THE IMPACTS OF MACROECONOMIC CHANGES ON AGRICULTURAL CREDIT RISK IN BRAZIL

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Abstract

This paper analyses the relationship between macroeconomic variables (gross domestic product, unemployment rate, public debt and balance of international investments) and credit risk, measured as non-performing loans—or credit default. This study uses quarterly data for macroeconomic variables and rural credit default for the Brazilian banking system from 2012 to 2022. The study finds that deterioration in macroeconomic conditions, such as GDP and unemployment, will increase agricultural credit risk. At the same time, positive changes, like a reduction in the balance of international investments' deficit, reduced credit risk levels. The research methodology involves a Vector autoregression (VARX) technique and Impulse Response Functions (IRFs). This study's findings can contribute to the existing literature on the relationship between macroeconomic variables and credit risk and provide insights for policymakers and financial institutions while addressing rural credit risk models.

Preface

The relationship between macroeconomic variables (Gross domestic product, unemployment rate, public debt and balance of international investments) and credit risk has become a subject of great interest since the 2008 global financial crisis and the recent COVID-19 pandemic. These events emphasized the crucial link between macroeconomic conditions and the stability of financial institutions. Understanding how macroeconomic factors influence credit risk is vital for effective risk management in the banking sector.

This paper aims to contribute to the existing literature on the relationship between macroeconomic variables and credit risk, focusing specifically on agricultural credit in Brazil. By investigating the implications of macroeconomic variables on credit risk, this study aims to provide valuable insights into the unique characteristics of the farming industry and its susceptibility to macroeconomic changes.

The problem statement highlights the need for comprehensive studies focused on specific credit types, such as agricultural loans, given the significance of agriculture in the Brazilian economy and its role in the global supply chain of agricultural commodities. By examining the association between macroeconomic conditions and agricultural credit risk, this research seeks to fill the gap in the literature and contribute to better risk management strategies and policies tailored to the farm sector.

The research objectives and hypotheses are outlined, providing a clear and specific focus for the study. The expected outcomes, methodology, and data description are also presented, demonstrating the research's empirical approach and the sources of data utilized. The limitations of the model and the analytical techniques employed are acknowledged, ensuring transparency and rigour in the research process.

Ultimately, this study aims to shed light on the macroeconomic factors influencing Brazil's agricultural credit risk. The significance of this study lies in its contribution to the existing literature and its potential to inform risk management strategies and policies, ultimately promoting the stability and resilience of the agricultural sector in Brazil.

Dedication

I dedicate this work to Grazielle and Melissa, my wife and daughter, for their fundamental support and love to complete this program during this challenging year.

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1. INTRODUCTION

1.1 Background to study

Brazil is one of the world's leading agricultural producers. It is renowned for its diverse agrarian sector and vast areas of arable land. The agriculture industry is pivotal in the country's economy, contributing significantly to GDP and employment. In 2021 livestock and crop production accounted for 8% of gross domestic product and 29% when considering food processing and distribution. Agriculture employs about 15.1 million people in rural properties, about 15% of Brazil's labor force (USDA, 2022). Given the sector's importance, agricultural credit has been critical in supporting farmers and promoting agricultural development. The study of how selected macroeconomic variables (GDP, unemployment rate, public debt and balance of international investments) affect rural credit risk is essential to the agricultural credit segment.

Like any credit market, agricultural credit in Brazil is exposed to many risks. Various factors, including macroeconomic conditions, weather patterns, commodity price fluctuations, government policies, and global market dynamics, influence agricultural credit risk in Brazil. These factors impact the financial viability of farming operations and the ability of borrowers to repay their agricultural loans.

Due to the 2008 global financial crisis and the recent COVID-19 pandemic, understanding the relationship between macroeconomic variables and credit risk in Brazil's agricultural credit structure has become increasingly crucial. This study aims to shed light on these intricate interconnections and contribute valuable insights to the existing literature on agricultural credit risk in Brazil, providing a comprehensive understanding of how macroeconomic conditions impact credit risk levels within the context of the country's vital agriculture industry.

This work will fit into the existing literature on the relationship between macroeconomic variables and credit risk. It contributes to the growing body of research to understand how macroeconomic conditions impact credit risk levels. Specifically, this study focuses on the Brazilian agricultural credit structure, providing insights into the implications of macroeconomic variables on credit risk.

1.2 Problem Statement

While there is plenty of research on the association between macroeconomic variables and credit risk in general, there is a lack of comprehensive studies specifically focused on credit types like agricultural loans. Given the importance of agriculture to the Brazilian economy and its role in the global supply chain of agricultural commodities, it is crucial to understand how macroeconomic conditions impact credit risk in this sector.

The current issue of agrarian credit in Brazil revolves around the challenges faced by financial institutions and farmers in assessing and managing credit risk effectively. As the farm sector remains exposed to various uncertainties, such as changing weather patterns, commodity price volatility, and government policies, there is an inherent complexity in determining creditworthiness and predicting the repayment capabilities of agricultural borrowers. Financial institutions struggle to establish appropriate risk models that consider the unique characteristics of agricultural loans. This leads to overly stringent lending criteria, hindering farmers' access to credit, or inadequate risk assessments, increasing the likelihood of loan defaults and potential financial instability within the banking sector.

One of the approaches can be improving risk models by developing and refining risk assessment models catering to agricultural loans' unique characteristics and challenges. These models should consider macroeconomic factors such as GDP, inflation, and unemployment, among others, to accurately predict credit risk and repayment capabilities.

This study hypothesizes that macroeconomic variables change would influence agricultural credit risk in Brazil. I will use the econometric technique vector autoregressive (VARX) model to analyze the relationship between macroeconomic variables and agricultural credit risk.

1.3 Research Objectives

This study investigates which macroeconomic variables are most associated with farm credit risk, measured here as non-performing loans or default, and the extent of their impacts. Adverse changes in these macroeconomic factors are expected to lead to higher credit risk. In contrast, favourable changes will result in reduced credit risk levels. This paper aims to contribute to understanding the specific macroeconomic factors that influence agricultural credit risk in Brazil, which can advise policymakers, financial institutions, and agricultural stakeholders by completing the data collection, analysis, and interpretation of results.

Research hypothesis: H0 - Negative variations in macroeconomic variables, such as GDP, will increase agricultural credit risk in Brazil. H1 - Positive macroeconomic changes reduce

Brazil's agricultural credit risk levels. These research objectives and hypotheses provide a clear and specific focus for the study, outline measurable outcomes, and align with the overall goal of investigating the relationship between macroeconomic variables and agricultural credit risk in Brazil.

1.4 Significance of the Study

The significance of this study lies in its contribution to the existing literature on the association between macroeconomic variables and credit risk. Additionally, this study addresses the gap in research focusing on agricultural credit in Brazil, a country with significant agrarian importance in the world's food and commodity supply. Understanding the specific macroeconomic factors that influence farming credit risk can help banks and policymakers design more effective risk management strategies and policies tailored to the unique characteristics of the farming industry.

