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THE AMERICAN UNIVERSITY IN CAIRO
الجامعة الأمريكية بالقاهرة

The American University in Cairo

School of Business

MACROECONOMIC SHOCKS AND CREDIT RISK STRESS TESTING: EVIDENCE FROM THE EGYPTIAN BANKING SECTOR

A Thesis Submitted to

Department of Economics

in partial fulfillment of the requirements for

the degree of Master of Arts in Economics

by Noha Mamdouh ElGaliy

(Under the supervision of Dr. Mohamed Bouaddi)

Fall 2021

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ABSTRACT

Stress tests can satisfy a range of policy objectives and ensure banks are adequately resilient to common economic shocks or specific financial risks. Though the growing body of literature on stress testing, the existing studies have usually focused on developed countries who have relatively stable macroeconomic indicator when compared developing countries. Therefore, this thesis aims to present a macroeconomic credit risk model that explicitly links a set of selected macroeconomic factors including gross domestic product, inflation, lending interest rates and exchange rate to banking non-preforming loans using evidence from the Egyptian banking sector over the time period from 2011 to 2020. We estimate a vector autoregression (VAR) model to analyze and discuss the effects of a variety of adverse macroeconomic scenarios on the Egyptian banking sector non-preforming loans. To the best of our knowledge, this is the first study to conduct an aggregate stress test and simulate the banking non-preforming loans under various scenarios concerning macroeconomic shocks for the banking system in Egypt using a vector autoregression model. The model in this thesis could be of considerable use to policymakers and supervisory authorities.

Keywords: *Stress testing, financial stability, vector autoregression, non-performing loans, macro-prudential analysis, Egypt.*

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LIST OF ABBREVIATIONS

ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller test
AIC	Akaike’s Information Criterion
BCBS	Basel Committee for Banking Supervision
BIC	Schwarz Bayesian Criterion
BIS	Bank for International Settlements
CAR	Capital Adequacy Ratio
CBE	Central Bank of Egypt
CPI	Consumer Price Index
FEVD	Forecast Error Variance Decomposition
FSAP	Financial Sector Assessment Programs
GDP	Gross Domestic Product
HQ	Hannah-Quinn Criterion
IMF	International Monetary Fund
LLP	Loan Loss Provision
NPL	Non-Preforming Loans
OLS	Ordinary Least Squares
PD	Probability of Default
QR	Quantile Regression
VAR	Vector Autoregressive
VECM	Vector Error Correction Model

1. Introduction

Aggregate stress testing for the banking sector involves modelling exercises preformed to analyze the resilience of the entire banking system to hypothetical adverse scenarios. These quantitative exercises are described as “what if” exercises to forecast the risk-bearing capacity of the entire financial system if specific shocks were to occur (IMF, 2012). However, “aggregate” or “system-wide” stress tests are more than just numerical calculations of the impact of a scenario. Aggregate stress tests can satisfy a range of policy objectives and ensure banks are adequately resilient to common economic shocks or specific financial risks. Stress tests can also be used to inform macroprudential policy settings, consequently, improve the calibration of macroprudential tools. Further, they can act as a tool for cross-checking outcomes of different banks’ internal models, hence allowing policy makers to examine the quality of banks’ internal models (BCBS, 2009).

Though the growing body of literature on aggregate stress testing, the existing studies have usually focused on developed countries who have relatively stable macroeconomic indicator when compared to developing countries. As a result, the existing research falls in providing and analyzing advanced aggregate stress testing models for developing countries, which is problematic because developed countries are generally more susceptible to macroeconomic shocks and have lower level of financial stability relative to developed countries. Developing countries, therefore, find themselves ill-equipped in terms of mitigating macroeconomic shocks. Hence, given the lack of research regarding aggregate stress testing implications for developing countries, this thesis aims to contemplate and analyze the effects of macroeconomic shocks to non-preforming loans using evidence from the Egyptian banking sector. In order to do so, this thesis is developed with objective of:

- Estimating a macroeconomic credit risk model that explicitly links a set of selected macroeconomic factors to the banking non-preforming loans using Egyptian data over the time period from 2011 to 2020.
- Using the model to analyze and discussing the effect of a variety of adverse macroeconomic shocks on the Egyptian banking sector non-preforming loans.

The model, therefore, will answer the research question of “What will be the implications of selected macroeconomic shocks on the Egyptian banking sector credit risk?”

The Egyptian case present itself as an interesting case study because Egypt has experienced a variety of extreme macroeconomic shocks in the past two decades. For instance, the political unrest the country faced due to two revolutions in 2011 and 2013. Further, the Egyptian pound floatation in 2003 and 2017. Hence, Egypt has faced major price changes, fiscal imbalances, and monetary expansions over the recent decades.

The model focuses on credit risk given that the Egyptian banking sector, like most of the banking sectors in developing countries, is the main provider of credit to the economy. Credit risk is defined as the probability of failure of a bank borrower or counterparty to meet its obligations in accord with agreed terms (BCBS, 1999). Further, credit risk is recognized in various research and working papers as the most distinguished banking risk, due to the fact that it covers the vast majority of the banking risk.

The model in this thesis could be of considerable use to policymakers and supervisory authorities. The model will be particularly helpful in informing the policy makers about the structural vulnerabilities of the banking system, and hence allowing the monetary authorities to take informative decisions to avoid financial crisis with economy-wide impact. To the best of our knowledge, this is the first study to conduct an aggregate stress test and simulate the banking non-preforming loans under various scenarios concerning macroeconomic shocks for the banking system in Egypt using a vector autoregression (VAR) model.

In this section, the context of the study has been introduced. The research objective and questions have been identified, and the significance of the research has been argued. In section two, we present a general overview on stress testing including its definition, history, process, and limitations. In section three, the existing literature will be reviewed to identify key methodologies of aggregate stress testing. Section four explains the empirical model including the methodology, variable choice, and model data structure. Section five presents the econometric results of the credit risk stress test model, followed by concluding remarks in section six.

2. Overview on stress testing

2.1. Stress testing definition

Basel Committee on Banking Supervision (BCBS), the primary global standard setter for the prudential regulation of banks, has first emphasized the importance of stress testing implementation in Basel Capital Accord of 1999. However, BCBS did not set a specific definition to what constitutes stress testing up until Basel II Capital Accords issued in 2006, where the committee has provided a rather broad definition to what stress testing is.

> *"…bank must have in place sound stress testing processes for use in the assessment of capital adequacy. Stress testing must involve identifying possible events or future changes in economic conditions that could have unfavorable effects on a bank's credit exposures and assessment of the bank's ability to withstand such changes."*
> (Basel Committee on Banking Supervision [BCBS], 2006, para. 343)

Generally, there are two types of stress tests: (1) stress tests focusing on an individual portfolio conducted by a financial institution, and (2) system-wide or aggregate stress test carried out by central banks or regulatory authorities. The definition slightly varies between these two types. Jones et al. (2004) defined stress tests for individual institutions as quantitative tools employed to obtain a numerical measurement of sensitivity of a portfolio to a variety of extreme but plausible hypothetical shocks. Similarly, Blaschke et al. (2001) defined aggregate stress tests as a range of techniques that attempt to identify the vulnerability of the portfolio to adverse changes in the macroeconomic environment or to exceptional, but still possible, events.

Further, the International Monetary Fund (IMF) has described aggregate stress tests as "what if" exercises to forecast the risk-bearing capacity of the entire financial system if specific shocks were to occur (IMF, 2012). Likewise, Borio et al. (2012) defined aggregate stress testing as a quantitative tool that examines the risk exposure of a group of financial institutions to 'exceptional but plausible' scenarios.

2.2. A brief history of stress testing

Since 1990s stress testing has become a vital tool to effective risk management that is used to complement a bank's internal model, as per Basel I framework. Especially, due to the inability of bank's internal models to detect the entity's exposure to extreme shocks (Blaschke et al, 2001). Therefore, in 2004, Basel II framework continued supporting the application of stress test to strengthen banks' internal models. Though stress tests were typically applied to individual institutions, central banks and regulatory authorities began considering the possibility of system-wide stress tests to assess the outcomes of aggregating bank-level results with respect to various methodologies and scenarios in the early 2000s (CGFS, 2000). Particularly, amid IMF and World Bank have first introduced the system-wide stress testing by establishing the Financial Sector Assessment Programs (FSAP) in 1999.

