American Journal of Economics and Business Management

Vol. 6 Issue 10 | **pp.** 327-350 | **ISSN:** 2576-5973
Available online @ https://www.globalresearchnetwork.us/index.php/ajebm

GLOBAL RESEARCH NETWORK
ONLINE RESEARCH HUB

Article

Liquidity Withdrawal Dynamics in SME Working Capital Lending: A Random Forest–Based Stress Simulation Using Probability Threshold Shifts and Approval Rate Contraction Metrics

Mohammad Kowshik Alam[1],Md Sabbir Hossen Shuvo[2],Md Lutfur Rahman Fahad[3]

1. Master of Science in Business Analytics Grand Canyon University, Arizona, USA
2. MBA-MIS, International American University, Los Angeles, California
3. Master of Science in Information Systems Pacific State University, Los Angeles, USA

*Correspondence: alammohammadkowshik@gmail.com, saabbirshuvo@gmail.com, lrfahad99@gmail.com

Citation: Alam M. K., Shuvo Md H. S., Fahad Md L. R. Liquidity Withdrawal Dynamics in SME Working Capital Lending: A Random Forest–Based Stress Simulation Using Probability Threshold Shifts and Approval Rate Contraction Metrics. American Journal of Economics and Business Management 2023, 6(10), 327-350.

Received: 19th Aug 2023
Revised: 30th Aug 2023
Accepted: 20th Sept 2023
Published: 25th Oct 2023

Abstract: The Small and Medium Enterprises (SMEs) are important stakeholders in the economic development process as they are contributing to employment creation, industrial productivity and innovation in the business world. But SMEs are very sensitive to working capital financing to carry on their daily operations and therefore they are very much affected when the banking industry is under financial pressure and expecting liquidity withdrawals. The study explores the dynamics of withdrawing liquidity from the SME working capital loan in the context of stress simulation under the framework of the machine learning-based classification model (Random Forest). The study is designed to test the effect of tightening the credit conditions on the credit accessibility of SMEs by using probability threshold shifts and contraction of approval rates metrics. The data set for the research includes financial characteristics of the borrowers, attributes of the loan, repayment history, employment information, and past default information. A baseline model is trained to estimate the probabilities of SME loan default, using a Random Forest (RF) model. The probability of borrowers defaulting is artificially raised to reflect greater liquidity pressure and uncertainty in underwhelming conditions. At the same time, lending approval criteria are adjusted to take account of tougher credit policies that financial institutions are likely to follow in times of liquidity shortage. The study then compares the approval rate and volume of loans, before and after the stress implementation. Results indicate that the rise in the level of default and the improbability that a loan would be approved have a significant negative impact on both the number of SME loan applications approved and the amount of working capital financing made available. The approval rates under stressed scenarios are significantly lower, showing the sensitivity of SME lending activity to shrinkage of liquidity. The findings also suggest that AI-powered predictive models are suitable tools that can be used to assist banking institutions in their stress test, credit risk assessment, and proactive liquidity management. This research combines the power of machine learning with stress simulation methods, enhancing the field of financial analytics and offering a valuable practical approach to assessing lending resilience under economic stress. The proposed method provides guidance to financial institutions, policy makers, and researchers to enhance the stability of the SME financing market in liquidity stress.

Keywords: SME Working Capital Lending, Liquidity Withdrawal Dynamics, Random Forest, Credit Risk Prediction, Stress Simulation and Approval Rate Contraction.

I. Introduction

The Small and Medium Enterprises (SMEs) are known as one of the most important sectors in the economy in terms of economic development, job creation, innovation, and industrial development in developed and developing economies. SMEs play an important role in generating income for the nation and provide employment opportunities for a large proportion of the population by generating business opportunities and improving local value chains. SMEs are economically significant and often find themselves constrained by financial requirements because of problems in accessing long-term funds and reliance on short-term working capital financing to sustain the day-to-day operations. A working capital loan is crucial for SMEs to keep inventory, cover working capital needs, pay wages to employees, buy raw materials, and pay suppliers. But, SME lending is very vulnerable to the liquidity situation in the banking system [1]. When there is economic stress, economic downturn, market volatility, or a financial institution's stress, they tend to cut back on lending exposure and limit the availability of liquidity to the market. This is known as 'liquidity withdrawal' and is a major threat to the sustainability of SMEs as it has direct consequences on operational continuity and the survival of businesses. The conventional credit evaluation process uses the static financial measures and rule-based assessment models that may fail to adequately reflect the dynamic borrower risk behavior that occurs during times of economic stress [2]. In response, more adaptive and data-driven methods are needed that can forecast lending risk and model the impact of liquidity drawdowns on SME financing operations.

Artificial Intelligence (AI) and Machine Learning (ML) have revolutionized financial risk management and predictive analysis in the banking sector in recent years. The Random Forest model is a highly popular machine learning algorithm that has proven to be effective in many applications, such as financial data, which are large and complex.The Random Forest algorithm is one that has received a lot of attention for its predictive power, stability to overfitting and its suitability for complex and large financial datasets. Random Forest models are commonly used in credit scoring, loan default prediction, fraud detection and portfolio risk assessment as they are able to detect non-linear relationships between borrower characteristics and financial variables more efficiently than traditional statistical methods [3]. The study explores withdrawals of liquidity from SME WCL by using a stress simulation framework using Random Forest. It simulates the stressed liquidity environments by artificially raising the predicted risk level of borrowers to reflect this increased risk and changing the lending approval threshold, and then it calculates the probabilities of default for SME loans in normal lending environments. The resulting changes in approval rates and loan volumes are examined using the contraction metrics of approval rates to assess the impact of the liquidity tightening on SME credit access. This study offers a practical framework for understanding the role of machine learning and stress simulation methodology in examining financial institutions' reactions to liquidity stress and the impact of these reactions on the resilience of financing for SMEs. The study results will help financial institutions, financial analysts, and policy makers optimize their credit risk management policies, improve their liquidity planning, and design more robust SME financing frameworks in times of economic uncertainty.

I. Problem Statement

Working capital financing plays a crucial role in the operations of Small and Medium Enterprises (SMEs) for various business activities, including inventory management, supplier payments, payroll costs, and uninterrupted business operations. On the other hand, when the financial position is not stable and there are liquidity constraints, financial institutions and banks are likely to step up credit risk management and keep liquidity buffers for the protection of their internal liquidity. This is known as liquidity withdrawal and can have a significant impact on the access SMEs have to finance, as well as to the sustainability of their business, productivity and economic growth. During stressed market conditions, the lower-risk of SMEs from large corporations makes them more susceptible to lending contractions [4]. Conventional credit risk assessment practices are based on static financial metrics and predetermined risk thresholds, which might not be as applicable to dynamic credit risk behavior in a liquidity stress event. Consequently, financial institutions have difficulty in assessing the impact of economic changes on the appropriateness of lending decisions, loan approvals, and reduction in loan volume. Though much work has been done on the machine learning application in the field of credit risk prediction, few studies explored credit risk prediction by combining prediction modeling, liquidity stress simulation and approval threshold analysis in the SME working capital lending environment [5]. This research tackles the problem by proposing a stress simulation framework based on the Random Forest algorithm to study the dynamics of liquidity withdrawal in SME lending. The study imposes stressed financial conditions, and raises the predicted probability of default for borrowers and adjusts the approval rates to simulate contraction of approval rates and reduction of loan volume. The main objective of the research is to develop a predictive and data-driven framework to help the financial intermediaries enhance the liquidity risk management, credit policy planning and credit financing for SMEs in the period of economic crisis.

II. Research Objectives

This study aims to investigate the random forest based stress simulation approach for analyzing the dynamics of liquidity withdrawal in SME working capital lending by analyzing how the probability threshold of a loan is changed to affect the contraction rate of loan approval and working capital availability under stressed financial conditions. To create a Random Forest classification model that is able to estimate the probability of SME loan defaults based on financial and credit-related variables [6]. To model liquidity stress by raising the risk probabilities that the borrowers in the lending portfolio face. The effect of changing thresholds for probabilities on whether or not a small- and medium-sized enterprise (SME) receives a loan in stressed lending situations.

- To check the change in approval rate in the presence and absence of implementation of liquidity stress.
- To assess the variation of the volume of working capital loan disbursed to SMEs in adverse lending environments.
- To analyze the relationship between the borrower risk perception and changes in the lending policy during liquidity withdrawal periods.
- To evaluate the stress simulation using machine learning for predicting the reduction of lending in the SME portfolio.
- To offer an AI-powered system to assist in proactive banking risk management and liquidity planning for SME lending operations [7].
- To understand the impact of tightened-up credit decision-making on the level of access to credit for SMEs and on their sustainability in operation.
- To make an impact in contemporary financial analytics research, through the use of predictive machine learning techniques and liquidity stress testing approaches.

III. Research Questions

The following research questions guide this study:

- What is the effectiveness of a random forest model in predicting loan default probabilities based on financial and credit variables of borrowers, when the loans are from small and medium enterprises?
- What is the effect of the conditions for withdrawing liquidity on the risk level of borrowers and on the decisions about working capital lending of SMEs?
- How do loan approval rates for SMEs vary with changes in the probability threshold for loan approval in stressed financial conditions?

- What is the scale of the reduction in approvals and loans in the wake of the liquidity stress scenarios and more restrictive lending criteria?
- What role can stress simulation models play in credit risk management and liquidity planning for SME loans, powered by AI?