Agricultural credit risk is significant due to its far-reaching implications for various stakeholders and the broader economy. Several reasons underscore the significance of understanding and managing agrarian credit risk:

Agriculture is critical in the Brazilian economy, contributing significantly to GDP, employment, and export earnings. The sector's stability and growth are crucial for overall economic prosperity. Agricultural credit risk directly impacts the financial health of farmers, agricultural businesses, and financial institutions, affecting investment decisions, productivity, and profitability within the sector. As a significant player in the global food and commodity supply chain, disruptions in the Brazilian agriculture sector can have a wave effect on food security and commodity prices worldwide. Effective management of agricultural credit risk ensures the continued production and supply of agricultural products, reducing the likelihood of supply shortages and price volatility in international markets. Agriculture is a significant segment of the loan portfolios of Brazil's two major public financial institutions. Poor credit risk management in the agricultural sector can lead to higher default rates, non-performing assets, and potential systemic risks for the financial system. Understanding agricultural credit risk helps banks and financial regulators assess potential vulnerabilities and implement measures to safeguard financial stability.

1.5 Organization of the Report

The remaining sections are organized into the following areas: Chapter two is dedicated to the literature review. In chapter three, I discuss the methodology. I discuss the results in chapter four and, in chapter five, the conclusion.

2. LITERATURE REVIEW

2.1 Introduction

Understanding the intricate relationship between macroeconomic variables and credit risk propels it to the forefront of academic and policy discussions. As financial institutions and policymakers seek to enhance risk management strategies and fortify the banking sector's resilience, comprehensive research on this association has become necessary.

This literature review addresses this crucial need by providing an in-depth and comprehensive overview of the existing body of research concerning the interplay between macroeconomic factors and credit risk. By consolidating and analyzing the findings of previous studies, this review aims to illuminate critical insights, identify gaps in knowledge, and lay the foundation for further investigations in this vital field of study.

2.2 Theoretical Framework

Studying credit risk, generally, we find two theoretical approaches to explain default in financial institutions, one focusing on the bank's client selection and portfolio management, and a more recent line in literature focuses on the association of macroeconomic variables to explain credit risk (Galvis-Ciro, Moraes, & García-Lopera, 2023).

The Business Cycle Theory, within the context of macroeconomic changes and credit risk, provides valuable insights into the relationship between the overall state of the economy (macroeconomic variables) and credit risk levels. As per this theory, macroeconomic fluctuations during different phases of the business cycle significantly impact the creditworthiness of borrowers and, consequently, the level of credit risk faced by financial institutions. For instance, during the business cycle expansion, characterized by increased economic activity and favorable macroeconomic conditions, borrowers generally experience improved income stability and business profitability. These conditions lead to a reduced likelihood of default and lower credit risk. On the contrary, during the contraction phase of the cycle, economic slowdown, rising unemployment, and declining business conditions increase the probability of default, thereby elevating credit risk for lenders.

Furthermore, Business Cycle Theory highlights the role of macroeconomic policies in influencing credit risk. During periods of economic expansion, central banks may tense monetary policy by increasing interest rates to control inflationary pressures. This constriction can impact credit risk by raising borrowing costs, reducing the affordability of loans, and potentially leading to a higher likelihood of default. On the other hand, during economic contractions, central banks may employ expansionary monetary policies, such as lowering interest rates and implementing liquidity measures, to stimulate economic growth. These measures can ease the credit burden on borrowers, potentially mitigating credit risk.

2.3 Review of Empirical Studies

The study of macroeconomic variables' impacts on credit risk became critical after the 2008 global financial crisis, especially after the Basel III framework[1] (Asghar, Rashid, & Abbas, 2022). Financial stability has always been a considerable concern among central banks, especially in developing countries. However, with the 2008 financial crisis, where rich countries also experienced substantial financial losses, it was clear that the regulation should change. Basel III has launched with a focus on increasing capital quantity and quality, improving liquidity and funding risk management and addressing risks the bank system poses. These changes aimed to make the system more resilient and capable of resisting financial shocks and economic downturns.

A study on the Colombian banking system (Galvis-Ciro, Moraes, & García-Lopera, 2023) found that GDP was negative and significantly associated with credit risk, confirming the authors' hypothesis that credit risk is procyclical. Also, they found that the correlation between credit risk and the unemployment rate is positive and significant, as is the interest rate. Another study analyzing Australian and U.S. economies found that the variances in selected macroeconomic indicators can partially explain credit risk (Ali & Daly, 2010).

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[1] The Basel III framework is a set of international banking regulations developed by the Basel Committee on Banking Supervision. It aims to strengthen the global banking system by introducing more stringent capital requirements, enhancing risk management practices, and promoting greater financial stability. The framework was introduced as a response to the 2008 global financial crisis, aiming to address weaknesses in the banking sector and reduce the likelihood of future financial crises. It comprises various reforms, including higher capital ratios, liquidity standards, and measures to address systemic risks. Basel Committee on Banking Supervision. (2017). Basel III: A global regulatory framework for more resilient banks and banking systems. Bank for International Settlements.

During economic expansion, credit portfolios are characterized by low non-performing loans because borrowers tend to have higher available income to repay their credits (Marouf & Guellil, 2017). On the contrary, an economic downturn can be characterized by reduced income, as the same authors found a high negative relationship between GDP and credit default. Also, they found a positive relationship between money supply, financial development and political stability and the increase in non-performing loans. This indicates that the credit risk could grow even with considered good macroeconomic indicators during economic expansions.

Castro (2013) explores the relationship between macroeconomic developments and banking credit risk in five countries - Greece, Ireland, Portugal, Spain, and Italy (GIPSI) – affected by unfavorable economic and financial conditions. The research indicates that various macroeconomic factors significantly influence banking credit risk. He concludes that credit risk increases when GDP and house price indices decrease and unemployment and interest rate increase, especially after the 2008 financial crisis.

In a recent study, Panda, Panda & Panda (2023) used a VAR model to analyze macroeconomic variables and stock market variations. They concluded that the equity market reacts negatively to inflation and foreign investment changes, and the macroeconomic variables significantly influence stock indicators. In addition to the importance of macroeconomic variables to explain (at least partially) credit risk, Jiménez & Saurina (2018) mentioned the significance of time in the equation and the role of lagged variables in VAR models.

2.4 Contribution to Literature

This paper aims to contribute to the economic literature by studying a specific subject: Macroeconomic implications in the agricultural credit risk in Brazil. Reviewing the literature, moving from the aggregate to the individual level (from credit as a whole to the agricultural niche) seems to be the better approach for more accurate results to understand the macroeconomic mechanisms and credit risk and contribute to better risk management and economic literature.

Through empirical analysis and data-driven approaches, this study seeks to unravel the specific factors that influence credit risk in the agricultural domain, offering valuable insights for risk management strategies in the banking sector. By narrowing its focus to the Brazilian agricultural credit market, this research intends to yield context-specific findings that can contribute to the broader economic literature. As agricultural credit plays a vital role in driving economic growth and stability in developing economies like Brazil, the study's outcomes can serve as a foundation for future research and policymaking in agricultural finance. By identifying and analyzing the macroeconomic determinants of credit risk in this unique context, this research provides a different perspective that can aid in designing tailored and effective policies to foster sustainable development and resilience within the agriculture sector. Ultimately, this study aims to enrich the economic literature by offering a deeper understanding of the interplay between macroeconomic conditions and credit risk, with specific implications for the Brazilian agricultural credit landscape.