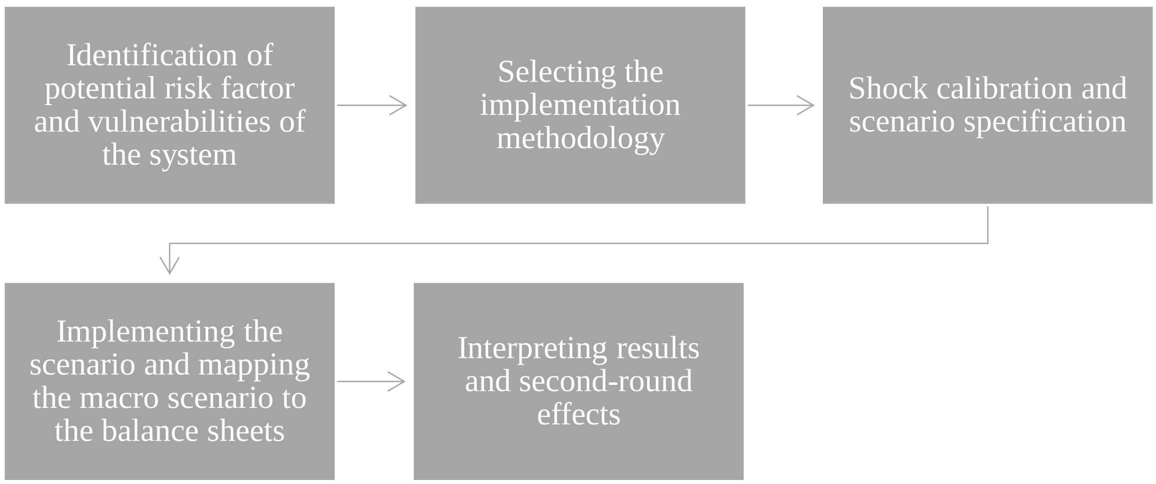
Since the Global Financial Crisis of 2007- 2008, system-wide stress tests have been conducted regularly and took a more prominent role in many jurisdictions (BCBS, 2017). For instance, the European Banking Authority has established a series of regular supervisory stress testing exercises across the European Union since 2011 (ECB, 2014). Meanwhile, the United States of America has been conducting annual system wide stress tests since the same year. In all cases, the focus of system-wide stress tests has been shifted from ensuring certain level of banks' capital adequacy to advising broader practical policies that are focused primarily on macroprudential measures.

In regulatory community, BCBS has evaluated practices and published principles for sound stress testing in 2009, later these standards were revisited in 2018 (BCBS, 2009; 2018). BCBS along with the official community have recently endorsed the addition of a macroprudential dimension in stress testing (BCBS, 2017) and hence now there is a growing body of literature on stress testing with a macroprudential dimension.

2.3. Stress-testing process

The process of aggregate stress testing requires the development of comprehensive technique, starting from the identification of potential risk factors and system vulnerabilities, selecting the implementation methodology, calibrating shocks, implementing scenarios, and finally interpreting the impact of macroeconomic shocks on the entire financial system in order to draw management and policy implication.

Figure 1. Key components of macroeconomic stress testing.



Source: author based on Blaschke et al. (2001), Quagliariello (2009) and Foglia (2009)

2.3.1. Identification of potential risk factor and vulnerabilities of the system

The process of stress testing commences with the identification of stress test coverage and selection of intermediaries, i.e., the main focus of the stress test. Stress tests can be classified in term of policy objectives as “macroprudential” or “microprudential”. The definition is rather obvious as macroprudential stress tests assess the resilience of the entire financial system to economic and financial shocks, whereas microprudential stress tests assess the resilience of an individual financial institution to economic and financial shocks. In this thesis we contemplate and analyze the outcome of the former type of stress testing.

However, considering the whole financial system will propose an extreme computational burden, therefore the majority of macro stress test primarily focuses on the main players in the financial system. Since banking sector is the most significant financial intermediary in many countries, macro stress tests typically run on the banking sector as a subset of the financial system (Quagliariello, 2009). Still, it is deserved to be mentioned that limiting the scope of the analysis to the banking sector only will lead to overlooking the impact of stressed scenarios on different categories of the financial intermediaries and hence may not provide a comprehensive assessment of the resilience of the system.

Further, the next step to stress testing involves the identification of major risks and vulnerabilities of the system. Yet again, since stress tests cannot cover every potential risk factor for the system, the researchers typically narrow down the focus on the main risk factors and vulnerabilities in the financial system, they are interested in understanding. This step allows the research to customize the stress test exercise to the conditions and need of the country. In fact, focusing on the country-specific significant exposures make the process of stress test more effective and prevents waste of time and resources (Jones et al., 2004). Given that our objective is to develop a macro stress test model for a developing country of interest, Egypt, we focus on credit risk. The Egyptian banking sector is the main provider of credit to the economy; therefore, credit risk is amongst the most significant banking risks.

2.3.2. Shock calibration and scenario specification

Upon the identification of the stress tests scope, main focus and key risk triggers for the system, the next step is to formalize a coherent stress test scenario. Stress test scenarios can be described as either “baseline” or “adverse”. Baseline scenarios does not usually yield stressed results, rather it produces results that are consistent with projection of probable future economic and financial conditions. On the contrary, adverse scenarios results are significantly stressed in comparison to baseline results. The adverse stress test scenarios are designed to introduce shocks to the performance of the banking sector, where the shock calibration is based mainly on the researcher judgment and assessment (Quagliariello, 2009).

Given the objective of the research, we focus on formulating adverse scenarios. Shocks presented in adverse scenarios have mainly two methods to formulate (1) **sensitivity analysis,** where the impact of a single macroeconomic factor on the main credit risk of risk factor is examined; or (2) **scenario analysis,** where the impact of multiple risk factors are encompassed. The scenarios used in this type of analysis are either historical scenarios (i.e., based on historical events) or hypothetical scenarios (i.e., based on the judgment of the analyst). In this thesis we are more interested in sensitivity analysis due to the insightful results it yields on the relationship between the macroeconomic factor and credit risk, also due to the easier implementation of the sensitivity analysis given our choice of a reduced form VAR model.

2.3.3. Implementing and mapping the macro scenario to the balance sheets

Once the stress test scenario is specified, the step of implementing the scenario follows. Economic models are usually employed to understand how the credit risk variable behaves when assuming the adverse shock to the selected macroeconomic variables (Quagliariello, 2009). There is a variety of economic models when it comes to assessing credit risk behavior, including models based on loans performance and models based on individual borrower's data. Both types will be discussed thoroughly in the literature review and our choice of model will be further discussed in section four. Though, it is deserved to be mentioned that the process of selecting an approach depends mainly on data availability, type of risk examined and the objective of the stress test.

2.3.4. Interpreting results and second-round effect

The last step in the stress testing framework is analyzing of the obtained results. When interpreting the results of stress test, it is important to distinguish between first-round effect and second-round effect. The first-round effect is concerned with analyzing the stress test results based on the existing statistical relationship between the macroeconomic factors and the credit risk. Whereas the second-round effect involves estimating the banking system losses and Capital Adequacy Ratio (CAR), that are typically computed to assess the ability of the whole system to withstand the hypothetical shock assumed. Though the importance of analyzing the second-round effect it is beyond our research scope. Nevertheless, when interpreting the results of stress test, it is also important to keep in mind the different issues that can arise when analyzing the results of the stress test.

2.4. Stress-testing Limitations

Even though the importance of aggregate stress tests to central banks and regulatory authorities, aggregate stress tests still have a number of limitations and methodological issues mainly connected with preforming the exercise on aggregate level. The following listing of limitations and methodological issues applies mainly to issues connected with stress testing on aggregate level.

a) Scope and choice of institutions

Aggregate stress tests for a country's financial system, as previously discussed, must have a defined scope of a selected of core financial institutions. Though the definition of the scope is to eliminate the computational burden, which is in itself a limitation, restricting the scope might lead to the underestimation of potential vulnerabilities and contagion channels in the system (Blaschke et al., 2001; Jones et al., 2004; Quagliariello, 2009).

b) Aggregation issue

Another limitation to the aggregate stress test is data aggregation. The aggregation issue eliminates the tailoring of a stress scenario to a specific bank and deal with the financial system as if it's homogenous. Further, specific risks and interconnections to an individual financial institute may vanish on the aggregate level and hence the results might be affected (Blaschke et al., 2001).

c) Data availability and model complexity

Finally, stress test outcomes are vulnerable to several factors, mainly, data availability and quality. Further, model risk imposes a limitation especially when using a more complex methodology, also severity and scope of the scenario could be a limitation of stress test (Jones et al., 2004; Borio et al, 2012).

It is important to keep in mind that aggregate stress tests do not predict banks futures, rather identify the impact of particular adverse scenario on banks, based on a number of hypothetical assumptions (Derhman et al., 2008; Borio et al, 2012).