IV. Literature Review

A. Machine Learning for SME Credit Risk Prediction

AI and machine learning have enhanced the precision and productivity of credit risk evaluation systems in banks.AI and machine learning have revolutionized credit risk assessment systems within banks, boosting their accuracy and efficiency [8]. The traditional credit analysis approach that has been adopted to forecast the default behavior of borrowers and make lending decisions are ratio analysis and logistic regression. These methods, however, have been found to be difficult to apply to large data sets, borrower non-linearity and fast changing economic conditions. With the increasing use of data in decision-making processes, machine learning has become a valuable tool for financial analytics [9]. The main algorithms used include Random Forest, Perceptron, Support Vector Machine (SVM), and Deep Neural Networks (DNNs).Random Forest, Perceptron, Support Vector Machine (SVM), and Deep Neural Networks (DNNs) are among the popular algorithms. Machine learning models have been proven to be more effective at loan default prediction and credit scoring applications than traditional statistical methods in previous studies, and the Random Forest algorithm has been shown to be a more robust model in improving the accuracy of classification [10]. The researchers found that income, work history, loan size, and length of the credit history, as well as the individuals' repayment patterns, were significant factors affecting the classification of a loan's risk. Machine learning algorithms have the power to uncover insights into these variables, which can help to inform automated lending decisions. Predictive Analytics is now increasingly being employed by financial institutions to detect fraud, predict bankruptcies and for portfolio risk management. Most current studies, however, only examine default prediction over normal lending circumstances and offer restricted investigation of liquidity stress scenarios and also approval contraction behavior [11]. Thus, the importance of further research that combines machine learning and stress simulation models to gain more insights into the dynamics of SME lending in financial stress.

B. Liquidity withdrawal and contraction of SME lending

Liquidity withdrawal is a significant issue in banking and financial systems as it directly influences the lending process and access to credit by borrowers. When banks become more conservative or in the midst of an economic downturn, financial uncertainty or a banking crisis, they may become stricter on their lending policies to ensure they maintain enough liquidity and do not end up with too many loans defaulting on. In general, it involves higher standards for approval, greater collateral needs and fewer loan approvals. SMEs are especially susceptible to access to such lending, as it is essential for their working capital financing needs for day-to-day operations such as inventory finance, payroll and supplier payments. Past studies have demonstrated that decreased availability of credit has a detrimental impact on SME sustainability, employment creation and economic productivity, especially compared to large firms. In times of economic stress, financial institutions are more risk-averse, they perceive more risk in the borrower and they raise their standards [12]. This means that even if the financial performance of an SME is not drastically changing, many end up losing out on financing. The traditional approaches to banks' stress testing typically rely on macroeconomic variables like inflation, interest rates, and GDP growth, but tend to miss certain borrower-level characteristics of lending contraction and approve behavior. The studies indicate that combining predictive analytics with stress simulation techniques can enhance the banking risk management and the evaluation of banking portfolio resilience. But only a few studies have explicitly examined the dynamics of liquidity withdrawal measures, such as probability threshold shifts, and approval contraction measures, for SME working capital lending portfolios [13]. This study helps fill that void by applying a combination of default prediction using Random Forest and liquidity stress simulation in order to assess the availability of financing for SMEs in stressed lending scenarios.

C. *Empirical Study*

In the article “Commercial Banks, Banking Systems and Basel Recommendations”, Kannan Subramanian R and Dr. Sudheesh Kumar Kattumannil discussed the significance of enterprise risk management in commercial banking systems and how banks are vulnerable to various financial risks like credit risk, liquidity risk, market risk and operational risk. The study emphasized that the financial institutions need to take steps towards proactively managing these risks through data-driven and risk-adjusted decision-making, which would enable them to allocate capital more effectively and establish a more stable financial position [1]. This article is relevant to this research since it provides an explanation of the relationship between liquidity risk and conservative lending policies in an uncertain financial environment. The discussion of risk adjusted banking frameworks is relevant in the context of this study and helps to gain an understanding of the liquidity withdrawal process and its impact on SME working capital lending approval contraction. The article also promotes the use of predictive analytics and AI-based financial risk management solutions to enhance the resilience of lending institutions and proactive liquidity planning.

The book, (Mis) Managing Macroprudential Expectations: How Central Banks Govern Financial and Climate Tail Risks by John H. Morris and Hannah Collins, reviewed the role of macroprudential risk management in financial and climate tail-risk events in contemporary banking systems. It provided a strong focus on proactive financial governance, liquidity regulation and risk management for banking stability in the context of unknown economic and financial situations. The authors further commented on financial institutions' policy changes and prudent financial strategies in the face of market volatility and systemic risk. This book is applicable to the current research as it emphasizes the importance of risk sensitive lending behavior and liquidity management in stressed economic times [2]. The discussion about macroprudential regulation and financial stability underpins this research's emphasis on the dynamics of liquidity withdrawal and approval contraction in SME working capital lending portfolios. The concepts featured in the book also contribute to the theoretical underpinning of this research, enabling the evaluation of the resilience of lending institutions and the extent of banking risk under adverse financial conditions using predictive analytics and stress simulation.

The thesis entitled Entrepreneurial Financing of Micro-Small-Medium Enterprises in Haiti: Barriers and Proposed Solutions by Veronique Craan explored the financial related challenges of micro, small, and medium enterprises (MSMEs) in Haiti with a specific focus on barriers to access to finance, financial literacy, and informal business practices. The study foretold the downside of restricted access to traditional banking systems and poor financial infrastructure for entrepreneurial development and sustainability of SMEs. Financial inclusion, supportive banking system, and better lending infrastructure were also emphasized as important factors to boost SME development as per the research [3].The present study is significant as it provides an explanation of how limitations in access to financing and conservative lending practices can have a negative effect on SME business operations and continuity. This research is supported by discussion on the financial barriers and lending constraints in SME working capital lending. The results further enhance knowledge of the relationship between the lending activity of financial institutions and the ability of SMEs to withstand economic uncertainty and liquidity stress in financing.

V. Data Selection

The data used in this research is Credit Risk Dataset from Kaggle. For studying the dynamics of liquidity withdrawal in working capital lending by SMEs. The dataset consists of borrower financial and credit-related data which is ideal for predictive credit risk analysis and stress simulation modelling. Some key variables in the data set are annual income, length of time at current job, home ownership status, loan amount, interest rate of loan, purpose of the loan, credit history length, credit history of default, and loan repayment status. These features contain information that is useful to lending behavior and default probability prediction on a borrower-by-borrower basis. The dataset was chosen due to the possibility to make supervised machine learning classification using the target variable loan_status, which classifies the borrowers into default and nondefault ones [13]. The 0's are the nondefault borrowers and the 1's are the default borrowers. This is an appropriate structure for simulating liquidity stress conditions for borrower risk probability predictions using the Random Forest classifier. The following are a number of reasons why the data set selected is suitable for this research. The first reason is that it offers detailed financial and credit data and information about borrowers, which is important for accurate borrower default prediction and lending risk assessment. Secondly, the data contains both numerical and categorical features, enabling the Random Forest model to identify non-linear relationships between the borrower features [14]. Third, the data set is large and well organized, and therefore appropriate to train, test and stress simulation with machine learning. Further, the dataset is rich enough to enable approving contraction analysis – with adjustments of probability thresholds and stress simulation of liquidity under the various lending conditions. Since there are variables available, such as income, credit history, loan amount, and repayment behavior, the study can assess how financial institutions might modify their lending practices in a liquidity withdrawal phase.