2.5 Insights from the Literature

After the literature review, I understood that models that capture time delay are necessary when analyzing macroeconomic dynamics in time series data. It is expected that macroeconomic changes take some time to reflect in credit default. The primary barrier is to be assertive when choosing the length of lagged variables. Also, to decide when analyzing credit risk and economic variables in pairs (1:1), reducing the complexity, or exploring all variables together as a whole system.

Another insight is related to which macroeconomic variables to choose since the literature has various indicators, and selecting the ones you intend to study can be challenging. In previous studies, GDP, inflation, unemployment rate and GDP debt ratio, among others, are the most common macroeconomic variables used in studies that cover credit risk.

The most used method in recent literature is dynamic panel data. However, as this study is limited to only one entity (Brazil), the best approach is to use a time series VARX model, controlling for explanatory variables, which is more suitable for analyzing time series data focusing on capturing contemporaneous relationships between variables.

3. RESEARCH METHODOLOGY

3.1 Introduction

The research methodology chosen for this study focuses on investigating the relationship between macroeconomic variables and credit risk in the Brazilian agricultural credit portfolio using a Vector Autoregression (VARX) model. This model was selected due to its suitability for analyzing time series data and capturing temporal relationships between variables. This methodology aims to reveal the short-term dynamics and interactions between macroeconomic indicators and credit risk metrics within the agricultural credit market.

The following section outlines the data description, which shows summarized information on time series data on selected macroeconomic variables, such as GDP, inflation, unemployment, and debt ratio—credit risk metrics measured by non-performing loans for the specified period. The data were collected from reputable international institutions and government agencies, covering eleven years and encompassing the recent COVID-19 pandemic to account for the impact of economic shocks on credit risk.

Subsequently, the study detail the application of the VARX model. The model will estimate the interrelationships between the selected macroeconomic variables and credit risk indicators, providing insights into how changes in the macroeconomic environment impact credit risk in the agricultural credit structure. The VARX model's dynamic nature allows for examining short-term responses and spillover effects between the variables, offering a deeper understanding of the transmission mechanisms within the system. Diagnostic tests and sensitivity analyses were conducted to validate the model's robustness and accuracy, ensuring reliable and consistent results.

In addition, I present the Impulse Response Functions (IRFs), which intend to simulate future outcomes. Overall, the VARX modelling approach and IRF analysis in this research methodology will enable a focused investigation into the dynamic interactions between macroeconomic variables and credit risk in the Brazilian agricultural credit market, contributing valuable insights to the farming finance and risk management literature.

3.2 Data Description

The study employs a range of quantitative variables and utilizes data from official and reputable sources (Central Bank of Brazil – BCB, International Monetary Fund – IMF, Brazilian Institute of Geography and Statistics- IBGE). Due to the challenges of different temporal frequencies and data availability, I decided to limit the macroeconomic variables to four, as other measures are not available for the entire period, or the data available are in annual format. Even having techniques to transform the data from annual to quarter, this approach could lead to bias and loss of time influence, an essential factor for time series analysis (Shellman, 2004).

In this project, I will use national-level, quantitative data for dependent variables (credit default) from the Central Bank of Brazil. As the variables are in a monthly format, I transformed these values into quarters using the previous three-month average. Then I combined six variables into three categories: Individual farmers and firms with market rate contracts (DEF14mkt), Individual farmers and firms with government-regulated rate contracts (DEF25reg), and both combined (DEF36tot).

For independent variables, I use national-level quarterly quantitative data from Brazilian federal public sources, like the Central Bank of Brazil (BCB), the Brazilian Institute of Geography and Statistics (IBGE), and international sources, like the International Monetary Fund (IMF).

The following table contains all variables used in this process to measure the relationship between macroeconomic changes and credit risk default.

Table 1. Variables Description

Variable	Acronym	Description
Default for market rate contracts	DEF14mkt	Percentage (%) of the rural credit portfolio with at least one installment overdue for more than 90 days, for firms and individuals, at market rates. Source: Central Bank of Brazil - BCB (Banco Central do Brasil)
Default for government-regulated rate contracts	DEF25reg	Percentage (%) of the rural credit portfolio with at least one installment overdue for more than 90 days, for firms and individuals, at government-regulated rates. Source: Central Bank of Brazil - BCB (Banco Central do Brasil)
Default total	DEF36tot	Percentage (%) of the rural credit portfolio with at least one installment overdue for more than 90 days, for firms and individuals, at market and government-

		regulated. Source: Central Bank of Brazil - BCB (Banco Central do Brasil)
Real Gross Domestic Product	GDP	Real gross domestic product. Domestic currency, seasonally adjusted. Source: International Monetary Fund IMF
Public sector net debt as a percentage of GDP.	DBT	Public sector net debt as a percentage of GDP, cumulative flow in 12 months at federal, state and municipal levels. Ratio Debit/GDP (%). Source: Central Bank of Brazil - BCB (Banco Central do Brasil)
Unemployment rate	UNP	Unemployment rate (%). Refers to people of working age (over 14 years old) who are not working but are available and trying to find work. Source: Brazilian Institute of Geography and Statistics- IBGE
Balance of international investments	BII	Balance of international investments = total assets minus total external financial obligations as a percentage of GDP. Source: Central Bank of Brazil - BCB (Banco Central do Brasil)

Table 2 is descriptive statistics for all variables in the original form (decimal values), which contains 44 quarters, ranging from the years 2012 and 2022.

Table 2. Descriptive Statistics

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variables					
DEF14mkt	44	0.0054	0.1173	0.0380	0.0311
DEF25reg	44	0.0149	0.0434	0.0305	0.0079
DEF36tot	44	0.0109	0.0852	0.0320	0.0202
Independent Variables					
GDP	44	0.0000	1.0000	0.6445	0.2018
DBT	44	0.3038	0.6033	0.4497	0.1081
UNP	44	0.0630	0.1490	0.1048	0.0265
BII	44	-0.5120	-0.2040	-0.3240	0.0578

The descriptive statistics offer a comprehensive overview of the dataset's variables. Among these, "DEF14mkt," representing a market-regulated credit default metric, ranges from 0.0054 to 0.1173, with a mean of approximately 0.0380 and a standard deviation of 0.0311. "DEF25reg," a regulated rate default, ranges from 0.0149 to 0.0434, with a mean of around 0.0305 and a smaller standard deviation of 0.0079. Similarly, "DEF36tot" spans from 0.0109 to 0.0852, with a mean of approximately 0.0320 and a standard deviation of 0.0202. The macroeconomic indicator "GDP" ranges from a minimum of 0.000 to a maximum of 1.000, with a mean of 0.6445 and a standard deviation of 0.2018, suggesting relatively significant variability. "DBT," "UNP," and "BII," each representing distinct economic aspects, exhibit varying ranges, means, and standard deviations, highlighting the diversity of their distributions. The valid number of observations for each variable is consistent at 44, representing quarters.

3.3 Analytical Approaches

I will adopt a time series data analysis for this study on macroeconomic variables' relationship with Brazil's agricultural credit risk. This methodology allows for considering the data's cross-sectional and time-series dimensions, which are crucial in capturing macroeconomic variables' dynamics and potential lagged effects on credit risk.