3. Literature review on stress testing methodologies

The aggregate stress-testing widespread has led to not only a growing body of literature discussing it, but also various proposed methodologies to conduct it. This section will focus on methodology approaches to stress testing rather than actual results of stress testing, since the former is the subject of the application in this thesis.

Several studies reviewed the various methodologies of stress testing, for example, Blaschke et al. (2001), Sorge (2004), Sorge and Virolanein (2006), Foglia (2009), Quagliariello (2009), etc. In general, studies on stress testing methodologies have identified two main categories of credit risk modelling: (1) models based on loan performance and (2) models based on data for individual borrowers.

3.1. Models based on loan performance

Models based on loan performance help in exploring the link between an individual financial soundness indicator, usually banks Non-Preforming Loans (NPL) or Loans Losses Provisions (LLP), and macroeconomic factors. The models based on loan performance entail estimating coefficients of banks' measures of vulnerability to economic downturns based on historical data. Later, the estimated coefficients are employed to project the impact of possible future stress test scenarios on the financial system. There are two main types of econometric models based on loan performance: (a) models using time series and panel data; and (b) reduced form and structural models.

Previous studies using time series analysis includes Kalirai and Scheicher (2002) who performed a sensitivity analysis stress test on the aggregate LLP of the Austrian banking system, using a simple linear regression model. Kalirai and Scheicher (2002) used an extensive array of macroeconomic variables. These include indicators of general economic activity, price stability, income, consumption and investment in the household and corporate sectors, financial market indicators and finally variables affecting external solvency . Hoggarth and Zicchino (2004) estimated a vector autoregressive (VAR) model focused on the link between loan write-offs and the UK output gap, inflation, nominal short-term interest rate and the real exchange rate.

Delgado and Saurina (2004) used a cointegration method in an attempt to explain for short-term and long-term properties of the relationship between LLP and macroeconomic conditions for Spain. Similarly, Zeman and Jurča (2008) applied a cointegration method using different used the annual percentage change in NPL ratio as a dependent variable to construct a simple stress test for the Slovak banking system. Zeman and Jurča (2008) found that the most significant risk factors determining the development of the NPL ratio was indicated the real GDP, inflation, financial market interest rates and exchange rate. Since timeseries analysis is particularly beneficial in determining the financial sector vulnerabilities over time, these studies found insightful relationships between that banks' measures of vulnerabilities and the macroeconomic risk factors.

Further, panel studies have additionally incorporated a cross-sectional dimension to the time series analysis, hence, panel studies can assess bank-specific or country-specific factors. For instance, Pesola (2001), Cavallo and Majnoni (2002) and Laeven and Majnoni (2003) have estimated reduced-form models using panel data for banking systems across different countries. Whereas Salas and Saurina (2002) and Gerlach et al., (2005) have estimated models for individual banks. These studies have employed either static or dynamic models where NPL, LLP and profitability measures are the dependent variable. The cross-sectional component allows the evaluation of the differential impact of economic conditions on the financial institutions' vulnerabilities and portfolio divergences.

Studies using structural macro-econometric models allow better characterization of stress scenarios. Hence, they allow the evaluation of costs and benefits of monetary policies, therefore, production flows and structural interdependencies within industries. Drehmann et al. (2004) expanded on the Bank of England macro-econometric model to incorporate the relation between write-off rates and the portion of credit card debt/ liquidation rates for the household/ corporate sector. Credit card debts and Liquidation rates were estimated as functions of macro-fundamentals. Additionally, Oung (2004) extended on the macro-econometric model of Banque de France to evaluate the effect of stress scenarios on the accounting measures of bank vulnerability and profitability. Oung (2004) has employed dynamic panel data techniques to estimate NPLs and interest margin, whereas he used a logit model to estimate migration of corporate obligors as a function of macro-fundamentals. Further, Evjen et al. (2003) projected the effects of both supply and demand shocks on the stability of the Norwegian banking system, using the model of the Norwegian Central Bank. Loan losses were projected as a function of debt-servicing capacity of corporate and household sectors.

The Bank of Japan (2007) conducted aggregate stress test using a reduced form VAR model. The VAR model contained five macroeconomic variables GDP, inflation rate, bank loans outstanding, effective exchange rate, and the overnight call rate. Similarly, Tracey (2006) used a reduced form VAR analysis for the banking sector NPL of Jamaica using real effective exchange rate, CPI index, terms of trade, aggregated loan stock, 180-day Treasury bill rate and growth of monetary aggregate M1.

Further, Castr´en, D´ees, and Zaher (2008) used a structural global vector autoregressive (GVAR) to estimate the impact of stressed the endogenous variables on credit risk, the endogenous variables included were real GDP, inflation rate, real equity prices, and short- and long-term interest rates. Further, Babouček and Jančar (2005) used a structural VAR analysis using the NPL ratio as a measure of credit quality indicator. Babouček and Jančar (2005) included in the VAR model number of macroeconomic variables: monetary aggregate M2 as a proxy for GDP, real effective exchange rate, imports and exports, aggregate banks loan, unemployment rate, inflation and interest rates.

Generally, the models based on loan performance are intuitive and straight-forward to execute, they also have boarder characterization of stress scenarios and can provide insightful results for monetary-policy formulation. However, the models based on loan performance have a number of limitations, for instance, these models portray the relationship between banking risk and macro-fundamentals as linear and rigid. Further, the models based on loan performance has limited applicability for calculating the bank's expected losses and second-round effect. Finally, a number of studies suggested that non-performing loans and loans loss provisions are lacking proxies of the banking sector's credit risk over the business cycle (Sorge and Virolainen, 2006).

3.2. Models based on data for individual borrowers

The models based on data for individual borrowers help in estimating the conditional probability distribution of losses for a single portfolio based on a combination of multiple risk factors. Consequently, the distribution is used to quantify the risk sensitivity of the portfolio to simulated adverse economic conditions. There exist two main approaches in the literature under this category, both building on the pivotal work by Merton (1974) and Wilson (1997 a, b). Merton approach models macroeconomic factors response to macroeconomic shocks, and then maps the movement into default probabilities. Whereas Wilson approach directly models the default probabilities and macroeconomic factors.

A number of papers used Wilson approach in order to analyze the impact of macro-fundamentals on the banks' credits risk. The main idea behind the approach is to model the relationship between default probabilities and macroeconomic variables, then project the development of default rate over simulated macroeconomic shocks to the system. The projected default rates allow the estimation of the expected and unexpected credit losses for a specified portfolio, on the basis of the present economic conditions. The estimated potential loss is later to be assessed given the banking system risk-bearing capacity.

Vlieghe (2001) estimated a model for the aggregate rates of default for the corporate in the United Kingdom, his findings suggested that GDP, the real interest rate, corporate indebtedness, and real wages have substantial explanatory power over the corporate sector default probability. Based on the empirical model of Vlieghe (2001), Benito et al. (2001) mapped a macro-econometric model that forecasted corporate failure using estimates of the corporate balance sheet. Benito et al. (2001) further evaluated the credit risk of the corporate sector in the UK by aggregating the debt of failed firms and examining their evolution over different stress testing scenarios.

Boss (2002) attempted to individually model industry-specific credit risk, to conduct a stress test for Austrian banks. However, due to data availability, it was unattainable, instead he modeled the total default probability as a logistic function of macroeconomic factors using a Wilson approach. Boss (2002) findings suggest that inflation, the nominal short-term interest rate, the stock index, industrial production, and oil prices have major explanatory power of corporate default rates. Later, Virolainen (2004), modeled a macroeconomic credit risk model for the Finnish corporate sector, using a Wilson approach was used to deduce industry-specific default probability for several Finnish industries. Further, by the means of SURE model, the effects of macroeconomic variables on sectoral probability of default were deduced. The study by Virolainen (2004) found that key macroeconomic variables: GDP, the interest rate and corporate sector indebtedness had the most explanatory power for sectoral default probability. Further, the model was used for stress testing on the aggregated corporate credit portfolio in Finland.

The firm level structural approach proposed by Merton (1974) is an alternate model to Wilson approach. Gray et al. (2002) extended on the Merton approach to inspect the sovereign and corporate default risk using for the US. Derviz and Kladlcakova (2005) developed a hybrid approach that included both reduced-form and structural approaches to incorporate business cycle effects on default probabilities. Tudela and Young (2003) analyzed individual firm failures using a hybrid model, the model added Mertonbased probability of default measures into a probit model. The Merton approach was found to outperform the model based on the company's accounting data. Pain and Vesala (2004) analyzed the determinants of firm risk of default using a dynamic factor model measured by Merton based Moody's KMV expected default frequencies. The study incorporated large panel data of companies in the European Union and found that the region and industrial effect were not the primary factors affecting the impacted on the movement of corporate default risk.