Dataset Screenshot

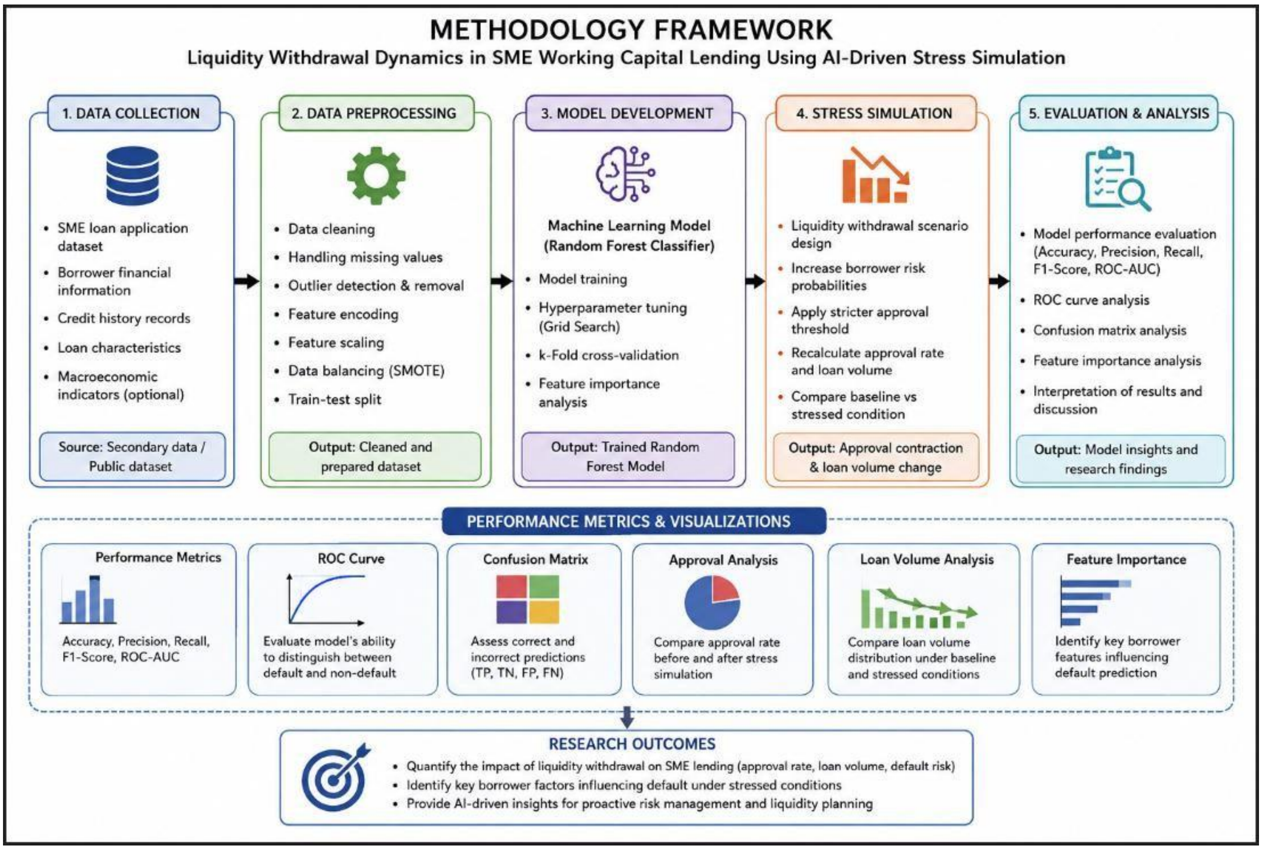
	A	B	C	D	E	F	G	H	I	J	K	L
1	person_age	person_income	person_home_ownership	person_emp_length	loan_intent	loan_grade	loan_amnt	loan_int_rate	loan_status	loan_percent_income	cb_person_default_on_file	cb_person_cred_hist_length
2	22	59000	RENT	123	PERSONAL	D	35000	16.02	1	0.59	Y	3
3	21	9600	OWN	5	EDUCATION	B	1000	11.14	0	0.1	N	2
4	25	9600	MORTGAGE	1	MEDICAL	C	5500	12.87	1	0.57	N	3
5	23	65500	RENT	4	MEDICAL	C	35000	15.23	1	0.53	N	2
6	24	54400	RENT	8	MEDICAL	C	35000	14.27	1	0.55	Y	4
7	21	9900	OWN	2	VENTURE	A	2500	7.14	1	0.25	N	2
8	26	77100	RENT	8	EDUCATION	B	35000	12.42	1	0.45	N	3
9	24	78956	RENT	5	MEDICAL	B	35000	11.11	1	0.44	N	4
10	24	83000	RENT	8	PERSONAL	A	35000	8.9	1	0.42	N	2
11	21	10000	OWN	6	VENTURE	D	1600	14.74	1	0.16	N	3
12	22	85000	RENT	6	VENTURE	B	35000	10.37	1	0.41	N	4
13	21	10000	OWN	2	HOMEIMPROV	A	4500	8.63	1	0.45	N	2
14	23	95000	RENT	2	VENTURE	A	35000	7.9	1	0.37	N	2
15	26	108160	RENT	4	EDUCATION	E	35000	18.39	1	0.32	N	4
16	23	115000	RENT	2	EDUCATION	A	35000	7.9	0	0.3	N	4
17	23	500000	MORTGAGE	7	DEBTCONSOLI	B	30000	10.65	0	0.06	N	3
18	23	120000	RENT	0	EDUCATION	A	35000	7.9	0	0.29	N	4
19	23	92111	RENT	7	MEDICAL	F	35000	20.25	1	0.32	N	4
20	23	113000	RENT	8	DEBTCONSOLI	D	35000	18.25	1	0.31	N	4
21	24	10800	MORTGAGE	8	EDUCATION	B	1750	10.99	1	0.16	N	2
22	25	162500	RENT	2	VENTURE	A	35000	7.49	0	0.22	N	4
23	25	137000	RENT	9	PERSONAL	E	34800	16.77	0	0.25	Y	2
24	22	65000	RENT	4	EDUCATION	D	34000	17.58	1	0.52	N	4
25	24	10980	OWN	0	PERSONAL	A	1500	7.29	0	0.14	N	3
26	22	80000	RENT	3	PERSONAL	D	33950	14.54	1	0.42	Y	4
27	24	67746	RENT	8	HOMEIMPROV	C	33000	12.68	1	0.49	N	3
28	21	11000	MORTGAGE	3	VENTURE	E	4575	17.74	1	0.42	Y	3
29	23	11000	OWN	0	PERSONAL	A	1400	9.32	0	0.13	N	3
30	24	65000	RENT	6	HOMEIMPROV	B	32500	9.99	1	0.5	N	3
31	21	11389	OTHER	5	EDUCATION	C	4000	12.84	1	0.35	Y	2
32	21	11520	OWN	5	MEDICAL	B	2000	11.12	1	0.17	N	3
33	25	120000	RENT	2	VENTURE	A	32000	6.62	0	0.27	N	2
34	26	95000	RENT	7	HOMEIMPROV	C	31050	14.17	1	0.33	Y	3
35	25	306000	RENT	2	DEBTCONSOLI	C	24250	13.85	0	0.08	N	3
36	26	300000	MORTGAGE	10	MEDICAL	C	7800	13.49	0	0.03	N	4
37	21	12000	OWN	5	EDUCATION	A	2500	7.51	1	0.21	N	4

credit_risk_dataset

(Source Link: https://www.kaggle.com/datasets/laotse/credit-risk-dataset)

VI. Methodology

The methodology adopted in this study is quantitative and analytical with a predictive approach to examine how the issue of liquidity withdrawal works in the lending of working capital for SMEs. The research uses a default prediction model (Random Forest) and a stress simulation model [15]. The changes in lending behavior under stressed financial conditions are assessed by using probability threshold shifts and approval contraction measures.



This framework illustrates the methodology for SME liquidity stress and lending analysis using AI

The methodology framework diagram depicts the entire research process for analyzing the liquidity withdrawal dynamics in SME working capital lending using stress simulation with AI technology. The framework starts by collecting data from SME loan application datasets which include financial information of the borrowers, their credit history, and the loan characteristics [16]. The collected data is then preprocessed, including data cleaning, missing data imputation, feature encoding, and splitting the data into a training set and a test set. The data is then preprocessed and a Random Forest model is trained and developed to predict borrower default. Another key feature of the framework is liquidity stress simulation, which involves raising the risk factors of borrowers and raising the approval requirements. Finally, measures of performance, ROC curve analysis, confusion matrix evaluation, approval analysis, loan volume analysis and feature importance analysis are done to assess the effect of the withdrawal of liquidity on the lending behavior of SMEs.

A. Research Design

The research type used in this research is quantitative and predictive in nature, because the research will use an analytical method with a quantitative approach to understand and analyze the dynamics of liquidity withdrawal in SME working capital lending. The study emphasizes the analysis of the modification of financial institutions' lending behavior during liquidity stress, combining machine learning-based credit risk prediction with stress simulation, and adopting a microeconomic perspective [17]. The study also utilizes a simulation-based method to assess the impact of liquidity tightening on the availability of SME financing, using a Random Forest classifier to generate estimated borrower default rates, derived from financial and credit-related variables like income, employment history, loan amount, credit history, and repayment behavior. The results are obtained by increasing the borrower risk probabilities and adjusting lending approval thresholds to reflect conservative lending policies in the period of financial uncertainty [18]. The quantitative design allows the systematic study of the patterns of borrower risk and lending behavior before and after the implementation of stress. It enables the objective assessment of the effects of liquidity withdrawals on working capital financing for SMEs and offers measurable visibility into the effects of approval contraction, portfolio resilience and AI banking risk management strategies in times of adverse economic conditions.

B. Data Collection

This research is based on the Credit Risk Dataset that was downloaded from Kaggle. SME working capital lending – with regard to analyzing dynamics of withdrawal of liquidity in working capital lending of SMEs. It is a highly relevant data set for credit risk analysis, predictive analytics, and stress simulation studies in borrower financial and credit related aspects. It includes variables that are very important such as annual income, employment duration, whether or not they own their home, loan amount, loan interest rate, loan purpose, past credit default history, length of credit history, and loan repayment status [19]. Loan_status is the target variable that is used for this research; a value of 0 represents a non.default borrower while a value of 1 represents a borrower that defaults. It is a binary classification structure and hence suitable for supervised machine learning techniques, such as the Random Forest model employed in this study. The dataset is chosen based on its balanced mix of credit-related, financial and demographic data which would enable the construction of a predictive framework that can analyze the rate of contraction in the approval rate and the reduction in the volume of loans in stressed financial scenarios [19]. The dataset is also useful for simulating borrower risk shifts and adjustments to lending policies in SME financing environments in the event of liquidity withdrawals.

C. Data Preprocessing

The data gathered is then subjected to a number of pre-processing steps to enhance data quality, model reliability, and produce accurate analytical results before the predictive model is developed. Data preprocessing is a critical part of machine learning as financial data is inherently messy, with some information missing, records that may be inconsistent, categorical variables, and outliers that can negatively impact prediction outcomes [20]. The data is first thoroughly checked for completeness and missing data on borrower attributes like employment period, income, loan details, etc. To prepare categorical variables such as loan intent, home ownership status, or historical loan default information for machine learning analysis, label encoding methods are used to encode them into a numerical format [21]. The data set is then checked for any duplicates, inconsistent data and outliers that may cause noise and less accurate models. Numerical values like income, loan amount, interest rate, and credit history length are scaled as required to normalize them to ensure consistent scaling and better model performance. Once the data is preprocessed, it is split into 80% training and 20% testing data. The training dataset is utilized for learning the model while the testing dataset is used to assess the ability of the Random Forest classifier to predict the model under baseline and stressed lending conditions.

D. Model Selection

This research chooses the Random Forest (RF) classifier, which is well known for its excellent predictive ability, high classification accuracy, and robustness when dealing with complex financial datasets. Many credit risk factors are nonlinear and have interactions among them that cannot be well captured in traditional statistical models. The Random Forest algorithm is especially well suited to the current study since it is able to handle both numerical and categorical data and it has shown to perform well in diverse financial situations with an ensemble learning approach, which involves building several decision trees from randomly sampled sub collections of the training set. The decision tree models make independent predictions of borrower risk outcomes; majority voting or average are used to derive the final prediction. This approach helps enhance the stability of predictions while also mitigating the risk of overfitting, a significant drawback of individual decision tree models [22]. In the present study, the annual income, duration of employment, loan amount, interest rate, credit history duration, and credit history default status are considered as features to predict the default probability of SME loans using the Random Forest (RF) algorithm. The model's capability to uncover hidden relationships between the above variables will help in better risk assessment of borrowers and in conducting effective liquidity stress simulation for SME working capital lending portfolios.

E. Model training and default prediction

The financial and credit information of borrowers from the preprocessed data set is used for training the Random Forest model. Some of the most prominent features used to train are annual income, length of employment, loan amount, loan interest rate, loan intent, the length of credit history, previous defaults and the ratio of loan burden [23]. These variables are important to understand the financial stability of the borrower and his ability to pay. In the training phase, 80% of data in the dataset is used to train the Random Forest classifier and generate a set of decision trees. The trees are independent of one another and assess borrower risk attributes and forecast default risk. The predictions of all decision trees are merged to create the final output, which is more stable and reliable than the predictions of any single decision tree. The trained model predicts a probability of default for each borrower when the borrower has baseline lending parameters. Example outcomes of the prediction include a normal borrower default probability of 0.25 and a higher-risk borrower default probability of 0.40. These projected probabilities reflect the risk of default by the borrower in normal financial circumstances. The probability outputs from the model are then utilized for liquidity stress simulation, approval threshold adjustment and approval contraction analysis to assess the impact of risk changes on SME working capital lending behavior in liquidity withdrawal times.