The empirical model for the estimation will be the Vector Autoregression model (VARX), controlling for explanatory variables. VARX is a powerful and flexible econometric tool that offers several advantages for addressing many aspects of an economic study. One of the advantages is its ability to capture dynamic relationships among multiple variables simultaneously. In economic systems, variables often interact and influence each other over time. VARX allows us to model these interdependencies and understand how shocks or changes in one variable can affect the entire system. By considering multiple variables together, VARX provides a more comprehensive and realistic depiction of the underlying economic dynamics compared to single-equation models.

Another advantage of VARX is its ability to handle endogeneity effectively and omitted variable bias. In traditional single-equation models, missing relevant variables can lead to biased and inconsistent parameter estimates. Conversely, VARX incorporates all the relevant variables as endogenous, allowing for a more rigorous analysis of their joint behavior. VARX is not limited to only examining the direction of causality between variables; it can also capture feedback effects, where variables influence each other bidirectionally, making VARX suitable for studying economic systems with feedback loops and interrelated factors.

The empirical model for a system with K variables (K > 1) can be specified as follows:

$$Y_t = \sum i \ (A_1 * Y_{t-i}) + \sum j \ (B_j * X_{t-j}) + C + E_t$$

Where:

Y_t Represents the dependent variable at time t, the default rates.

A_i These are coefficients associated with the lagged values of the dependent variable Y.

Y_{t-i} These are the lagged values of the dependent variable Y at different time points. They capture the effect of the variable's historical values on its current value.

B_j These are coefficients associated with the lagged values of the regressor variables X.

X_{t-j} These are the lagged values of the regressor variables at different time points. They represent the historical values of external factors that might influence the dependent variable.

C Is the constant term.

E_t Is the error term or residual at time t.

The selection of the VARX model is justified based on its suitability for analyzing the dynamic relationships among multiple interrelated time series variables in an econometric study. Firstly, the VARX model aligns with the economic theory that suggests these variables influence each other over time, reflecting the complex interactions within the system. By treating all variables as endogenous, the VARX model allows for capturing feedback effects and simultaneous interactions, making it an appropriate choice when there is no clear distinction between dependent and independent variables. This flexibility is precious in situations where traditional regression models may not adequately account for the interdependence among variables.

Secondly, the VARX model is well-suited for forecasting future values and conducting impulse response analysis. It is a valuable tool for understanding how shocks or innovations in one variable propagate throughout the system. This ability is crucial for policymakers and researchers seeking to make informed decisions and anticipate the consequences of policy interventions.

3.4 Limitations of the Model

The VARX model can suffer from overparameterization, especially when dealing with many variables and lags. As the number of parameters increases, the model becomes more complex and may be prone to overfitting, leading to reduced forecasting accuracy and difficulty in interpreting the estimated coefficients. Moreover, with limited sample size, estimating a high-dimensional VARX model can be problematic due to increased uncertainty and potential multicollinearity issues.

Another limitation is that the VARX model is not well-suited for addressing the issue of endogeneity. While it treats all variables as endogenous, it does not provide a causal interpretation of the relationships among variables. Instrumental variable approaches or structural VARX models may be more appropriate if endogeneity is a concern. Additionally, the VARX model relies on the assumption of no omitted variables, which can be restrictive in real-world scenarios where unobserved factors might influence the variables of interest.

3.5 Data processing

For this project, I have used Stata and SPSS software to calculate the estimated results of the model and variables statistics. I have also used Microsoft Excel for data cleaning, manipulation and construction of new variables. The first step was transforming the variables from percentage format (e.g., 10%) to decimal form (e.g., 0,10). The second step was to combine variables according to their type. Initially, I intended to examine six rural credit default types: Risk for firms considering the market and regulated interest rates, the risk for individual farmers, also considering the market and controlled interest rates, and lastly, the total for market and regulated interest rates. The next step was to set the GDP variable on a scale of percentages considering the entire period, using Min-Max Scaling: $X_{scaled} = \frac{(X - X_{min})}{(X_{max} - X_{min})}$ since this variable was measured in monetary values, ultimately, I applied first-order differencing in my dataset to stabilize the mean and remove the trend component, making the series stationary.

4. RESULTS AND DISCUSSION

4.1 Introduction

In this chapter, I provide the estimation results for the Vector Autoregression (VARX) methodology. The initial step was to test for stationarity using the decimal dataset format using the Dickey-Fuller test. Next, I will determine the appropriate lag order for the VARX model. To achieve this, I have used various information criteria, such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Information Criterion (HQIC), to compare different lag specifications. The chosen lag order is the one that minimizes these criteria, ensuring a parsimonious yet effective representation of the dynamic relationships. Once the lag order is determined, I will estimate the VARX model and the Impulse Response Functions (IRFs).

4.2 Diagnostic Test Results

In the first step, I transformed the original data from percentage form to decimal. Then I tested for stationarity using Dickey–Fuller GLS and Phillips–Perron tests. The results showed that my variables were stationary, as shown in the following tables. We can observe that the test results in p-values larger than the minimum considered statistically significant to reject the null hypothesis. The null hypothesis in the Dickey-Fuller and the Phillips–Perron tests is the presence of a unit root (non-stationarity), and the alternative hypothesis is stationarity.

Table 3. Unit Root Tests - Original Form

	ADF Test		PP Test	
Variables	Test Statistic	P-value for z(t)[1]	Test Statistic	P-value for z(t)[1]
DEF14mkt	-1.516	0.526	-2.021	0.278
DEF25reg	0.225	0.974	-0.490	0.894
DEF36tot	-1.240	0.656	-1.790	0.386
GDP	-1.995	0.307	-2.021	0.278
DBT	-0.219	0.936	-0.430	0.905
UNP	-1.107	0.712	-1.294	0.632
BII	-3.978	0.002	-4.038	0.001

ADF - Augmented Dickey-Fuller; PP - Phillips-Perron

N = 43. [1]MacKinnon p-values.

Table 3 presents the results of the unit root tests conducted on the original form of the variables. Two widely used unit root tests, the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test, were employed to assess the presence of unit roots in the time series data. The ADF test statistic was calculated for each variable, and the corresponding MacKinnon p-values were also derived. Similarly, the PP test statistic and its corresponding p-values are reported. Both tests suggest strong evidence of a unit root for all variables except for the BII variable, with ADF and PP tests with a p-value of 0.002 and 0.001, respectively.

Since the test statistic in both cases is higher than the critical values at all significance levels (1%, 5%, and 10%), and the p-values are higher than the typical significance level of 0.05, we fail to reject the null hypothesis of a unit root. In other words, there is insufficient evidence to conclude that the variable is stationary. The data appears to be non-stationary or contains a unit root. Since the VARX model assumes stationarity, I applied first-order differencing in my dataset to stabilize the mean and remove the trend component, making the series stationary. Then, I tested for stationarity again, as shown in Table 4, and the data became stationary.