Drehmann and Manning (2004) and Pesaran et al. (2004) employed a Merton approach to model and stress test the relationship between macroeconomic factors and default probabilities. The modelling of the relationship involved three stages, first an assumption on the combined progression of market and macroeconomic factors. Drehmann and Manning (2004) assumed normal distribution while Pesaran et al. (2004) estimated a global vector autoregression (GVAR). Second, a multifactor regression was used on panel data of firms, and finally, individual firms' probabilities of default was obtained via a proxy for equity returns and asset value entered into a Merton framework.

The models based on data for individual borrowers are able to integrate the analysis of more than one type of banking risk. Further, the models based on data for individual borrowers can utilize the value of an individual stressed macroeconomic variable to simulates shift in entire loss distribution. The models based on data for individual borrowers are also particularly helpful to capture non-linear effects of macro shocks on credit risk. However, the models based on data for individual borrowers are often criticized due to their non-additivity of value-at-risk measures across institutions, and the limited to a short-term horizon of their stress tests. Further, it is also argued that available studies following this approach have not dealt with the second-round effects or parameters instability over a longer horizon (Sorge and Virolainen, 2006).

4. Empirical model

This section represents the core analysis of the thesis. In the first part, we discuss the macroeconomic variables and their expected relationship with the growth of non-preforming loans. Second, we focus on the empirical application. Following we discusses the econometric model data and description.

4.1. Identification of significant risk factors to the credit risk factor

In this sub-section we use the literature review (section 3) to identify and categorized the key macroeconomic factors that were found to have a significant impact on credit risk. Further, we contemplate these macroeconomic variables expected relationship with the banking credit risk.

This sub-section follows the grouping of macroeconomic variables presented by Kalirai and Scheicher (2002) who, to best of our knowledge, utilized the most extensive array of macroeconomic factors in their research. Kalirai and Scheicher (2002) covered almost all of the frequent macroeconomic variables used for stress testing, they divided macroeconomic variables affecting credit risk into 5 categories: 1) cyclical indicators, 2) price stability indicators, 3) household indicators, 4) financial market indicators and lastly 5) external indicators.

1. Cyclical indicators

Cyclical indicators are indicators that characterize the consolidate economic activity and hence they are related directly to the economic cycle. In general, the direction movement of these indicators is procyclical, countercyclical or acyclical. The main cyclical indicators that were used in the literature are found to be GDP and industrial productivity according to the literature review.

The credit risk is assumed to depend on the development of economic activity and the business cycle, that is mainly accounted for by GDP. In period of expansion, it is assumed that favorable economic development lead to rising in income, hence obligors have better ability to service their debts and the non-preforming loans ratio decreases. Conversely, in recission period the overall economic activity deteriorates leading to decrease in income for households and corporates. This translates for obligors as hardship paying of their debts and hence the non-preforming loans ratio increases (Pesola, 2001; Kalirai and Scheicher, 2002; Delgado and Saurina, 2004; Bank of Japan, 2007; Castr´en, D´ees, and Zaher, 2008).

Correspondingly, industrial production is considered to be an indicator of the overall economic activity as well. Further, industrial production is positively related to GDP growth rate and leads to the acceleration GDP growth rate in a time expansion. Therefore, increase in industrial production should lead to a decrease in the non-preforming loans ratio, as industrial production anticipates economic growth (Kalirai and Scheicher, 2002; Boss, 2002; Delgado and Saurina, 2004).

2. Price stability indicators

Typical measures of price stability according to Kalirai and Scheicher (2002) are Consumer Price Index (CPI) and monetary aggregate. The overall relationship between price stability indicators and credit risk is rather ambiguous as inflation is a double-edged sword. Though higher inflation is an indication that the economy is operating beyond its capabilities, higher inflation also decreases the real value of money and hence the value of outstanding debts for obligors. Therefore, higher inflation might lead to the decrease of the non-preforming loans ratio.

Kalirai and Scheicher (2002), as well as Zeman and Jurča (2008) argued that higher inflation decreases credit risk on the short run. However, on the long run, lenders would recognize that inflation will decrease and hence the value of their claims as well, therefore they raise their interest rate in order to compensate for their loss. Further, Festić and Romih (2008) argued that higher inflation leads to less transparent macroeconomic environment and hence higher credit risk.

On the other hand, decreasing inflation increases real interest rate which directly increase the cost of borrowing and therefore might increase the non-preforming loans ratio. Virolainen (2004) and Tracey (2006) claimed that the rising information asymmetry due to the increase in inflation might lead to adverse selection of loan clients in banks and hence increase of credit risk.

Further, due to the quantity theory of money which assumes direct relationship between money aggregates and inflation, money aggregate is often included as a price stability indicator (Kalirai and Scheicher, 2002; Babouček and Jančar 2005; Tracey, 2006).

3. Household indicators

Household indicators are mainly indicators that directly relates to the condition of the household sector. Therefore, unemployment which is a proxy for disposable income availability to households is widely used as a household indicator. In general, decrease in unemployment rate leads to an improvement of disposable income to a household and hence improves their ability to service debt and decrease the non-preforming loans ratio. On the contrary, higher unemployment rate increases the difficulty of repaying loan obligations for households and hence increase in the non-preforming loans ratio (Vlieghe, 2001; Kalirai and Scheicher, 2002; Babouček and Jančar, 2005).

4. Financial market indicators

Financial market indicators are to provide an outline for the financial market situation. Nominal and real interest rates and the stock price index are usually the indicators included in the literature. Interest rate represents the direct cost of borrowing; therefore, interest rate increases is assumed to have negative effect on the non-preforming loans ratio (Pesola, 2001; Kalirai and Scheicher, 2002; Delgado and Saurina, 2004; Bank of Japan, 2007; Castr´en, D´ees, and Zaher, 2008).

Further, stock market indices are also a key indicator of the economic activity. Stock markets provide a forward-looking view of the market conditions, as it reflects the future expectations of their participants. Hence, rising stock market often indicates a period of economic expansion and therefore decrease in the non-preforming loans ratio (Kalirai and Scheicher, 2002; Boss, 2002; Delgado and Saurina, 2004).

5. External indicators

External indicators do not originate from the domestic economy, though they can have important impact on it. For instance, external indicators relate to international foreign trade, terms of trade or volume of traded goods, exchange rates and oil prices.

There is no doubt that open economies can be significantly impacted by changes in exports or imports as they represent an important part of the GDP. Increase in exports consequently increases GDP growth, therefore positively affects export-oriented sectors, and improve their ability to service debt. Hence, increase in exports is expected to decrease the non-preforming loans ratio (Kalirai and Scheicher, 2002; Festić and Romih 2008).

Further, oil prices represent a major direct cost for many firms in the corporate sector and hence can present a threat to loan portfolio quality if increased. For instance, higher oil prices will lead to increase of energy prices for households and businesses, consequently, increase the non-preforming loans ratio (Kalirai and Scheicher, 2002; Boss, 2002).

The impact for foreign exchange rate on credit risk is generally vague in the literature. Depreciation of the domestic currency may stimulate not only exports but also the production of import competing goods. Further, depreciation of the local currency will lead to the improvement of the obligor's position, as the obligor is required to repay less than the initial value of the loan. Hence, depreciation of the domestic currency can potentially lead to a decrease the non-preforming loans ratio. On the other hand, depreciation of the domestic currency has the same effects but reversed if the obligors are borrowing in foreign currency (Kalirai and Scheicher, 2002; Boss, 2002; Bank of Japan 2007; Zeman and Jurča 2008).

4.2. VAR model

4.2.1. Introduction to VAR models

Christopher Sim first introduced the Vector Autoregression (VAR) model in 1980, the VAR model is a framework to model and understand the dynamic relationship between a set of stationary variables. Since then, the VAR approach has been widely used by economists to model the dynamic and causal relationship among various set of macroeconomic variables.

To formalize the VAR approach, we first consider a time series $\{Y_t, t \in T\}$, where T is the time index, and the considered realizations of a random variable that can be described by some stochastic process. Hence, we consider a **univariate autoregression** equation as follow:

$$y_t = \alpha + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t$$

Where the error is white noise. This process is also known as autoregressive process of order *p* (AR*(p)* process). Though AR*(p)* process describes the dynamic relationship of one random variable as a function of its own past value, macroeconomic variables usually interact each other. Hence, the vector autoregression models are formalized to capture the rich dynamic relationship between more than one variable (i.e., for multiple time series). Vector autoregression models are a system of linear equations where each variable is affected by not only its own past value but also the past value of the remaining endogenous variables.