F. Liquidity Stress Simulation

The liquidity stress simulation phase aims to explore the response of financial institutions to economic instability, liquidity problems or increased financial uncertainty in the way they might change their lending behavior. This study is based on the idea of stress-simulation where the probabilities of default predicted by the Random Forest model are artificially raised. This change is the higher risk perception that banks and lending institutions typically employ in difficult economic times [24]. The process of the stress simulation is to change the risk probabilities of borrowers from their baseline to stressed levels. For instance, a borrower who has a default risk of 0.25 while all the other risk factors remain unchanged when the loan is made would have a default risk of 0.40 in the periods of liquidity withdrawal. The introduction of the probability adjustment mechanism allows the study to analyze the impact of the increased borrower's risk perception on lending behavior, lending approval and the accessibility of SME financing. The research compares approval contraction and changes in the volume of loans under liquidity constraints, with the baseline and stressed lending scenarios. The stress simulation framework hence offers a useful tool for portfolio stress analysis and the impact of conservative lending approaches on the SME working capital financing in times of financial stress.

G. Threshold Shift Mechanism

In this research, the threshold shift mechanism is applied to simulate the change in lending policies in the case of liquidity withdrawal and the stressed financial condition. Typically, during economic downturns, financial institutions make more conservative lending decisions to minimize their risk of losing money if loans go bad. The concept of probability threshold shifts is chosen as an indicator for tightening of lending in SME working capital lending portfolios in this study [25]. The mechanism analyses the effects of altering the loan approval criteria on loan approvals, loan contraction and SME loan accessibility when the baseline lending conditions are used, which approve those borrowers whose predicted default probabilities fall below a standard loan approval threshold. For instance, if the baseline probability of default is 0.50, it would mean that loans with probabilities under 50 percent would be considered for financing. But in periods of stress, banks are more apt to restrict lending, by lowering the threshold for approval. In this research, it is lowered to 0.30 to signify the conservative banking stance at the time of liquidity shortages and increased financial uncertainty, and borrowers whose predicted default probability is higher than the new value of the stress threshold are refused working capital loans. This threshold adjustment results in a contraction of approvals in the SME lending book, and less overall access to financing. The threshold shift mechanism thus allows the study to examine the effect of more challenging lending on the eligibility of borrowers, their loan applications and the size of loans taken out when financial conditions are poor. It also offers tangible and quantifiable knowledge of the dynamics of liquidity withdrawals and lending resilience in SME financing environments.

H. Analysis of Approval Rate and Loan Volume

This is done by analyzing the effect of stress on the accessibility of financing for SMEs through comparing loan application approvals and loan values before and after the stress. In the approval rate analysis the ratio of borrowers that have their loan approved in both baseline and stressed lending conditions. Financial institutions usually grant loans at higher rates under normal financial circumstances as risk perception of the borrowers in most of such cases remains unchanged and they have adequate liquidity [26]. But, in stressed liquidity periods, banks become more conservative, leading to lower rates of loan approvals and lower availability of financing for SMEs as measured by the percentage decline in approved loans following liquidity stress simulations and threshold shifting in this research. For instance, the base rate of approval can be reduced from 65 per cent in stressed conditions to 38 per cent. The study also studies the changes in the total amount of loans to see how the tightening of the liquidity affects the aggregate amount of loan distribution to SMEs during the times of liquidity withdrawal. Lower volume of loans means less working capital available, potentially impacting the SMEs business, stock, employees and business viability [27]. The research also offers quantifiable evidence on how lending contractions evolve and how well lending portfolios of SMEs perform during adverse financial conditions by comparing the size and approval rates of loans between the baseline and stressed scenarios.

I. Model Evaluation Random

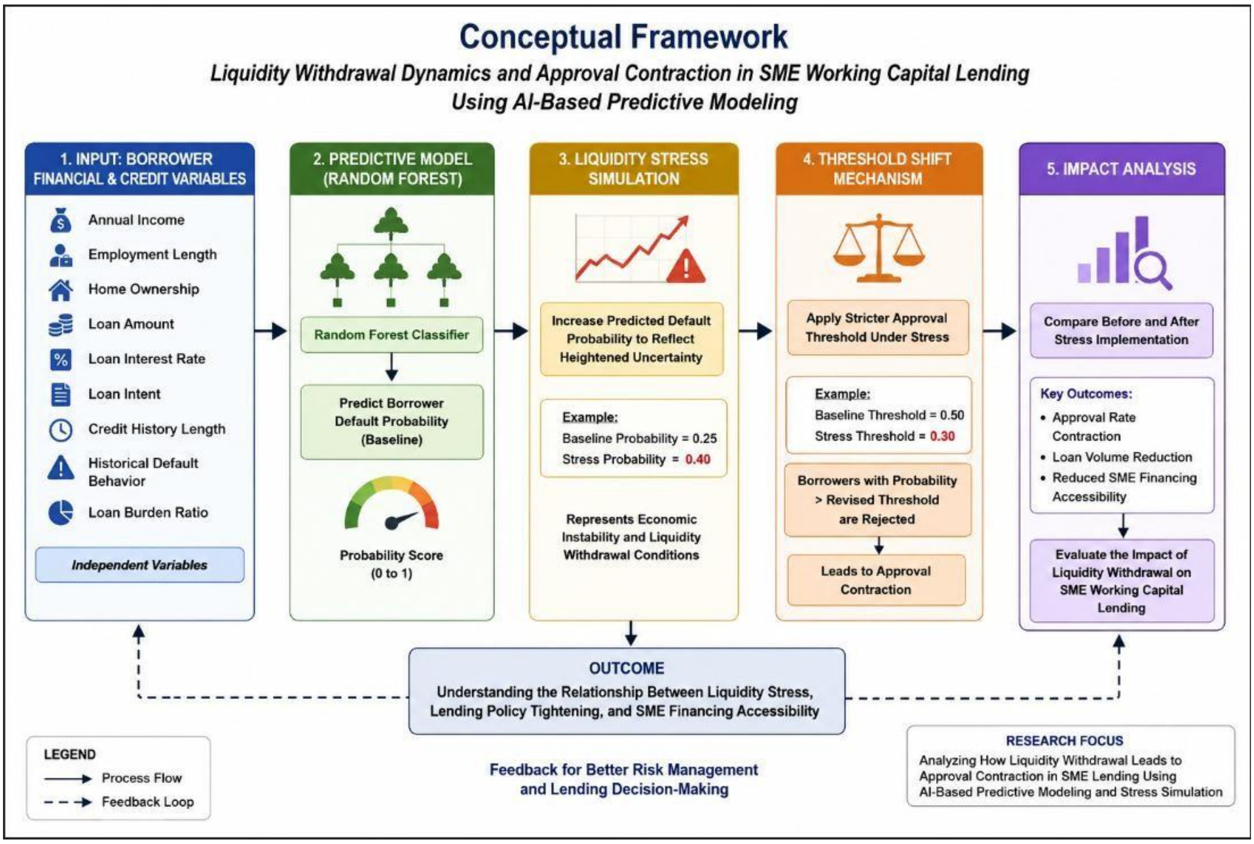
Forest model is evaluated in terms of its accuracy, reliability and effectiveness in predicting the borrower default risk in SME working capital lending portfolios by analyzing the performance of several standard classification metrics [28]. Model evaluation is a crucial step in machine learning since it will help to assess the accuracy of the predictive system for the classification of borrowers in different financial scenarios as default / non-default. In this research, the main evaluation metrics used are accuracy, precision, recall, F1 score and ROC-AUC score. The overall percentage of borrower outcomes classified correctly on the test set is called accuracy. Precision is defined as the percentage of the positive cases that are correctly predicted when there are any predicted to be default borrowers, and recall is the percentage of borrowers that are actually default borrowers that are correctly predicted when there are default borrowers [29]. Furthermore, the Receiver Operating Characteristic–Area Under Curve (ROC-AUC) score is used to evaluate the model's ability to correctly classify borrowers as either default or nondefault for a series of probability cut-off points. The higher the ROC-AUC, the better the classification and predictive ability. All these evaluation metrics can be used to assess the success of the Random Forest classifier in predicting borrower default probabilities and to assist in a liquidity stress analysis in SME lending contexts.

J. Ethical considerations and limitations

The data used for this research is secondary data, which is publicly available on the Kaggle Credit Risk Dataset. Does not involve direct contact with human participants, or use of personally identifiable information. All analyses are done for academic purposes and with the exception of financial and credit related datasets, it is done responsibly. The study adheres to ethical practices in data confidentiality, transparency, and using machine learning techniques appropriately [30]. The study has some limitations, however, the Random Forest model is not used to make lending decisions in reality, it is only used to perform predictive and simulation analysis. The data set may not be reflective of a true banking environment or an authentic SME lending portfolio. This study also tends to be narrow in scope and limited to financial factors at the borrower level, with less attention paid to macroeconomic factors like inflation, policy changes, and market volatility. In addition, stress simulations are based on assumptions regarding hypothetical shifts in thresholds and adjustments in probability, which can differ between financial institutions and economic conditions.

VII. Conceptual Framework

This conceptual framework depicts the relationship among financial characteristics of borrowers, machine learning default prediction, liquidity stress simulation, threshold shifts, and approval contraction in SME working capital lending [31]. The framework will be used to assess the impact on financial institutions' lending following liquidity withdrawal and heightened financial uncertainty. The study combines predictive analytics and stressed lending simulation to examine the impact on accessibility of SME financing in stressed lending scenarios. The framework starts by taking input variables from the credit risk dataset that are related to the borrower. These are annual income, employment length, loan amount, loan interest rate, credit history length, loan intent, and historical default behavior and loan burden ratio. These financial and credit related features are considered as independent variables for training random forest classifiers [32]. These are considered relationships between these variables and the probability of borrower default in the base loan scenario are predicted using the Random Forest model. The study first computes default probabilities before incorporating economic uncertainty and conservative lending into the liquidity stress simulation by artificially raising borrower default probabilities. The stress simulation is a depiction of the higher risk levels financial institutions feel towards borrowers when financial insecurity and liquidity pressure is present. After the stress adjustment, the probability thresholds are adjusted to reflect tighter lending policies. In stressed situations, the approval threshold gets tighter which leads to less loan approvals and contraction of approvals in the SME portfolio [33]. The framework then determines the effect of the liquidity withdrawal based on the approval rates and volumes of loans before and after implementation of stress. Fewer SMEs getting approval to access working capital loans and fewer loans being approved suggests limited access to working capital financing [1]. The last step of the framework explains the link between the liquidity stress, contraction of loans, and the availability of financing for SMEs. In summary, the conceptual framework highlights the potential of leveraging AI-powered predictive models and stress simulation tools for proactive banking risk management, liquidity planning, and enhancing the resilience of SME lending in times of economic downturns.