Table 4. Unit Root Tests -First-Difference Form

	ADF Test		PP Test	
Variables	Test Statistic	P-value for z(t)[1]	Test Statistic	P-value for z(t)[1]
DEF14mkt	-4.324	0.000	-4.287	0.001
DEF25reg	-3.023	0.033	-2.826	0.055
DEF36tot	-3.944	0.002	-3.927	0.002
GDP	-6.522	0.000	-6.565	0.000
DBT	-3.744	0.004	-3.660	0.005
UNP	-5.638	0.000	-6.565	0.000
BII	-9.973	0.000	-11.27	0.000

ADF - Augmented Dickey-Fuller; PP - Phillips-Perron
N = 43. [1]MacKinnon p-values.

The differencing process is as follows. For a time series $\{yt\}$, the first-order difference series $\{\Delta yt\}$ is calculated as: $\Delta yt = yt - yt_{-1}$

Where: yt is the value of the time series at time t.

yt_{-1} is the time series value at the previous period.

Using a regression approach, I tested independent variables for multicollinearity, considering the credit default variables as dependent and macroeconomic variables as independent.

The Variance Inflation Factor (VIF) test measures multicollinearity among the independent variables in a regression model. It quantifies how much the variance of an estimated regression coefficient increases when the predictor variables are highly correlated. A VIF value close to 1 indicates low multicollinearity, meaning that the variable is not highly correlated with other variables in the model. Generally, a VIF value greater than five is considered a sign of significant multicollinearity. In this case, all the VIF values are relatively low (less than 5), suggesting no multicollinearity among the independent variables in the regression model. The mean VIF is also low at 1.47, indicating that the variables are not highly correlated. This is a positive result, as multicollinearity can cause instability in coefficient estimates and affect the interpretation of the model. With low multicollinearity, the estimates are more reliable and interpretable.

Table 5. Variance Inflation Factor test (VIF)

Variable	VIF	1/VIF
GDP	1.360	0.733
DBT	1.240	0.807
UNP	1.160	0.863
BII	1.120	0.896
Mean VIF	1.220	

The last step is determining the lag length, shown in Table 6. Conducting Selection-order criteria tests, such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Information Criterion (HQIC), is essential in econometric studies, especially when dealing with VARX models. These criteria help determine the appropriate lag order for the VARX model, which is decisive for capturing the correct temporal dynamics and avoiding issues like misspecification or overfitting. Selecting an optimal lag order helps balance model complexity and explanatory power, ensuring that the VARX model effectively captures the short-term interactions among the variables without introducing unnecessary noise or complexity. In the following table, I have tested the order criteria for DEF14mkt, GDP, DBT, UNP and BII and got two results (AIC and HQIC) for four lags and one (SBIC) for one lag. All other tests get the same pattern. Then I decided to use a lag range from one to four lags in the models.

Table 6. Selection-order criteria test

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	439.807				2.50E-16	- 21.7404	- 21.6640	- 21.5292
1	492.473	105.330	25	0.000	6.30E-17	- 23.1237	- 22.6657	- 21.857*
2	515.454	45.9610	25	0.006	7.40E-17	- 23.0227	- 22.1831	- 20.7005
3	541.828	52.7480	25	0.001	8.20E-17	- 23.0914	- 21.8701	- 19.7136
4	591.735	99.815*	25	0.000	3.3e-17*	- 24.3368*	- 22.7338*	- 19.7136

Endogenous: DEF14mkt GDP DBT UNP BII

Exogenous: _cons

4.3 Findings

This study aims to verify which macroeconomic variables are more associated with credit. To reach this, I conducted a Vector Autoregression (VARX) analysis controlling for explanatory variables to examine the dynamic relationships among critical macroeconomic variables: GDP, DBT, UNP, and BII and rural credit default: DEF14mkt, DEF25reg and DEF36tot. The dataset spans 2012q1 to 2022q4, encompassing 44 observations. As Osmani, Kambo & Andoni (2018) mentioned, I also need to emphasize that I considered all variables endogenous in this study. However, the interrelationship between macroeconomic variables is not the main focus here, so I omitted these results from the analysis. The results are presented as follows intend to check both hypotheses mentioned in section 1.3.

In the first analysis, Table 7 presents the results of a Vector Autoregression (VARX) model showing the coefficients and standard errors for the variables impacting DEF14mkt at different lags. DEF14mkt is influenced by two variables: GDP and the lagged DEF14mkt. Each row in the table corresponds to a specific lag, ranging from L1 to L4. This result shows that the current level for DEF14mkt will rise 0.6204363 for each unit growth in the lagged DEF14mkt. In the opposite direction, as one unit of GDP grows, it will result in a 0.0727885 decrease in the levels of DEF14mkt, which are compatible with the theory since GDP growth tend to reduce non-performing loan levels and also confirm the H1 hypothesis. However, the other macroeconomic variables did not appear to affect DEF14mkt at this lag range.

Table 7. Vector autoregression - DEF14mkt

Sample: 2013q1 - 2022q4		No. of obs	40
Log-likelihood = 591.7353		AIC	-24.33677
FPE = 3.32e-17		HQIC	-22.73382
Det(Sigma_ml) = 9.73e-20		SBIC	-19.90346

Equation	Parms	RMSE	R-sq	chi2	P>chi2
DEF14mkt	21	0.013194	0.6728	82.25026	0.0000
GDP	21	0.121997	0.5984	59.60028	0.0000
DBT	21	0.009975	0.7515	120.9938	0.0000
UNP	21	0.005580	0.8305	195.9415	0.0000
BII	21	0.048599	0.7200	102.8341	0.0000

DEF14mkt		Coef.	Std. Err.	z	P>z
DEF14mkt	L1.	0.6204363***	0.1492174	4.16	0.000
	L2.	-0.1155676	0.1770104	-0.65	0.514
	L3.	-0.0363236	0.1955474	-0.19	0.853
	L4.	-0.1384154	0.1517085	-0.91	0.362
GDP	L1.	-0.0727885***	0.019056	-3.82	0.000
	L2.	-0.0272111	0.0270875	-1.00	0.315
	L3.	0.0139492	0.0238615	0.58	0.559
	L4.	0.0060638	0.0223036	0.27	0.786
DBT	L1.	-0.4290297*	0.2560476	-1.68	0.094
	L2.	0.3941476	0.2914139	1.35	0.176
	L3.	0.4379797	0.3373282	1.30	0.194
	L4.	-0.4269141*	0.2510231	-1.70	0.089
UNP	L1.	-0.5726022*	0.2975035	-1.92	0.054
	L2.	0.1936659	0.2570362	0.75	0.451
	L3.	-0.0822554	0.2397748	-0.34	0.732
	L4.	0.0750277	0.2510194	0.30	0.765
BII	L1.	-0.0706651	0.0465456	-1.52	0.129
	L2.	-0.0632583	0.0495005	-1.28	0.201
	L3.	-0.027992	0.0678266	-0.41	0.680
	L4.	0.0074434	0.0438801	0.17	0.865
cons		0.0001806	0.0022421	0.08	0.936

***, **, and * denote significance at the 1, 5, and 10% level, respectively

In Table 8, the results show the coefficients and standard errors for the variables impacting DEF25reg at different lags. DEF25reg is influenced by three variables: UNP and BII, and the lagged (1 and 4) DEF25reg. Each row in the table corresponds to a specific lag, ranging from L1 to L4.