The reduced form VAR model of order *p*

An *n*-dimension vector autoregression model of order *p,* VAP(*p*), is a system of a number of linear equations with the same number of variables. Each equation of the VAR system describes one variable as a function of its own lag and the lag of other variables in the system and serially uncorrelated error term.

$$Y_t = \varphi + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + u_t$$

Where,

- $\varphi =$ (N x 1) vector of intercept
- $A = (A_1, A_2, \dots, A_p)$ is a (N x N) coefficient matrix
- $Y_t = (y_{1,t}, y_{2,t}, \dots, y_{N,t})$` is a (N x 1) vector of macroeconomic variables
- $u_t = (u_{1,t}, u_{2,t}, \dots, u_{N,t})$` interpreted as n-dimensional vector of shocks (innovations) and $u_t \sim WN\ (0, \Omega)$ (i.e., white noise).

This system can be interpreted as AR(p) processes allowing more variables that contains the lagged values of each variable in each process. Ordinary least Square (OLS) can be used to produce consistent and asymptotically efficient estimates of each equation in the system, due to the symmetrical property of the reduced form vector autoregression model. The error terms are serially uncorrelated but correlated across equations.

Vector autoregression models are divided into three categories: reduced form, recursive form, and structural form of VAR. Each equation in the recursive form, likewise the reduced form, can be estimated by OLS and the errors are uncorrelated across equations. However, results of the recursive are heavily dependent on the order of the variables in the equations. For instance, any change in the order of VAR equation will lead to change in the coefficients and residuals. Therefore, the recursive VAR approach propose a burden for the computation of large models, especially there are *n!* possible arrangements in a *n*-equation VAR system (Stock and Watson, 2001).

Finally, the structural VAR propose a contemporaneous links among the variables that needs economic theory to understand it. The variables of the structural form VAR are correlated with error terms; hence this model cannot be estimated using standard techniques. Rather the variables of the structural VAR are estimated using instrumental variables regressions and require identifying assumptions in order to model the causal links among the variables (Stock and Watson, 2001). Therefore, we employ a reduced form VAR to avoid the limitations of structural and recursive VAR and due to its easier implementation.

4.2.2. Characteristics of VAR models

The vector autoregression models' popularity is due to their easy implementation. The reduced VAR model symmetric property allows it to be easily estimated by ordinary least squares. Drehmann (2008) argued that macroeconomic models usually follow three main objectives: validation, forecast performance and communication. The validation aspect of the models is basically the description and summarization of the data. Whereas the forecast performance simply denotes to making macroeconomic forecasts. Lastly, communication aspect is concerned with the advising of policy makers. Though VAR model usually outperform more complicated models in the validation and forecasting aspects, however, they fall short for the communication aspect.

Vector autoregression model captures the capture co-movements in the variables over time as they contain the current and lagged value of multiple time series. Further, there exist a variety of standard data generating techniques in VAR analysis (example the impulse response functions) that facilitates the interpreting the co-movements in the variables.

Small-scale vector autoregression model have exceptional ability in forecasting, that can surpass the classical macro models. However, as the number of variables increase, the number of parameters estimated dramatically increase. Therefore, the estimation procedure becomes rather complicated when inserting additional variables and/or permitting time-varying parameters (Stock and Watson, 2001). Further, though Vector autoregression model may yield better results than simultaneous equations, the VAR models are criticized for their ad hoc specification. Since the VAR models are not dependent on the economy, they barely address the structure of the economy. Hence, there is no clear procedure when choosing variables to the VAR model. This is particularly a limitation when the causal relations between the variables have to be investigated for communication purpose.

4.2.3 Selection of variables

In this sub-section we discuss the selection of the endogenous variables that we used for our vector autoregression model. The Vector Auto Regression (VAR) model is an ample macroeconomic model that facilitates the understanding of the dynamic relationship between macroeconomic variables and the assessment of shocks impact on the variables throughout a period of study. Though, the VAR model operates with a limited number of variables due to the fact that it is data intensive, especially in the case of absence of high frequency data. Consequently, our selection is limited to few variables from the potentially impactful macro variables on the credit risk. Deserve to be mentioned that due to data availability, we have selected banking non-preforming loans ratio to aggregate loans as the credit risk proxy.

As discussed in the literature and in sub-section 4.1, the variables with potential impact on the non-preforming loan ratio includes gross domestic product growth, industrial production, inflation rate, consumer price index, aggregate money, unemployment rate, real interest rate, nominal interest rate, stock price index, imports, exports, exchange rate and oil prices. There is a variety of approaches when it comes to selecting variables from a pool of potentially impactful variables given the objective of the research. For example, specific-to-general approach begins with one variable then proceeds with the addition of other variables one at a time. On the contrary, the general-to-specific approach which commence with all the potential variables remove the variables stepwise. In whichever case, significance level of the estimated coefficients and measures of prediction errors or other metrics are employed to reach the right model (Jarocinski and Mackowiak, 2011).

Since our objective is to assess the impact of macro shocks on non-preforming loans, the significant relation between the macro variables and the credit risk would be a suitable criterion for the variable selection. Therefore, we applied a series of univariate and multivariate regression models where the non-preforming loans variable was regressed against identified macroeconomic indicators (sub-section 4.1), in order to select the most effective indicators are selected. Upon implementing our methodology in choosing variables and due to data availability, we found that GDP, consumer price index, nominal lending interest rate, and exchange rate would constitute a proper inclusive model to assess credit risk measure by the non-performing loans ratio to aggregate loans.

The competitiveness of the Egyptian economy is reflected in the data on real GDP and EGP/USD exchange rate. While the financial sector is defined by consumer price index and nominal lending interest rate.

4.2.4. Data sources and description

Quarterly data spanning from Q1 2011 to Q4 2020 were used. Quarterly data on banking non-preforming loans ratio to aggregate loans were obtained from the Central Bank of Egypt data monthly statistical bulletin. Non-performing loans are defined as loans in which the borrower is in default due to the fact that they failed to meet the scheduled debt obligation for a specified period. Deserve to be mentioned that the CBE does not provide a clear definition for NPL, given that the specified period varies, depending on the industry and the type of loan. Generally, however, the period is 90 days or 180 days.

Financial data on nominal GDP at market prices were obtained from the Egyptian Ministry of Planning and Economic Development as it is the sole responsible on calculating the Egyptian GDP. Further, consumer price index data were obtained from the Egyptian Central Agency for Public Mobilization and Statistics (CAPMAS). The base year for CPI from 2011 to 2018 was the year 2010, whereas the base year for 2019 and 2020 was the year 2018. The CPI index data were obtained on monthly basis, hence we obtained quarterly averages to match the research desired data frequency. Further, data on exchange rate and lending interest rate was obtained from the CBE data base. Deserve to be mentioned that obtained on daily basis, hence we obtained quarterly averages to match the research desired data frequency.

Table 1. Description of the original time series data.

Time series	Denotation	Unit	Data Span
NPL ratio	npl	%	Q1 2011 -Q4 2020
GDP	gdp	Bn EGP	Q1 2011 -Q4 2020
Consumer price index	inf	Index=100	Q1 2011 -Q4 2020
Lending interest rate	I	%	Q1 2011 -Q4 2020
Exchange rate	egp_usd	Amount of one USD per EGP	Q1 2011 -Q4 2020

Descriptive statistics together with the plot of the original time series can be found in the Appendix in table 8 and figure 2 respectively.

4.2.5. Stationarity in time series

The VAR approach require timeseries data to be stationary in order to formulate our model. Stationary of the time series has mainly three features: 1) constant mean, 2) constant variance and covariance and 3) error is white noise. Time series stationarity is particularly important for the introduction of shocks on various variables in the model. The non-stationarity of time series is characterized with infinite long memory; hence any introduced shock will permanently affect the process, opposed to stationary time series where the effect of the shock is temporary (Verbeek, 2004).

Plotting the time series data graphically is particularly helpful to perform a visual inspection of any potentially problematic development in the time series. In general, if the time series data do not oscillate around a constant value (mean) or have constant variance, the time series is most likely to be not stationary. Upon the visual inspection of our selected time series data, we can conclude that the data are not stationary and follow some stochastic trend.

Another useful method to visually inspect the non-stationarity of the time series would be plot the time series in levels and inspecting its correlogram. Correlogram refers to the autocorrelation function (ACF) which demonstrates to what extent there is a correlation among the realizations and hence ACF displays the strength and length of the memory of the time series over time. Usually as the lag order grows the correlogram of a stationary time series diminishes. As expected, visual inspection of the autocorrelation function graph of all endogenous variables reveled high like-hood of the non-stationarity of original time series.