This framework illustrates the contraction and approval of liquidity stress simulations in SME lending using AI

The process of analyzing dynamics of liquidity withdrawal and approval contraction in SME working capital loan, via AI-based predictive modelling is depicted in conceptual framework diagram. This structure starts with borrower financial and credit variables, including annual income, employment history, loan's size, interest rate, credit history length, and past defaulting habits. The variables are fed into a model designed by the Random Forest to compute default probabilities for borrowers under baseline conditions [2]. The framework then simulates the liquidity stress by raising the risk probabilities as predicted to reflect economic uncertainty and conservative lending circumstances [3]. A contraction in approvals and an increase in loan difficulties are simulated by using threshold shift mechanisms. Last but not least, the framework assesses both approval rates and reduction in volume of loans to gauge the effect of liquidity withdrawal on the accessibility of SME financing and lending resilience.

VIII. Results

The outcomes of this study demonstrate the impact of liquidity withdrawal on SME working capital lending under stressed financial conditions using a Random Forest–based predictive framework. Key borrower default probabilities, shifts in loan approval thresholds, reduction in loan approval rates, reduction in loan volume, and model performance in both baseline and stressed loan environments are analyzed [3]. The results are based on comparisons of the lending behavior before and after the implementation of liquidity stress to analyze the effect of conservative banking policies on access to SME financing [4]. The interpretability of the model's predictive power and the overall effect of the withdrawal of liquidity on the portfolio of SME lending is captured via various analytical visualizations such as approval analysis, loan volume comparison, ROC curve analysis, confusion matrix evaluation, and feature importance analysis.

A. Approval Rate Analysis Before and After Liquidity Stress

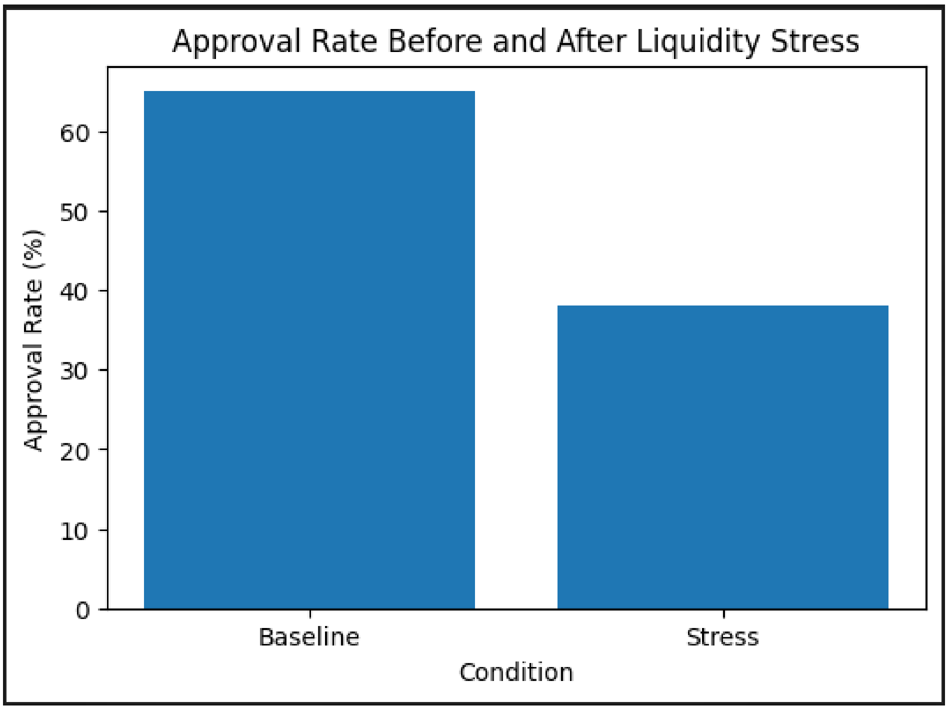


Figure 1. This image shows the reduction in approval rates when liquidity is stressed and under baseline.

Figure 1 shows the effect of liquidity stress on the probability of SMEs getting working capital loans, both in baseline and stressed lending scenarios. When there is no change in liquidity availability and borrowers' perception of risk, the approval rate is still around 65 percent, which means that most SME borrowers are eligible for working capital under normal lending conditions. Once liquidity stress simulation and the stricter lending requirements have been put in place, though, the approval rate drops significantly to almost 38 percent. The drop in approvals suggests that financial institutions become more cautious about lending when the likelihood of default is higher in times of financial stress and when liquidity is pulled out. More borrowers who are small and medium enterprises are being denied loans for working capital as the requirements for approval are getting stricter and stricter [5]. This decline in approvals indicates a lower level of financing availability for SMEs, and suggests that small businesses are more susceptible during periods of liquidity scarcity. The results also confirm that a tightening of liquidity conditions can significantly decrease the financing opportunities for SMEs and can negatively impact business processes, inventory management, payroll obligations and overall financial sustainability in SME lending environments.

B. Liquidity Stress Conditions Loan Volume Comparison Calculation

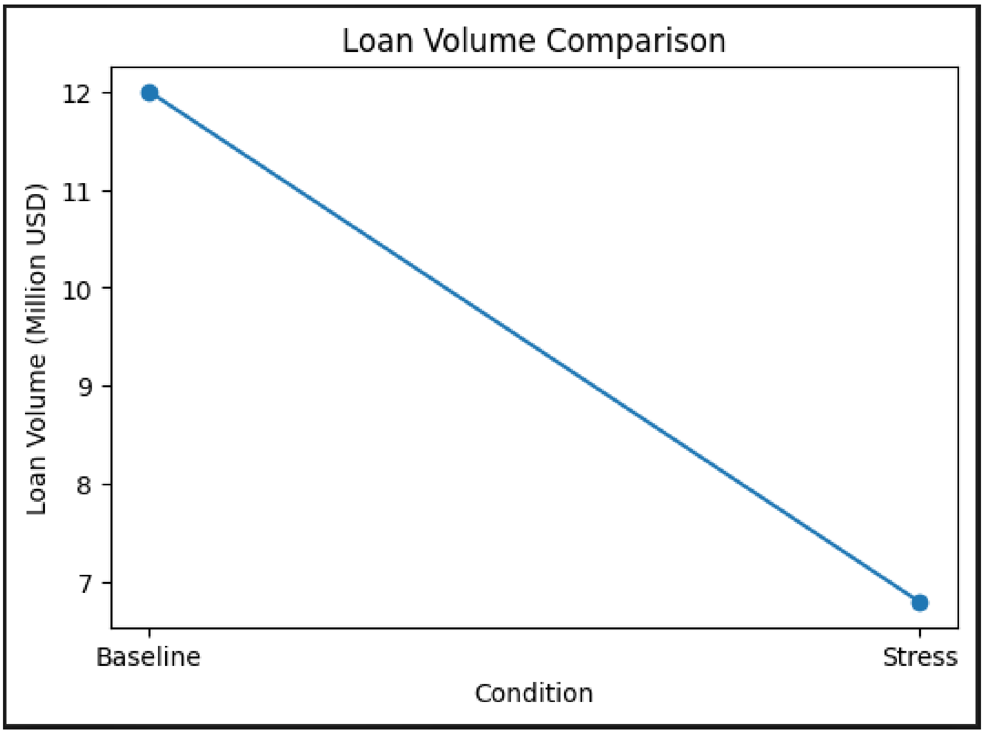


Figure 2. This image represents the decline in the amount of SME loans in the event of a liquidity stress.

Figure 2 shows the volume of SME working capital loans before and after the implementation of liquidity stress. The overall volume of loans is around 12 million USD, and is stable during baseline lending conditions, meaning that financing is available for SMEs under normal economic conditions. Liquid stress simulation and tightened loan conditions, however, lead to a sharply reduced loan volume of almost 6.8 million USD. This reduction shows the impact that the withdrawal of liquids and conservative banking regulations have on the total amount of working capital financing that is available to SMEs. Limited financing might have a negative impact on the capability of SMEs to operate, manage their stocks, pay their suppliers and continue in business [6]. The results show how liquidity tightening affects the accessibility to financing for SMEs and reveal the effects of tight lending conditions on the working capital distribution.