Table 8. Vector autoregression - DEF25reg

Sample: 2013q1 - 2022q4		No. of obs	40
Log-likelihood = 664.1763		AIC	-27.95881
FPE = 8.87e-19		HQIC	-26.35587
Det(Sigma_ml) = 2.60e-21		SBIC	-23.52551

Equation	Parms	RMSE	R-sq	chi2	P>chi2
DEF25reg	21	0.001536	0.7552	123.3732	0.0000
GDP	21	0.127467	0.5616	51.23455	0.0001
DBT	21	0.011282	0.6822	85.8582	0.0000
UNP	21	0.005168	0.8546	235.0724	0.0000
BII	21	0.061465	0.5521	49.29729	0.0003

DEF25reg		Coef.	Std. Err.	z	P>z
DEF25reg	L1.	0.9950826***	0.1646716	6.04	0.000
	L2.	-0.3369831	0.2275711	-1.48	0.139
	L3.	-0.2991777	0.2157016	-1.39	0.165
	L4.	0.5398709**	0.1706238	3.16	0.002
GDP	L1.	-0.0044386*	0.0024311	-1.83	0.068
	L2.	-0.0018057	0.0029875	-0.60	0.546
	L3.	-0.0023844	0.0028302	-0.84	0.400
	L4.	-0.0004363	0.0026469	-0.16	0.869
DBT	L1.	-0.0037460	0.0284939	-0.13	0.895
	L2.	-0.0207644	0.0338241	-0.61	0.539
	L3.	-0.0165672	0.0347134	-0.48	0.633
	L4.	0.0111824	0.0263324	0.42	0.671
UNP	L1.	-0.1064130**	0.0363402	-2.93	0.003
	L2.	0.0392595	0.0329475	1.19	0.233
	L3.	0.0977518**	0.0332063	2.94	0.003
	L4.	-0.0036539	0.036155	-0.10	0.920
BII	L1.	-0.0115945**	0.0057877	-2.00	0.045
	L2.	-0.013402**	0.0054669	-2.45	0.014
	L3.	0.0068007	0.0071255	0.95	0.340
	L4.	0.0022438	0.0050412	0.45	0.656
cons		0.0000381	0.0002749	0.14	0.890

***, **, and * denote significance at the 1, 5, and 10% level, respectively

The result shows that the current level for DEF25reg will rise to 0.9950826 for each unit growth in the lagged (L1) and 0.5398709 for lag 4 of DEF25reg. In the opposite direction, as one unit of BII grows (the value is negative, so when BII grows means a deficit reduction), it will result in a 0.0115945and 0.013402 decrease in the levels of DEF25reg at lag 1 and 2, respectively, which are compatible with the theory since an improvement in the Balance of international investments tends to reflect in a good economic environment, leading to reducing non-performing loan levels, and confirms the hypothesis H1.

However, for the UNP variable, we had an ambiguous result for this analysis since we have two statistically significant effects, both for lags 1 and 3, in opposite directions. The third lag is compatible with the theory since one unit increase in unemployment tends to increase default, in this case by 0.0977518, confirming the H0 hypothesis. For the first lag, the results go against the expected in theory. It can be explained for several reasons, from labor regulations to the choice of lag numbers used in the model. However, it would be necessary a further study to investigate. The other macroeconomic variables did not affect DEF25reg at this lag range.

In Table 9, the results show the coefficients and standard errors for the variables impacting DEF36tot at different lags. DEF36tot is influenced by two variables: GDP and the own lagged DEF36tot. Each row in the table corresponds to a specific lag, ranging from L1 to L4. Again, GDP presents a strong relationship by reducing 0.0349011 units for every unit growth in GDP, which is aligned with the theory and H1. However, the other macroeconomic variables did not appear to affect DEF14mkt at this lag range.

Table 9. Vector autoregression - DEF36tot

Sample: 2013q1 - 2022q4		No. of obs	40
Log-likelihood = 624.1438		AIC	-25.95719
FPE = 6.57e-18		HQIC	-24.35424
Det(Sigma_ml) = 1.93e-20		SBIC	-21.52388

Equation	Parms	RMSE	R-sq	chi2	P>chi2
DEF36tot	21	0.007685	0.6404	71.2375	0.0000
GDP	21	0.109247	0.6780	84.20451	0.0000
DBT	21	0.009079	0.7942	154.3265	0.0000
UNP	21	0.005076	0.8597	245.1518	0.0000
BII	21	0.044214	0.7682	132.5716	0.0000

DEF36tot		Coef.	Std. Err.	z	P>z
DEF36tot	L1.	0.6582575***	0.1461838	4.50	0.000
	L2.	-0.1367048	0.1950445	-0.70	0.483
	L3.	0.0875393	0.2323768	0.38	0.706
	L4.	-0.2857998	0.1874867	-1.52	0.127
GDP	L1.	-0.0349011**	0.0110743	-3.15	0.002
	L2.	-0.0013227	0.0160916	-0.08	0.934
	L3.	0.0091676	0.0140123	0.65	0.513
	L4.	0.0082129	0.0132029	0.62	0.534
DBT	L1.	-0.1011860	0.1533003	-0.66	0.509
	L2.	0.1436691	0.1614623	0.89	0.374
	L3.	0.2842390	0.1834701	1.55	0.121
	L4.	-0.2068032	0.1388045	-1.49	0.136
UNP	L1.	-0.2153978	0.1683157	-1.28	0.201
	L2.	0.1113619	0.1530181	0.73	0.467
	L3.	-0.1210638	0.1396733	-0.87	0.386
	L4.	-0.0060380	0.1428031	-0.04	0.966
BII	L1.	-0.0283692	0.0274278	-1.03	0.301
	L2.	-0.0127327	0.0291956	-0.44	0.663
	L3.	0.0094396	0.0375897	0.25	0.802
	L4.	0.022112	0.0244477	0.90	0.366
cons		-0.0006593	0.0013107	-0.50	0.615

***, **, and * denote significance at the 1, 5, and 10% level, respectively

4.4 Description of behavior of the Dynamic System

The next step in the analysis is to present the Impulse Response Functions (IRFs) in the following figures. These graphs show each variable's dynamic response in the VARX model (basic) to a one-unit shock in one of the variables while holding all other variables constant. These graphs provide valuable insights into shocks' effects on the system and help understand the variables' interrelationships.

The utility of IRFs lies in their ability to complement the analysis of VARX models. While the coefficients in the VARX model provide information on the contemporaneous relationships between variables, they do not capture the dynamic adjustments and response patterns that occur over time. IRFs, on the other hand, address this limitation by showcasing the time-varying nature of the interactions, thereby enabling the examination of both short-term and long-term effects.

The analysis below will show the response of the credit risk variables after a simulated shock (one standard deviation) in the macroeconomic variables. The results are in the Y axis, while the X axis refers to the time variable, in this case, quarters. For this study, I selected two quarters ahead because long periods can result in ambiguous results and a flat line at the end, and also to reduce complexity in interpreting the results.