Though visual inspection is important before commencing the time series analysis, it is not the main method to detect the presence of unit roots in the time series. Unit roots are the most significant reason for the non-stationarity of the time series data. Therefore, we employ the Augmented Dickey-Fuller test (ADF test) to test the presence of unit roots in all original time series.

Table 2. Summary of the ADF test results for the original time series data.

Variable	p-value
NPL ratio	0.8535
GDP	0.1860
Consumer Price Index	0.8969
Lending interest rate	0.9395
Exchange rate	0.5414

Notes: Under null hypothesis the time series has a unit root and is non-stationary, regarded as stationary if the null hypothesis is rejected. Optimal number of lags was chosen according to the information criteria.

The ADF test reveals that all the original time series are non-stationary in their level values. Since all the original time series data contain trend, the test results come with no surprises. Hence, we employ either log first difference or log growth rate transformations to the time series data. We formulated the growth rate of the GDP, CPI, and exchange rate to transform their units to percentage. Whereas we took the first difference for NPL loans ration and interest rate to consider the growth in the time series data. The transformation has been employed to ensure the stationarity of the time series.

Further, we de trended the time series using the Hodrick-Prescott filter as we are more concerned with studying the cycle of the time series data. Nonetheless, we adjust the data for seasonality as all of the data was not seasonally adjusted. Upon the transformation of the time series, the ADF results prove that the transformed version of the time series is stationary.

Table 3. Description of the transformed time series data.

Time series	Denotation	Data Span	Notes
NPL ratio	d_npl	Q2 2011 -Q4 2020	log(npl)-log(npl(-1))
GDP	d_gdp	Q2 2011 -Q4 2020	dlog(gdp)
Consumer Price Index	d_inf	Q2 2011 -Q4 2020	dlog(cpi)
Lending interest rate	d_i	Q2 2011 -Q4 2020	log(i)-Log(i(-1))
Exchange rate	d_egp_usd	Q2 2011 -Q4 2020	dlog(egp_usd)

Notes: The original time series has been transformed into growth rates.

Descriptive statistics as well as graphs of the transformed time series can be found in the Appendix in table 9 and figure 3 respectively.

Table 4. Summary of the ADF test results for the transformed time series data.

Variable	p-value
d_npl	0.0000
d_gdp	0.0000
d_inf	0.0000
d_i	0.0368
d_egp_usd	0.0025

Notes: under null hypothesis the time series has a unit root and is non-stationary, regarded as stationary if the null hypothesis is rejected. Optimal number of lags was chosen according to the information criteria.

4.2.6 Model description

In this sub-section we present the reduced form vector autoregression model description, the VAR model presented will be used to estimate and forecast the macroeconomic variables of the model. The vector autoregression model examined has a symmetric structure, and hence it supports the application of ordinary least square estimator.

The reduced form vector autoregression model can be formalized in the matrix notation as following:

$$Y_t = \varphi + \sum_{i=1}^{p} A_i \Delta Y_{t-i} + u_t$$

Where,

- p denotes the optimal (examined) length of lags
- Δ denotes to the quarterly percentage change
- $Y_t = (y_{1,t}, y_{2,t}, \dots, y_{p,t})$` is a (5 x 1) vector of endogenous macroeconomic variables
- $A = (A_1, A_2, \dots, A_p)$ is a (5 x 5) coefficient matrix
- $\varphi = (\varphi_1, \varphi_2, \dots, \varphi_n)$ (5 x 1) vector of intercept
- $u_t = (u_{1,t}, u_{2,t}, \dots, u_{n,t})$` interpreted as n-dimensional vector of shocks (innovations) and $u_t \sim WN\ (0, \Omega)$ (i.e., white noise).

The selection of the optimal lag length of the endogenous variables is the key specification issue in the vector autoregression models. For instance, selection of higher lag order than optimal (i.e., over-fitting of the model) decreases the precision of the VAR forecast; likewise, selection of lower lag order than optimal (i.e., under-fitting of the model) may produce autocorrelated errors. Hence, the misspecification of the VAR model affects its outcome (Lütkepohl, 2005).

There is a range of criteria to help detect the optimal lag length of the vector autoregression model. For instance, Akaike's Information Criterion (AIC) and Schwarz Bayesian Criterion (BIC), Hannah-Quinn Criterion (HQ) etc. are particularly helpful in that matter. Typically, the lower the information criterion the better the model. We employed the AIC, BIC, and HQ to identify the optimal lag length of the endogenous variables. All three criteria showed that the optimal lag length for the examined model is six.

However, Lütkepohl (2005) argued that selecting the optimal lag length might not be desired if the model is estimated for a specific purpose. Generally, the aggregate stress tests for the banking sector are conduct on a one-year span, this would in our case mean a lag structure including four lags on endogenous variables.

5. Econometric results

The VAR output (estimated via Eview10 software package) can be found in table 10 in the Appendix. The table displays the estimated coefficients and the standard statistics of the model in a summarized and transparent manner. Further, the standard R^2 measure is also displayed for each of the system equations since each equation is estimated by OLS.

The model contains 105 coefficients that have to be estimated. According to the standard econometric conventions in displaying the significance conveyed by t-statistics and its corresponding p-values, the results show, that there are only 24 (i.e., approximately 23%) significant coefficients of the endogenous variables in the model. The remaining coefficients are insignificant on the 10% significance levels.

However, Sims (1980) stated that estimated coefficients of the VAR model "tend to oscillate" and usually contain some "cross equation feedbacks", and hence there is no surprise in the insignificance of individual coefficients. Further, Lütkepohl (2005), claimed that it is difficult to analyze the coefficients of the VAR model as elasticities between its endogenous variables due to the dynamic structure of the model. Rather, the VAR model is utilized for forecasting and testing hypothesis through experiments.

5. 1. Granger causality

In VAR models, it is quite helpful to test for causality between the variables. Hence, we apply the concept of Granger causality to analyze the causality of each individual equation in the context of the VAR model. The idea behind the Granger causality is to analyze wither a variable depends on the lag of other variables or not, this is particularly helpful to identify the ability of one variable to forecast another. The Pairwise Granger causality test is usually constructed as F-test, where the null hypothesis is that the lagged information of a variable x_t has no statistically significant information about a variable y_t.

Though Granger causality is a standard tool for investigating in autoregression models, but it has a number of limitations. One of which is that it yields the most effective and least distorted results in a bivariate setting, therefore the clarity of the causality decreases as the number of variables increases. Further, the choice of the variables and sampling period may be a drawback of the Granger, for instance, Lütkepohl (2005) proved that the results vary when considering monthly data and when considering quarterly data. Likewise, he proved that seasonally adjusted data may lead to different results relative to seasonally unadjusted data. Hence, the lack of causality between the variables does not necessarily imply that absence of a cause-and-effect relationship (Lütkepohl, 2005).

Table 5. Pairwise Granger causality test results.

	d_npl	d_gdp	d_inf	d_i	d_egp_usd
d_npl		0.5794	**0**	**0.0006**	
d_gdp	0.5773		**0.1329**	**0.0453**	**0.779**
d_inf	**0.0722**	0.1594		**0.0002**	0.6848
d_i	0.9769	0.3056	**0.028**		0.8642
d_egp_usd	0.8033	**0.0083**	**0.0717**	**0.0038**	0.1785
All	0.4506	**0.0338**	**0**	**0**	0.6995

Notes: The results presented show the p-values of the corresponding F-test. The null hypothesis is that the beta coefficients are not significantly different from zero. Rejecting the null hypothesis means that the regressor Granger causes the dependent variable. The results are in bold for p-value less or equal 0.1

Table 5 shows the p-values of the Pairwise Granger causality test for the VAR model with lag order 4. On the significance level of 10% we can reject the null hypothesis of Granger non-causality in the system for all of the variables. Hence, we can conclude that all variables are endogenous, and that the Granger causality test revealed some causal relationship between the variables in the model.

5.3. Impulse response analysis

This sub-section presents the impulse responses of the VAR model. Given the previously discussed hardship of analyzing the individual coefficients of the VAR model, the optimal method to interpret the model is analyzing the model response to random shocks (impulses) according to Sims (1980). Impulse response function is an essential tool when investigating the empirical causal relationship in the model, as it traces the impact of a change in one variable on other variables over time.

The impulse response function is presented as the stress test for credit risk, where we present shocks of three standard deviation to the error term of the macroeconomic variables and analyze their effect on credit risk presented as NPL ratios. The impulse response simulation has been performed with period of 4 quarters (i.e., 1 year) to match the conventional stress testing horizon used in the banking sector. Deserve to be mentioned that the impulse response function was obtained using a Monte Carlo distribution as the variables were not normally distributed according to their Jarque-Bera test (the test can be found in table 9 in the appendix).