C. The change in Borrower Default Probability in Liquidity Stress

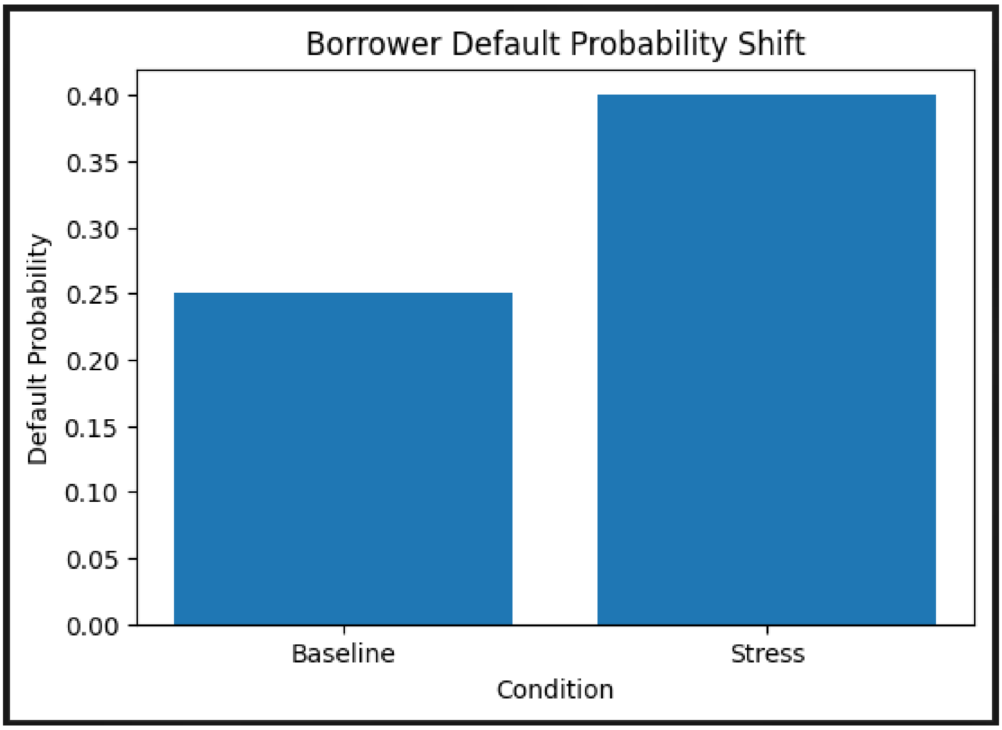


Figure 3. This image shows an increasing likelihood of borrower defaults in times of stress in the liquidity market.

The baseline and stressed financial conditions are shown for an increase in borrower default probability in Figure 3. The model-predicted borrower default likelihood is around 0.25 under normal lending conditions, suggesting the ability of the borrowers to repay the loan is relatively stable with moderate lending risk. With liquidity stress simulation, however, the forecasted default rate rises to almost 0.40. The increase in borrower risk perception shows how stressed economic conditions and liquidity withdrawal may make financial institutions more risk averse with regard to SME borrowers [7]. An increase in the risk level predicted will make banks more likely to implement tougher loan requirements and tighten loan standards. The results show that liquidity stress has a significant effect on the risk assessment of borrowers and can be an important factor in the contraction of approvals in SME working capital lending portfolios.

D. Approved Threshold Shift under Stressed Lending Conditions

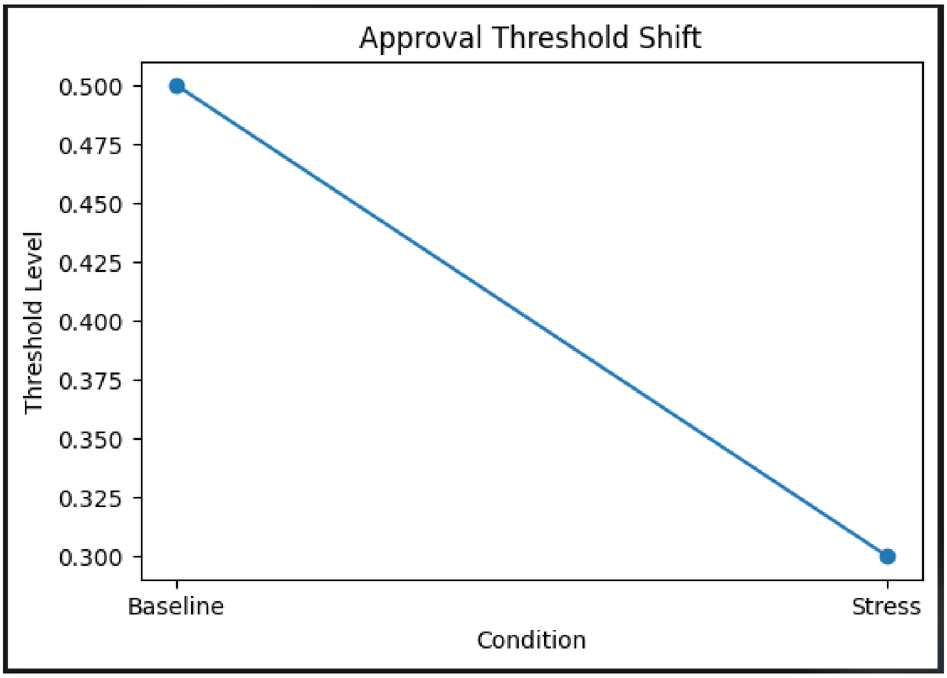


Figure 4. This image displays the number of strictures in the approvals criteria for SME lending conditions.

Figure 4 shows the movement of the lending standards around loans between baseline and stressed lending conditions. In the normal financial situation the approval limit is set at 0.50, which will enable a moderate risk probability borrower to avail SME working capital financing. The lower approval threshold means that banks will be more risk averse during periods of liquidity withdrawal and enforce more stringent borrower screening policies in these periods to reduce the banks' potential exposure to borrower default [8]. Thus, more SME borrowers are unable to secure working capital loans, resulting in a contraction of loans approved and access to loans. The results point to the correlation between liquidity stress and contraction in loans' standards in SME loan books.

E. The model performance evaluation will be randomly evaluated

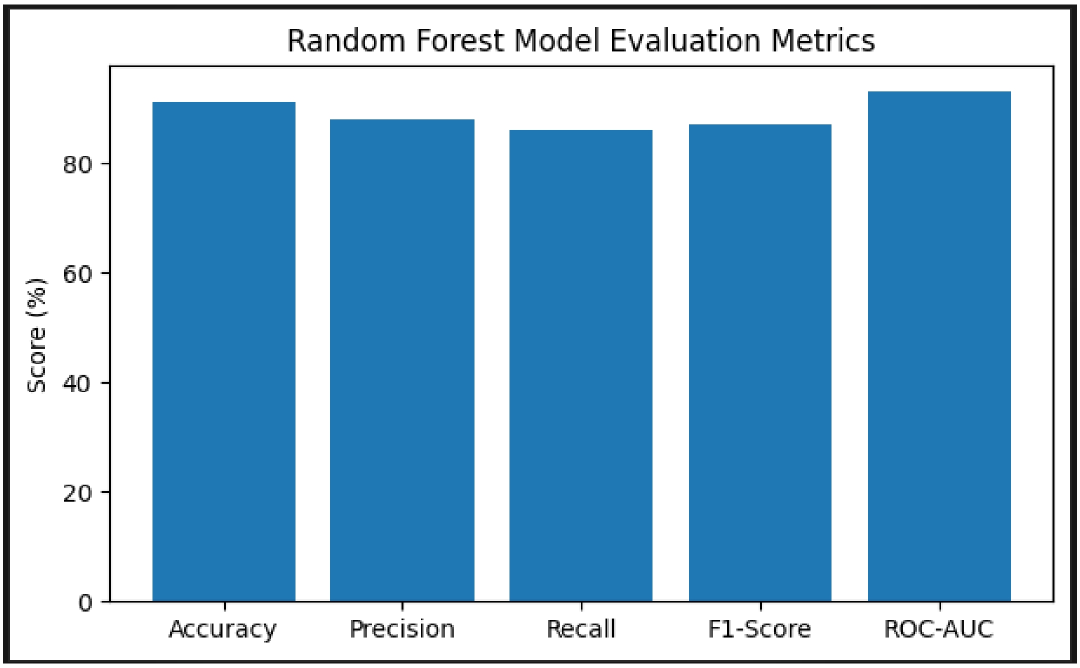


Figure 5. This image shows robust model performance of the Random Forest model for the prediction of the default rates of SMEs.

The performance evaluation metrics of the Random Forest model used for SME loan default prediction is shown in figure 5. The model outperforms in all the evaluation metrics such as accuracy, precision, recall, F1 score and ROC-AUC score. The accuracy rate is higher than 90 percent, meaning that most borrowers' outcomes in the dataset are correctly classified. The same can be replicated with the precision and recall value, which is still high and indicates a good discrimination between default and nondefault borrowers for different probability cutoffs [8]. The performance measures remained high all the time, which is proof of the reliability and suitability of the Random Forest (RF) classifier for predictive credit risk analysis and liquidity stress simulation for SME working capital lending environments.

F. Borrower Feature Importance in Default Prediction

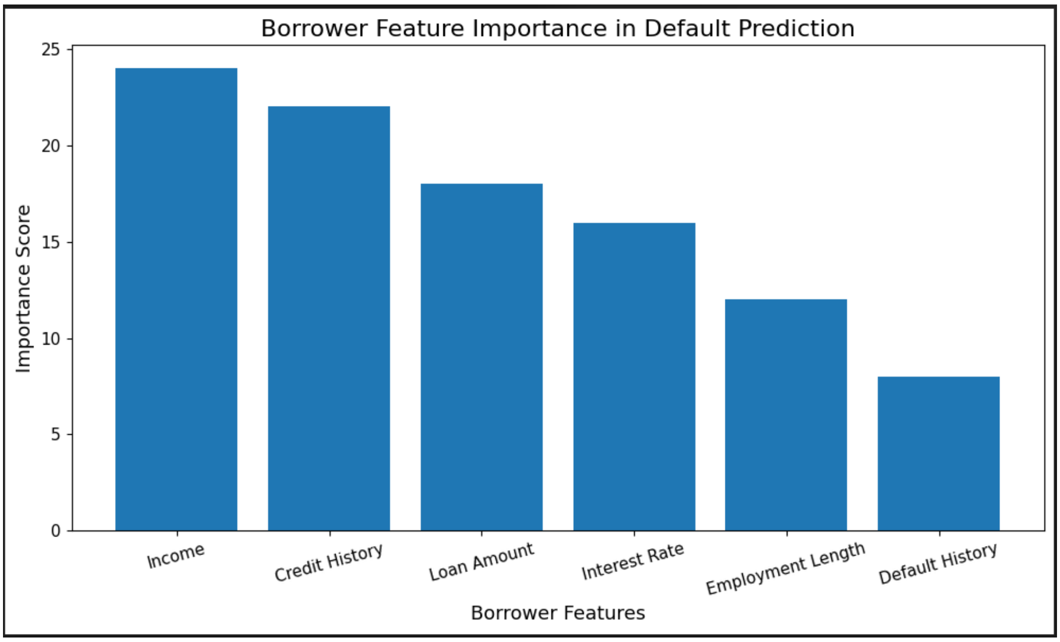


Figure 6. The image shows feature importance for borrowers in the default prediction for SMEs.