The results are in line with what I have presented so far. For example, figure 1 shows that a shock in GDP of one standard deviation brings a change of about -1.2 standard response of DEF14mkt in the first quarter of the future time horizon. The Impulse Response Functions (IRFs) graphs:

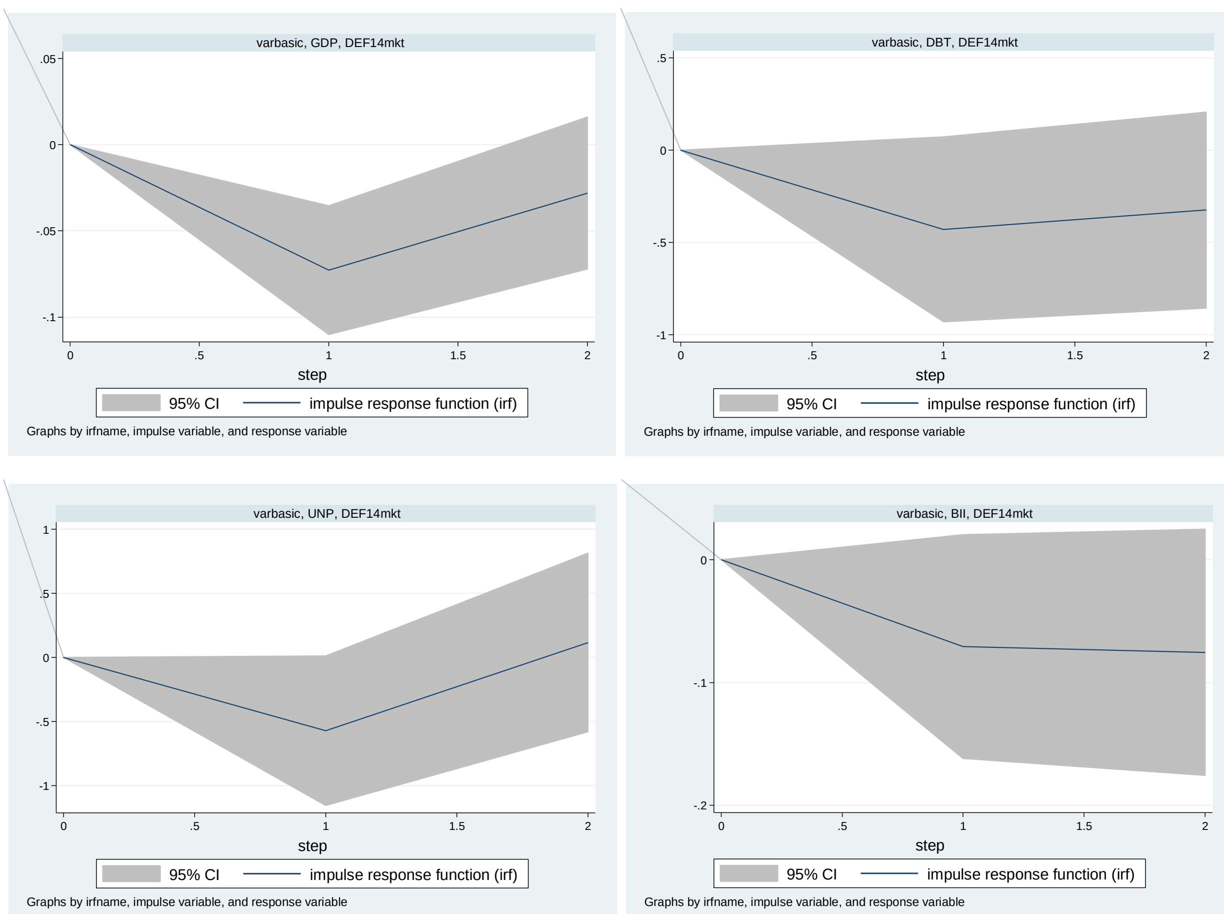


Fig. 1 Response for market rate contracts (DEF14mkt) due to shocks

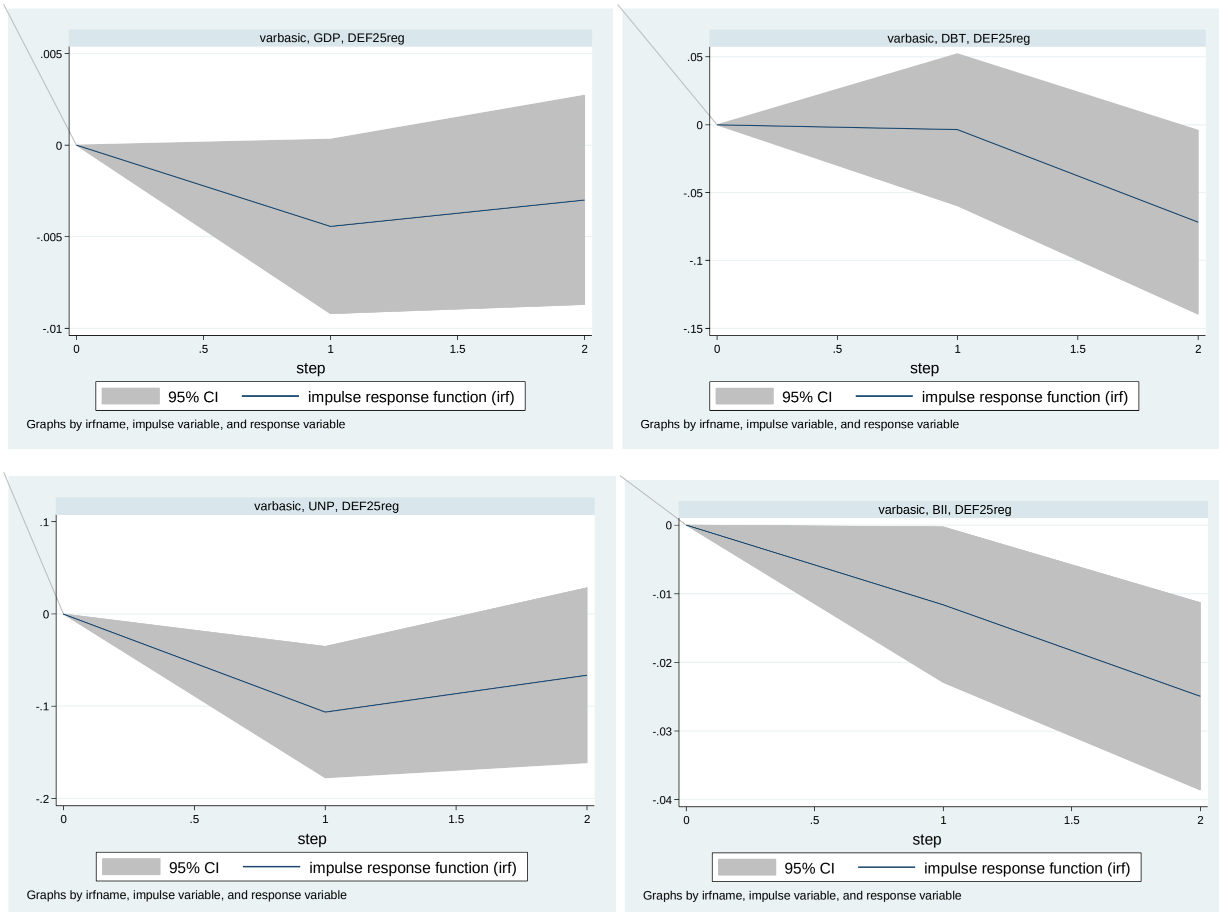
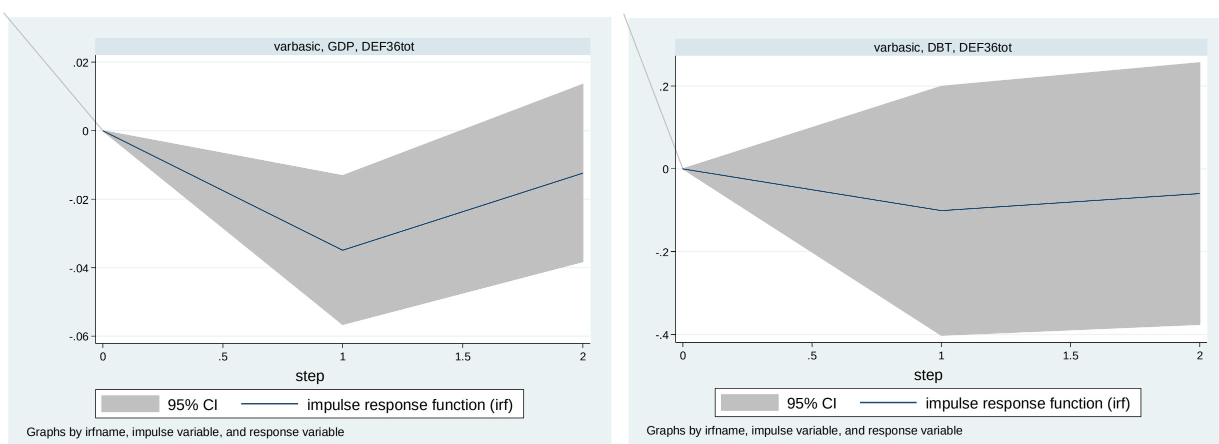