According to the theoretical literature, we formalize five empirical *a-prior* hypotheses with regard to the non-preforming loans ratio (as a measure of credit risk) response to macroeconomic variables impulses. The hypotheses are presented below to be tested for by our VAR model:

1. The non-preforming loans ratio is exogenous. In other words, a shock in NPL ratio itself will be the main driver of change for NPL ratio (i.e., NPL is an autoregressive process).
2. A positive shock to income level (accounted for as an increase in GDP growth rate) improves the ability to repay dept and hence the non-preforming loans ratio will decrease.
3. A positive shock to inflation (accounted for as an increase consumer price index) is associated with a decrease in the non-preforming loans ratio in the short run.
4. A positive shock to lending interest rate (which represents the direct cost of borrowing money) will lead to an increase in the non-preforming loans ratio.

5. A positive shock to the foreign exchange rate (EGP depreciation) should lead to the increase in the non-preforming loans ratio.

The response of a NPL ratio to a shock in three standard deviations to error term in macroeconomic variable, can be found in Appendix figures 5 to 9.

The results prove that non-preforming loans ratio is autoregressive, in other words, the response of NPL to the shock is mainly dominated by the direct impact of the NPL ratio itself. These results match the findings of Babouček and Jančar (2005), who found the same direct negative relationship. but in the contradiction to findings of Festić and Romih (2008) for the Czech Republic. Deserve to be mentioned that even though the response of NPL ratio to a shock in lending activity is positive over the first two periods, the response dies out quickly.

Further, the results support the hypothesis that a positive shock in GDP growth rate is negatively related to the NPL ratio. Higher GDP growth rate is not only an indicator for favorable economic outlook, but also an indicator for increasing economic activity and hence decrease in non-preforming loans ratio. The results are in line with the literature , for instance, Pesola (2001); Kalirai and Scheicher (2002); and Delgado and Saurina (2004) found the same negative relationship between GDP and NPL when applying time series analysis for the data of Sweden, Austria, and Spain respectively.

The results indicated that a positive shock to consumer price index is positively related to the non-preforming loans ratio. Therefore, the results failed to support the hypothesis that a positive shock to inflation increases the non-preforming loans ratio in the short run. The relationship between inflation and credit risk is rather ambiguous, for instance a higher inflation rate causes reduction in the real value of money, hence reduction in the real value of debt and improvement in the value of assets. Also, higher inflation might also indicate a deterioration of resources available for fixed income earners and increase in cost of goods sold for corporates. Further, increase in inflation leads to the increase of nominal lending interest rate which is considered the direct cost of borrowing. Eventually, given that the overall effect of inflation on the non-preforming loans ratio is indicated by the aforementioned forces, the negative effect implies that later effect is stronger. These results are in line with Boss (2002) and Virolainen (2004) findings who argued that higher inflation increases non-preforming loans ratio on the short run.

Similarly, the response of non-performing loans ratio to an impulse in nominal interest rates supported the basic hypothesis that a positive shock to the cost of borrowing has a direct positive impact on the non-preforming loans. In other words, increasing the nominal lending rates, increases the non-preforming rates ratio. The results come of no surprise as the nominal interest rate, as aforementioned, is considered the direct cost of borrowing. In general, the results are in line with the literature, for instance, Kalirai and Scheicher (2002), Delgado and Saurina (2004), Bank of Japan (2007), Castr´en, D´ees, and Zaher (2008) found that increase in interest rates causes acceleration in non-performing loans ratio.

Nevertheless, the results imply that a positive shock to the foreign exchange rate leads to the increase in the non-preforming loans ratio, hence, the results support the a-prior hypothesis. The relationship between exchange rate and credit risk is rather ambiguous. Depreciation may enhance exports as well as the production of import competing goods and hence improve the loan portfolio quality. On the other hand, depreciation might as well severely harm importers. Given that Egypt relies extensively on imports according to its GDP, the results correspond with the country-specific feature.

5.4. Variance decomposition

Forecast error variance decomposition (FEVD) is a useful analytical tool when employing a VAR model, the FEVD represents the decomposition of forecast error variance of one variable, explained by innovations to the remaining variables (Lütkepohl, 2005). To rephrase, FEVD shows the percentage of how much the unexpected change of one variable is explained by various shocks to other variables in the VAR system.

Table 6. The FEVD of the banking NPL ratio to aggregate loans.

Period	S.E.	d_npl	d_gdp	d_inf	d_i	d_egp_usd
1	0.04918	100	0	0	0	0
2	0.05161	93.1878	1.6066	2.8126	1.7416	0.6514
3	0.05406	86.01367	2.2848	6.9250	2.7450	2.0316
4	0.05579	82.47609	4.3446	7.3450	2.5873	3.2470

The figure clearly reveals that the non-preforming loans ratio is strongly exogenous, as the main explanation comes from the variable itself. Further, consumer price index inflation exhibits the second largest effect on non-preforming loans followed by GDP growth effect and lending interest rate effect. Nevertheless, the effect of the foreign exchange rate on the development of the NPL ratio is the smallest.

5.5. Residuals analysis

Lütkepohl (2005) highlighted the importance to perform the residual check of the estimated VAR model. In general, if the model is specified correctly, the residuals will be whit noise (i.e., *i.i.d*. processes). The residual analysis has been employed to investigate the robustness of the model. The autocorrelation tests Ljung-Box Q-test and the residuals' covariance matrix were examined.

Table 7. Results of Ljung-Box Q-test for residuals.

Lag	AC	PAC	Q-Stat	Prob
1	0.049	0.049	0.0924	0.761
2	0.013	0.01	0.0988	0.952
3	0.159	0.158	1.121	0.772
4	-0.045	-0.062	1.2042	0.877
5	-0.039	-0.038	1.2713	0.938
6	-0.16	-0.187	2.4202	0.877
7	0.242	0.297	5.1383	0.643
8	-0.143	-0.202	6.1168	0.634

Notes: The null hypothesis in the Ljung-Box Q-test test is that residuals are white noise. The test was run using lag order 8.

At the 10% significance level, the Q-test failed to indicate any significant autocorrelation in all of the residuals. Table 11 and table 12 in the Appendix represent the residual analysis of the model, and figure 4 represents a plot of the model residuals. The results for the Jarque-Bera test for normality, indicates that at 1% significance level, we reject the null hypothesis of residuals normality. Meanwhile, the descriptive statistics shows that the contravention of the normality is due to the high kurtosis, hence the investigated time series come from a fat-tailed distribution.

6. Conclusion

The financial system instability roots from various factors including macroeconomic fluctuations, the growing financial innovations and delicate loan policy. However, the macroeconomic fluctuations have remained the main reason for banks losses in any economic crisis. This fact accompanied with the recent BCBS regulations (2018), lead central banks across the world to aim their efforts in order to develop comprehensive models and analytical frameworks to evaluate financial stability with a macroprudential dimension.

In this thesis, we focused mainly on the assessment of the credit risk in the Egyptian banking sector over the time period starting from the year 2010 to the year 2020. A vector autoregression approach was employed to analyze the effect of various macroeconomic variables on the non-preforming loans as a proxy of Egyptian banks' credit risk.

In the theoretical part of the thesis, we begin by defining stress testing and presenting a brief history of its development over the years. Further, we specified the general stress testing process and limitations. The literature review presents various methods/approaches of employing stress tests along with their advantages and disadvantages.

Following, the empirical model part represents the core macro model that the thesis mainly aims to investigate. The part contained details about the variable choice, data discerption and transformation, and the econometric model that we used. The results of the VAR model have shown some insightful causal relationship between the non-preforming loans ratio and various macroeconomic variables.

The outcome of the sensitivity analysis stress test (i.e., impulse function) indicated that the biggest effect on the deterioration of the non-preforming loans ratio is a positive shock of the NPL ratio itself. Further, the model results showed that a positive shock to the GDP is negatively associated with the increase in non-preforming loans ratio. This denotes that an improvement in the overall economic leads to the decrease of the non-preforming loans ratio. Further, the model results indicate that a positive shock to lending interest rate is positively associated with the increase in non-preforming loans ratio. Similarly, the response of the non-preforming loans to a positive shock in foreign exchange rate (EGP depreciation) supported the hypothesis that depreciation in EGP exchange rate increases the non-preforming loans ratio. On the contrary, the results failed to support the rest of the *a-priori* hypotheses concerning the relation between the non-preforming loans ratio and inflation as the results indicated that an increase in inflation would lead to the increase of non-preforming loans ratio.