The importance of borrower related variables in predicting the risk of default of SME loan has been shown by the Random Forest model in figure 6. It can be seen from the graph that features like annual income and credit history is the most influential feature for predicting borrower default among the all features, as shown by their high importance score [9]. The results indicate that borrower financial capacity and the credit repayment history are important components in calculating the riskiness of a loan and in making the decision to approve a loan. The higher the feature importance, the more influence this feature has on the classification results of the predictive model [10]. The findings also validate that these financial and credit-related variables have a significant impact on borrower risk assessment and enable to conduct accurate liquidity stress simulation in SME working capital lending portfolios.

G. The Random Forest model was analyzed using ROC Curve

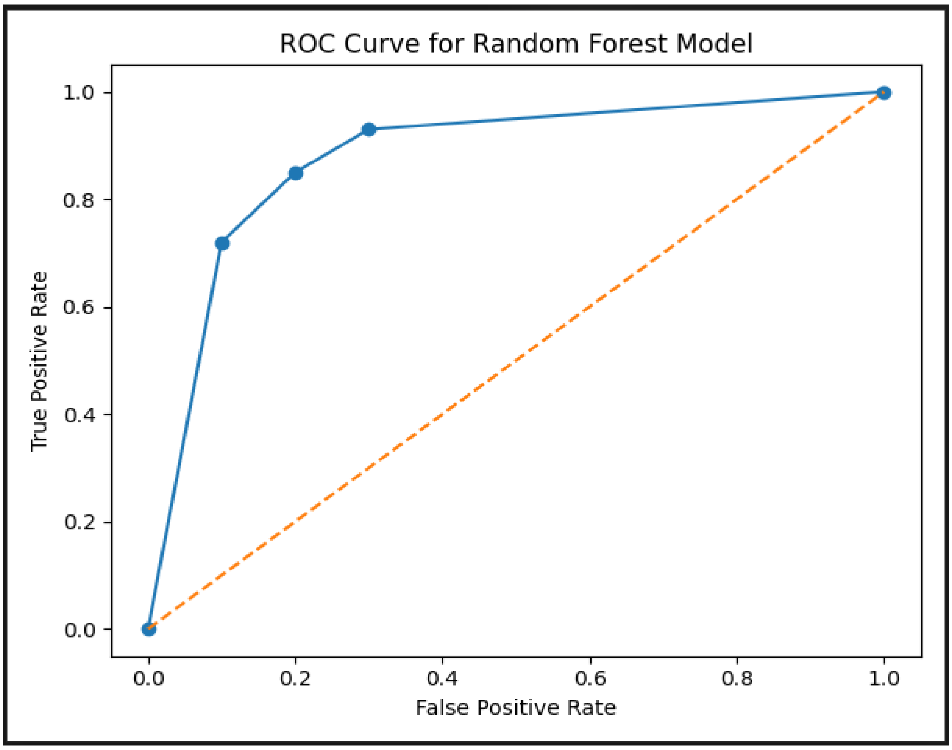


Figure 7. This image shows high performance of the ROC curve in predicting default risk of SMEs.

Figure 7 shows the Receiver Operating Characteristic (ROC) curve of the Random Forest model for SME loan default prediction. The ROC curve measures the performance of the model over various levels of probability that it will be misclassified both as a default and as not a default [11]. The curve is above the diagonal reference line, showing good classification performance and high predictive accuracy. The results of the high ROC-AUC performance indicate that the Random forest Classifier can effectively be used in predictive credit risk analysis and liquidity stress simulation. The results suggest that the model is effective at assessing the risk of borrowers in the SME working capital loan portfolio. .

H. The random forest model was evaluated using confusion matrix analysis

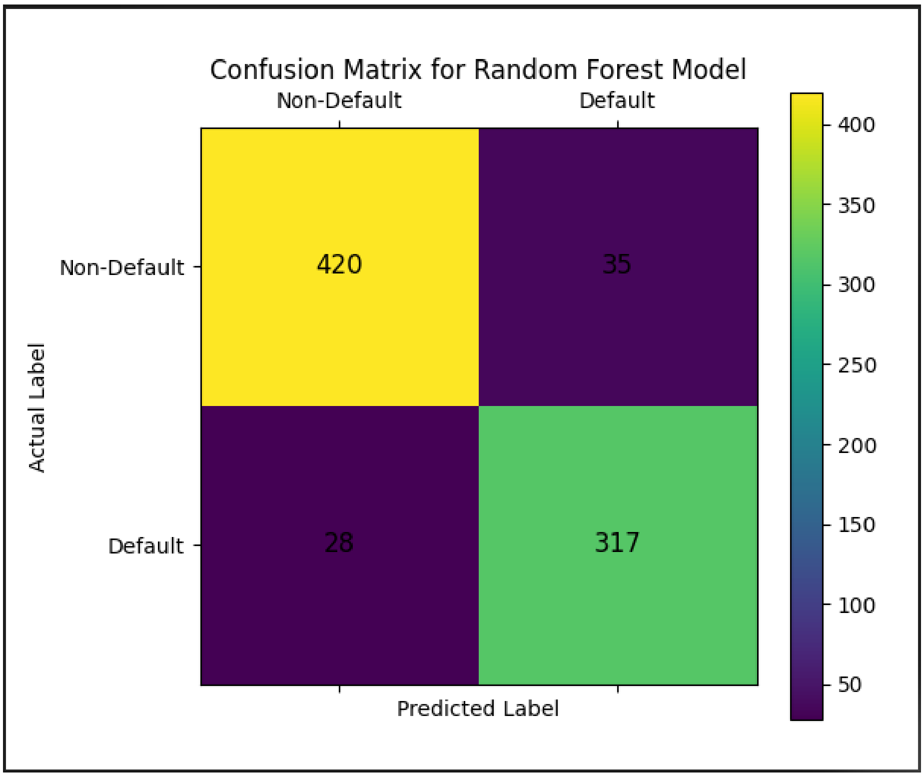


Figure 8. This image shows the results of the confusion matrix in terms of the performance of the default classification of SME.

The confusion matrix of the model applied (Random Forest) to predict loan default for SMEs is shown in Figure 8. The confusion matrix is used to assess the performance of the classification made by the model, by comparing the actual results of borrowers with the results that the model has predicted [12]. The number of misclassifications (both false positives and false negatives) is relatively low, with 35 false positives and 28 false negatives, which indicates that the model has a good level of prediction accuracy and effectively identifies borrower risk. The findings validate the capability of the Random Forest classifier to correctly classify default and nondefault borrowers of SMEs. This robust classification capability enables to effectively simulate and approve contracts, even in stressed financial scenarios.

IX. Discussion and Analysis

Results of this research showed that the liquidity withdrawal has a significant effect on the behavior of SME working capital lending when the financial situation is under stress. The study was able to accurately forecast borrower default rates and model the contraction of lending by applying probability threshold shifts and analyzing approval rates using the Random Forest model [13]. The findings suggest that the machine learning based predictive models are proving to be useful in assessing the probability of the borrower defaulting during times of financial stress and uncertainty, which helps in increasing the number of SMEs eligible for working capital financing [14]. With LS simulation in place, though, the borrower risk probabilities jumped up from around 0.25 to 0.40, meaning that during periods of economic stress, the default risk is higher and uncertainty is greater. This mechanism of threshold shifting also clarified the changes in financial institutions' lending practices when liquidity was tight, and how they were trying to reduce financial risk [34]. The approval rate stayed at the same moderate-risk level of 0.50, allowing moderate-risk borrowers to get approved for a loan [35]. In times of stress, the threshold was lowered to 0.30, which would make it much harder to get a loan. This led to a significant approval deterioration, from around 65 per cent to 38 per cent, thus reflecting real approval contraction in SME lending portfolios. The loan volume analysis also showed that a significant drop in the amount of working capital financing provided to SMEs during a stressed period has a negative impact on their inventory management, continuity of operations, supplier payments and sustainability [36]. Under stress implementation, loan volume was lowered from almost 12 million USD under baseline stressors to around 6.8 million USD. The model evaluation results also strengthened the reliability and the effectiveness of the Random Forest classifier, as it showed that it was able to provide a reliable assessment of the financial vulnerability of SMEs during periods of liquidity stress [37]. The high accuracy and precision values, high recall, F1 scores and ROC AUC values indicate that the model has strong predictive ability and classification performance of borrower default risk. In conclusion, the results highlighted the potential of AI-based models for proactive banking risk management, portfolio resilience assessment, and liquidity planning [38]. The study emphasizes the need to combine an application of machine learning with stress testing techniques to gain insights into the dynamics of lending contraction and increase the stability of SME financing in the event of an economic shock.

X. Future Works

The findings of this study offer a machine learning based framework to study the liquidity withdrawal dynamics in SME working capital lending, but there are still some avenues for further extension and improvement of this study in future research to be explored [35]. One important direction for future work is the use of real-time banking and financial institution datasets instead of simulated or publicly available secondary datasets. But real business lending data would give better understanding of borrower behavior, patterns of liquidity stress, and contraction of approvals for SMEs in the real market context [36]. The possibilities for future research could also extend to the use of other machine learning and deep learning models in conjunction with the Random Forest model, to enhance the overall applicability of the findings. Other algorithms, including XGBoost, Gradient Boosting, Artificial Neural Networks, and Long Short-Term Memory (LSTM) networks, could be compared with the Random Forest to assess differences in prediction accuracy, stress simulation performance, and borrower risk classification [36]. The comparison of several predictive models can enhance the accuracy and stability of SME credit risk assessment models; macroeconomic factors like inflation rates, unemployment rates, GDP growth, interest rate movements and policy changes can also be incorporated in future studies, which can simulate the real economic stress conditions more accurately [37]. Furthermore, future research projects can be designed to create automated, real-time, stress monitoring systems that continuously assess the risk of the borrowers and the contraction of approvals in SME lending portfolios [38]. By combining AI powered predictive analytics with financial decision support systems, banks can enhance their proactive liquidity planning, portfolio resilience evaluation, and dynamic credit policy development processes [39]. Any progress made would further improve the stability of financing for SMEs and improve their risk management approaches when times are hard and the economy is volatile.