Fig. 2 Response for regulated rate contracts (DEF25reg) due to shocks



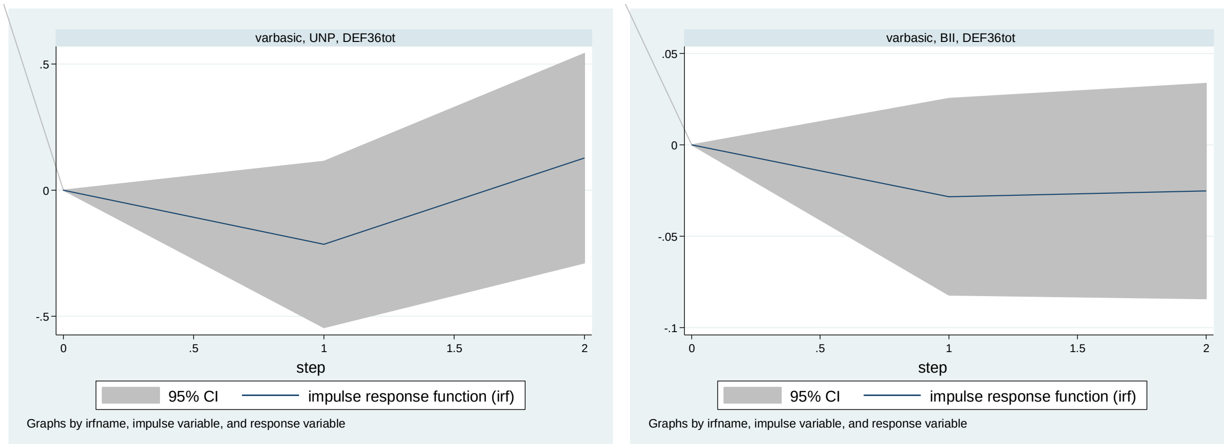


Fig. 12 Response for regulated and market rate contracts of DEF36tot due to shocks

4.5 Conclusion

These findings provide important insights into the interdependencies among the macroeconomic variables, their lagged values and the agricultural credit risk, measured as a percentage of the portfolio at the default, shedding light on the short-term and long-term relationships within the economic system. The significance of these relationships can have implications for policymakers and investors in understanding the dynamics and potential impact of changes in these macroeconomic variables, especially dealing with lags, an essential component in this analysis. Further analysis and interpretation of these results can provide valuable guidance for decision-making and policy formulation in the economic context.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

In this section, I present a comprehensive summary of the research findings and discuss their implications for the broader field of study. I reflect on the research questions posed at the outset of this study and provide an overview of the methodologies employed to address them. Furthermore, we highlight this research's key results and significant contributions to the existing body of knowledge in the area.

This conclusion chapter aims to tie together all the study results, drawing connections between the empirical evidence and the theoretical framework. It analyzes the research outcomes, shedding light on any unexpected findings and their potential implications. Moreover, this section critically evaluates the study's limitations, identifying potential areas for future research and methodological improvements. It also addresses our research's broader practical and policy implications. It suggests possible avenues for applying the findings to real-world scenarios.

5.2 Summary of the study

In conclusion, this paper employed a Vector Autoregression (VARX) model, controlling for explanatory variables to analyze the dynamic interactions among rural credit default and macroeconomic variables, including GDP, DBT, UNP, and BII. In complementing the VARX analysis, I presented IRFs function graphs. The results revealed significant relationships and response patterns between some macroeconomic variables at the selected lag level, especially GDP, shedding light on their interdependencies and the transmission of shocks within the system. By employing time series data and examining the impacts over multiple periods with IRFs, this study provided comprehensive insights into the short and mid-term dynamics of the macroeconomic variables under investigation.

Overall, the combination of VARX analysis and IRFs contributes to a more comprehensive understanding of the macroeconomic system, emphasizing the importance of considering both short-term dynamics and mid-term trends for informed decision-making and, if necessary, to expand to the long term.

5.3 Policy implications

The findings of this research hold significant implications for policymakers and the bank industry in understanding the complexities of the macroeconomic landscape. The VARX model presented in the analysis is further complemented by the impulse response functions (IRFs) showcasing the temporal effects of shocks and the persistence of their impacts. It offers valuable information for designing effective policies and interventions in response to economic fluctuations. The results can help Central Banks change the credit requirements regulations to protect the financial system from economic shocks. Banks can adapt their risk models by adopting macroeconomic variables in their rural credit risk models to better respond to fluctuations in the macroeconomic scenery.

5.4 Further research area

As mentioned during the analyses, not all variables presented a significant (1% or 5%) relationship with credit default at the level of the lag I selected. Studying these variables with a larger sample or different lag orders could give us more understanding. Introducing new macroeconomic variables would also help better understand these relationships since the VARX model analyses everything as a whole system. In addition, the unemployment (UNP) variable presented ambiguous results, making it necessary to better understand Brazil's labour market, their regulations and the lags associated with rural credit default.

5.5 Study Limitations

The study presented some limitations related to the data availability. Even though some consider eleven years a suitable timeframe, the analysis becomes limited to only 44 observations for each variable when converted to quarters. Also, some important variables, like GDP per capita, are only available yearly and altering it to a quarter would lead to distortions of time effects. Due to this, some critical macroeconomic variables were not included in this study.

Another limitation is related to the credit risk variables since only aggregate values are available. A better study would have separate credit default by bank institutions, and inside each bank, the customer characteristics, like size, year of experience, and type of agricultural production, among others.

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