk due to borrowers' ability in holding more debt than the lower income borrower. This could lead to the higher total amount of debt incorporated into higher exposure to default risk. However, the negative relationship in NPLs and household income is proven in this research. In conclusion, higher income significantly enables greater obligation repayment ability of borrowers.

5.2 Policy Implication

Microfinance is the most effective method of reducing poverty in India. Microfinance in India has a wide range of policy ramifications. For the development of microfinance in India, the government must first provide a supportive regulatory environment. This involves rewarding MFIs, controlling interest rates, and guaranteeing loan repayment transparency. Yet municipal governments ought to refrain from overrepresentation. A properly strengthened legal framework would also aid in preventing boom-and-bust dynamics and limiting the rise in lending rates that happens as portfolios rapidly deteriorate. This would include the wider use of credit bureaus, better corporate governance principles, regular and timely reporting (Bella, 2011).

Secondly, by engaging in small-scale businesses or other small-scale economic activities, the people of India can work towards the objective of eradicating poverty. The profitability and sustainability of microfinance organizations would ultimately be guaranteed by the effective promotion of productive economic activity among borrowers and capacity-building training programs. Concentrating on solvency factors will aid institutions in surviving and providing the most effective service to underserved communities.

Finally, in order to improve profitability and the future of microfinance organizations, solvency must be a top priority. A difference will be made by implementing better financing strategies and developing goods that meet market demands. Microfinance organizations focus on insufficient funding, where there are many chances for abuse. Authorities should increase the level of oversight of the loan and collection processes so that adequate oversight will assist the non-compliant portion and prevent microfinance institutions from deviating from accepted norms (Chitra, 2021).

5.3 Limitation of study

First, insufficient sample size for statistical measurements, this research's data mainly rely on the annual report of six MFIs in comparing each of the financial information selected, the result and explanation may not wholly represent the credit performance in India. Moreover, the six MFIs selected do not represent the entire MFIs industry in India since it is limited to the type of the MFIs providers. Next, the financial report is provided on a yearly basis. It is difficult to enlarge the data scale by transferring the data on a quarter basis that better reflects the dynamic change between variables from the MFIs annual report. Thus, lack of data may affect the significance of independent variables for NPLs in India.

Moreover, most of the studies are outdated and were conducted before Covid-19 pandemic occurred. The previous studies reviewed less taken into account the effect of the crisis that happened in early 2020 reflect on the economic condition in India. There is missing data for the gross disposable income from 2019 to 2021, which gives the insight that the household income data failed to capture the impact of Covid-19, which could affect the consumption and credit decisions made by Indian households. Therefore, the result is limited in this research.

5.4 Recommendations

There are several recommendations suggested for the limitations. First, augmenting the sample size is the fundamental method to overcome the issue of insufficient sample size. To this end, research can be conducted in multiple ways, including but not limited to expanding the scope of the study population, increasing the number of data collection channels by increasing the number of targeted MFIs, and extending the study period. Furthermore, comprehensively measuring MFIs from diverse perspectives can be achieved by increasing the measurement indicators of variables. For instance, the loan amount, loan term, repayment history, and customer background of clients can be considered.

Next, MFIs have the potential to establish collaborative relationships with various entities, such as government agencies, non-governmental organizations (NGOs), academic research institutions, and social enterprises, in collecting and exchanging data and information. Such partnerships can involve joint research initiatives and data sharing projects, thereby expanding the size and accessibility of the dataset. Through such collaborations, MFIs can gain access to additional resources and expertise, while enabling academic research institutions to obtain a deep understanding with the operations and impacts of MFIs. Moreover, such collaborations would ensure access to current and relevant information across different institutions, especially during epidemics, preventing the stagnation of data.

Since this research is focusing most on MFIs in India and is not representative of the entire microfinance market. Sample selection bias may lead to distorted study results because it is only able to leave an impact in the India situation. Therefore, subsequent scholarly research on MFIs could employ comparative data from diverse nations. An increase in the number of nations considered would augment the available dataset and consequently facilitate a more comprehensive comprehension of microfinance as a cohesive entity to ensure that the result of the study could be applied into other microfinance markets and serve for reference purposes for other countries.

5.5 Conclusion

In India, microfinance can be a useful instrument for reducing poverty and promoting inclusive growth. This study examined the factors that influence credit risk in microfinance institutions (MFIs) in India, utilizing the statistical software Eviews 12 and incorporating six key variables, namely GDP, RIR, CAR, LS, HI, and NPLs. The results showed GDP, RIR and CAR have an insignificant impact toward NPLs. In contrast, LS and HI were found to exert significant effects on NPLs. This study's objective is to provide guidance for MFIs in India and to contribute to future research efforts by analyzing the credit risk effects in India NPLs. To make sure that the advantages of microfinance reach the intended recipients, the government must implement the proper steps.

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