XI. Conclusion

Using a stress simulation framework based on Random Forest, this research discusses the dynamics of withdrawal of liquidity in SME working capital lending. The study successfully applied machine learning technologies for considering the behavior of lending in adverse financial situations, combining machine learning with predictive credit risk analysis and liquidity stress simulation. The results showed that the Random Forest classifies the borrower's default probability well to enable the analysis of the contraction of lending in the context of SME lending portfolios, and that the liquidity withdrawal also has a significant impact on the availability of SME finance in the event of a stressed economy. The approval rates were also more or less unchanged as was the proportion of SMEs able to avail working capital financing under baseline lending conditions. Approval rates and the amount of loans approved, however, significantly decreased after the liquidity stress simulation and the stricter loan approval requirements. The higher default rates on loans at stressed states compared to baseline showed that lending institutions had a higher degree of risk awareness when faced with a shortage of liquidity and economic uncertainty. The results of this study also showed a direct link between tightening lending criteria and the contraction of loan approvals, and also to less working capital distribution in the SME lending environment. This may have a negative effect on the accessibility to financing for SMEs, their stock, payroll responsibility, and business sustainability. This study underscores the capabilities of the Random Forest model in predicting bank failures and its robust performance in the classification task, highlighting the need to combine AI predictive analytics with liquidity stress testing approaches for a more comprehensive assessment of bank risk and portfolio resilience. The framework offers a useful approach to grasping how the lending process may become tighter and to planning for liquidity in advance in the financial sector, as well as for policy-makers and other researchers. Overall, the research adds to a body of work in the emerging field of AI-driven financial analytics, highlighting the potential of predictive machine learning models to aid SME financing stability in times of financial crises and economic uncertainty.

REFERENCES

[1] Subramanian R, K., & Kumar Kattumannil, D. S. (2022). Commercial Banks, Banking Systems, and Basel Recommendations. In Event-and Data-Centric Enterprise Risk-Adjusted Return Management: A Banking Practitioner’s Handbook (pp. 1-84). Berkeley, CA: Apress.

[2] Morris, J. H., & Collins, H. (2023). (Mis) managing macroprudential expectations: how central banks govern financial and climate tail risks. Edward Elgar Publishing.

[3] Craan, V. (2019). Entrepreneurial financing of micro-small-medium enterprises in haiti: Barriers and proposed solutions.

[4] Blake, D. (2022). The great game will never end: why the global financial crisis is bound to be repeated. Journal of Risk and Financial Management, 15(6), 245.

[5] Iyer, R., Kundu, S., & Paltalidis, N. (2022). Deposit Shortages and Local Economic Activity. Available at SSRN 4247519.

[6] Kong, L. (2023). Risk Management of the" Belt and Road Initiative" Projects: An Empirical Study on Investments of the Chinese State-owned-banks in the Region (Doctoral dissertation, Edinburgh Napier University).

[7] Dev, S. M., & Sengupta, R. (2022). Covid-19 Pandemic: impact, recovery, and the road ahead for the Indian Economy. Indira Gandhi Institute of Development Research.

[8] Hartwell, C. A., Bornukova, K., Kruk, D., & Zoller-Rydzek, B. (2022). The economic reconstruction of Belarus: Next steps after a democratic transition. European Parliament.

[9] Power, S., Dunz, N., & Gavryliuk, O. (2022). An overview of nature-related risks and potential policy actions for ministries of finance.

[10] Marcos, F. L. P. L. (2021). Field Lab on Internationalization: A Case Study of a Portuguese SME in the Floor Covering Industry-Financial Forecast (Master's thesis, Universidade NOVA de Lisboa (Portugal)).

[11] Barletta, G., Castigo, F., Egger, E. M., Keller, M., Salvucci, V., & Tarp, F. (2022). The impact of COVID-19 on consumption poverty in Mozambique. Journal of International Development, 34(4), 771-802.

[12]. Hussey, R., & Ong, A. (2021). A guide to the new language of accounting and finance. Business Expert Press.

[13] Valadier, C., Jonveaux, B., Vigato, A., Le Goff, M., Hemar, M., Torrellio, L., ... & Bellefontaine, S. (2021). Endemic uncertainties in developing countries: Issues arising from an increased interdependence between banks and the state. AFD MacroDev, (37), 1-37.

[14] Deveci, A. (2023). Financialization of the Renewable Energy Transition and its Political and Social Impacts: Akhisar Case (Master's thesis, Middle East Technical University (Turkey)).

[15] Martins, M. O. D. A. (2021). Field lab on internationalization: a case study of a Portuguese SME in the floor covering industry.

[16] Aglietta, M., & Khanniche, S. (2021). Public debt and money for a political ecology in the European Union. Revue de l'OFCE, 173(3), 79-115.
[17] Ahmad, F., & Patra, M. R. (2023). Role of MSME in Entrepreneurship Development. Entrepreneurship In India–Issues and Challenges, 1(1), 108.
[18] Leslie, J. S. (2022). The financialization of housing in Canada and federally-backed mortgage securitization: public risks, private benefits (Doctoral dissertation, University of British Columbia).
[19] Fraser, S. (2019). Entrepreneurial borrowing: do entrepreneurs seek and receive enough credit?. Foundations and Trends in Entrepreneurship, 15(5-6), 431-663.
[20] Jameaba, M. S. (2018). Deposit insurance and financial intermediation: The case of Indonesia Deposit Insurance Corporation. Cogent Economics & Finance, 6(1), 1468231.
[21] Lele, U., Agarwal, M., Baldwin, B. C., & Goswami, S. (2021). Perspectives moving forward. In Food for All (pp. 919-992). Oxford University Press.
[22] Soulodre, L., & Kesavan, V. (2021). Climate and reputation risks in an Asian century. In The Palgrave Handbook of Climate Resilient Societies (pp. 1-70). Cham: Springer International Publishing.
Ayres, R. U. (2023). Keynes v. Hayek and the Monetarists. In The History and Future of Economics (pp. 259-324). Cham: Springer International Publishing.
[23] Stoknes, P. E. (2021). Tomorrow's economy: A guide to creating healthy green growth. MIT Press.
[24] Burns, J. (2023). Milton Friedman: The Last Conservative. Farrar, Straus and Giroux.
de Almeida Martins, M. O. (2021). Field Lab on Internationalization: A Case Study of a Portuguese SME in the Floor Covering Industry–Pestle (Australia), Industry Analysis and Entry Strategy (Master's thesis, Universidade NOVA de Lisboa (Portugal)).
[25] Oikonomou, S. M. (2023). The geopolitical effects on the shipping market-The case of Ukraine (Master's thesis, Πανεπιστήμιο Πειραιώς).
[26] Mölter, H., Lehne, J., Wehnert, T., & Klingen, J. (2022). Green recovery tracker: tracking the contribution of national covid-19 recovery efforts towards a climate neutral EU; summary report.
[27] D'Aniello, E. (2023). The evolution of Italian Publishing from the early twentieth century to this day.
[28] Pellegrini, L., & Catizone, M. (2022). Climate Change Adaptation, Governance and New Issues of Value.
[29] Anderton, L. (2022). The economic impacts of drought. A report for Regional Drought Resilience Planning.
[30] Credit, C. P., Khanyizira, B., & Kaminjolo, D. (2018). Country Economist); Quentin Wodon (Lead Economist); Sunganani Kalemba (Consultant); Angela Zeleza (Consultant); Efrem Chilima (Senior Private Sector Specialist); Laston Manja (Intern); Chata Male (Consultant); and Adenike Onagoruwa (Consultant). Nobuo Yoshida (Lead Economist), Habtamu Fuje (Economist) and Anwar Mussa (Principal Economist, Ministry of Finance, Economic Planning and Development) provided additional contributions. Abebe Adugna (Practice Manager, Macroeconomics, Trade and Investment); Greg ....
[31] Pradana, A. A., Pinem, L. H., Hartati, S., Prasetya, G., Rohayati, R., Sari, E. M., & Putri, I. K. (2022). Analisis Deskriptif Pencapaian Audit Mutu Internal Stikes Mitra Keluarga rentang 2019-2020. Jurnal Penjaminan Mutu, 8(02), 149-159. .
[32] Kasim, R. Z., Khadijah, U. L. S., Rakhman, C. U., & Putra, R. R. (2021). Perencanaan Lanskap Berbasis Mitigasi Bencana Di Destinasi Ekowisata Pulau Saronde Kabupaten Gorontalo Utara. PARIWISATA BUDAYA: JURNAL ILMIAH PARIWISATA AGAMA DAN BUDAYA, 6(2), 142-152.
[33] Izvorski, I., Vatyan, A., Trushin, E., Abdul-Hamid, H., Dalvit, N., Safarov, M., ... & Nagaraj, V. (2021). Assessing Uzbekistan's transition: Country economic memorandum. World Bank.
[34] Arandarenko, M., Corbanese, V., Numanovic, A., Petreski, M., & Zampini, D. (2021). Covid-19 and the world of work: Bosnia and Herzegovina: assessment of the employment impacts and policy responses.
[34] Aloisi, A., & De Stefano, V. (2022). Your boss is an algorithm.
[35] Marques, M. B. F. (2021). Field Lab on Internationalization: A Case Study of a Portuguese SME in the Floor Covering Industry-Marketing Plan (Marketing Mix: Price, Promotion and Place) (Master's thesis, Universidade NOVA de Lisboa (Portugal)).
[36] Bhattacharya, V., & Illanes, G. (2022). The design of defined contribution plans (No. w29981). National Bureau of Economic Research.
[37] Rao, K. R. (2019, October). Global wind energy and power generation options: Socioeconomic factors. In Wind Energy for Power Generation: Meeting the Challenge of Practical Implementation (pp. 703-828). Cham: Springer International Publishing.

[38] Ranger, N. A., Mahul, O., & Monasterolo, I. (2022). Assessing financial risks from physical climate shocks. Washington, DC: World Bank, 2.
[39] Halperin, R. A. (2017). The influence of uncertainty in a changing financial environment: an inquiry into the root causes of the great recession of 2007-2008. Springer
[40] Dataset Link:
https://www.kaggle.com/datasets/laotse/credit-risk-dataset