Eventually, though the limitations of the VAR model, we believe that this thesis has contributed to the understanding of macroeconomic factors the Egyptian banking sector has credit risk exposure. Hence, the model represents a solid base for further investigation.

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APPENDIX

Table 8. Descriptive statistics of the original time series data.

	NPL	GDP	INF	I	EGP_USD
Mean	0.070875	846.5375	170.4833	0.136233	11.15021
Median	0.067500	675.4500	149.0500	0.122122	7.860552
Maximum	0.112000	1664.000	301.1000	0.197000	18.01821
Minimum	0.034000	316.2000	104.1667	0.098333	5.836734
Std. Dev.	0.026172	413.3576	63.23052	0.028617	5.058007
Skewness	0.136880	0.581297	0.835832	0.866788	0.306955
Kurtosis	1.489578	1.948823	2.342082	2.319444	1.222205
Jarque-Bera	3.927196	4.094328	5.378863	5.780737	5.895732
Probability	0.140352	0.129101	0.067920	0.055556	0.052452
Sum	2.835000	33861.50	6819.333	5.449333	446.0084
Sum Sq. Dev.	0.026714	6663716.	155925.9	0.031939	997.7538
Observations	40	40	40	40	40

Figure 2. Plot of the original time series data.

Table 9. Descriptive statistics of the transformed time series data.

	D_NPL	D_GDP	D_INF	D_I	D_EGP_USD
Mean	-7.68E-16	3.74E-15	3.35E-15	1.85E-16	2.96E-15
Median	0.001717	-0.021740	0.007038	-0.002324	-0.021239
Maximum	0.096799	0.225293	0.106285	0.099935	0.441838
Minimum	-0.113349	-0.127366	-0.994012	-0.078227	-0.060358
Std. Dev.	0.045960	0.106223	0.168165	0.036276	0.082286
Skewness	-0.264698	0.839329	-5.467568	0.565054	4.277618
Kurtosis	3.168738	2.344820	32.98975	3.954666	22.85809
Jarque-Bera	0.501690	5.276620	1655.814	3.556362	759.7457
Probability	0.778143	0.071482	0.000000	0.168945	0.000000
Sum	-2.99E-14	1.46E-13	1.31E-13	7.26E-15	1.15E-13
Sum Sq. Dev.	0.080268	0.428765	1.074625	0.050006	0.257299
Observations	39	39	39	39	39

Figure 3. Plot of the transformed time series data.

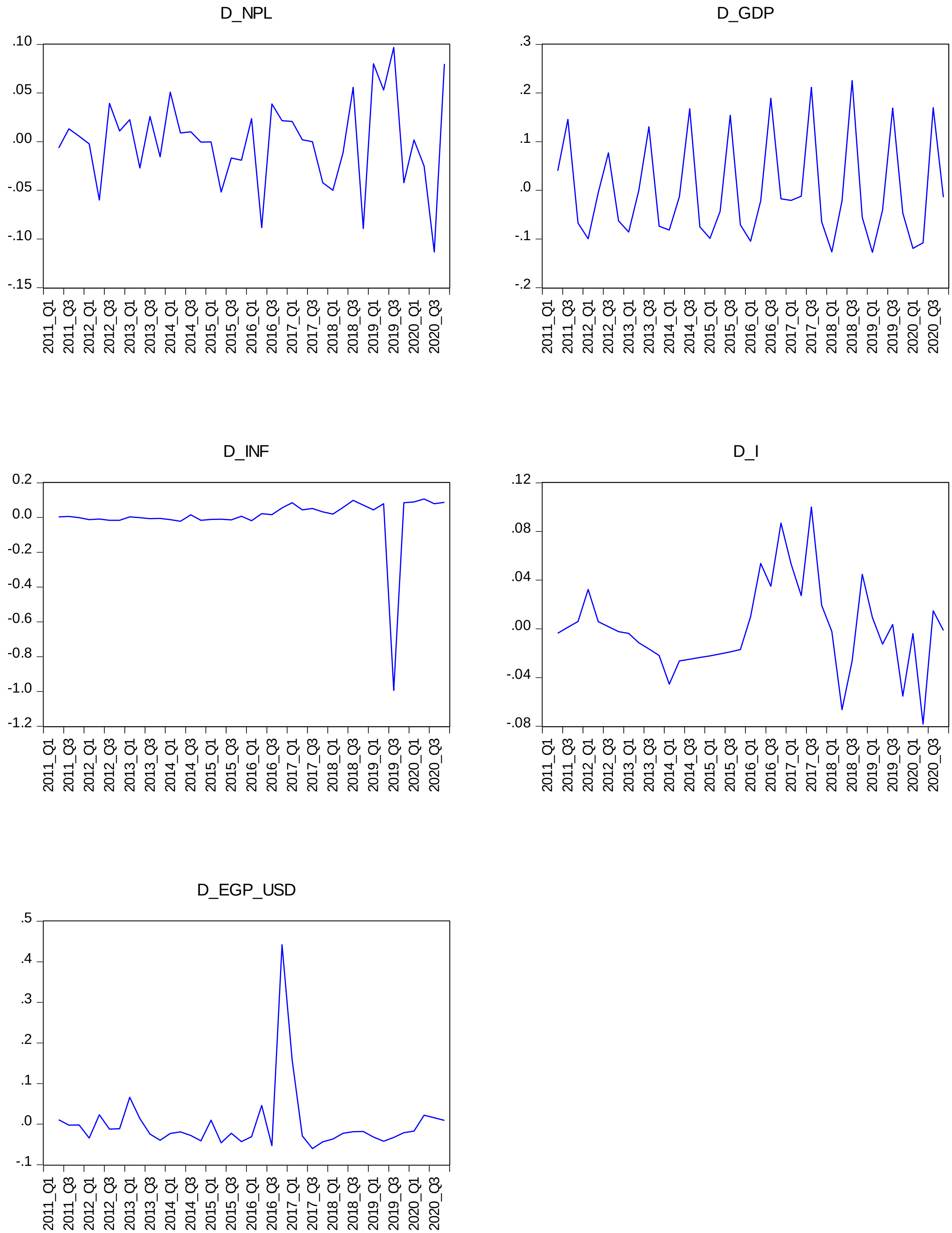

Table 10. E-views output of the VAR model.

Sample (adjusted): 2011Q2 2020Q4
Included observations: 35 after adjustments
Standard errors in ( ), t-statistics in [ ] & p-values in {}

	D_NPL	D_GDP	D_INF	D_I	D_EGP_USD
D_NPL(-1)	-0.001672	0.206332	-1.037866	0.186586	0.559289
	(-0.2932)	(-0.18654)	(-0.7049)	(-0.12227)	(-0.563)
	[-0.00570]	[1.10609]	[-1.47236]	[1.52604]	[0.99341]
	{0.9955}	{0.2725}	{0.1454}	**{*0.1315}**	{0.3239}
D_NPL(-2)	0.134334	-0.282025	-3.511623	-0.207042	-0.428241
	(-0.37624)	(-0.23937)	(-0.90455)	(-0.1569)	(-0.72245)
	[0.35704]	[-1.17817]	[-3.88219]	[-1.31960]	[-0.59276]
	{0.7221}	{0.2427}	**{***0.0002}**	{0.1913}	{0.5553}
D_NPL(-3)	0.322239	0.096152	1.684202	-0.458929	-0.204039
	(-0.4986)	(-0.31722)	(-1.19873)	(-0.20792)	(-0.95741)
	[0.64629]	[0.30310]	[1.40499]	[-2.20720]	[-0.21312]
	{0.5202}	{0.7627}	{0.1644}	**{**0.0306}**	{0.8319}
D_NPL(-4)	0.550567	0.217577	-0.026585	-0.607616	-0.059643
	(-0.53494)	(-0.34034)	(-1.28609)	(-0.22308)	(-1.02719)
	[1.02922]	[0.63928]	[-0.02067]	[-2.72379]	[-0.05806]
	{0.3069}	{0.5247}	{0.9836}	**{***0.0081}**	{0.9539}
D_GDP(-1)	-0.486091	-0.286614	-0.17827	0.168135	-0.129089
	(-0.32067)	(-0.20402)	(-0.77094)	(-0.13372)	(-0.61574)
	[-1.51588]	[-1.40485]	[-0.23124]	[1.25734]	[-0.20965]
	{*0.1341}	{0.1645}	{0.8178}	{0.2128}	{0.8346}
D_GDP(-2)	-0.339805	-0.207698	0.719132	0.201001	-0.193733
	(-0.31342)	(-0.19941)	(-0.75352)	(-0.1307)	(-0.60183)
	[-1.08419]	[-1.04158]	[0.95437]	[1.53787]	[-0.32191]
	{0.282}	{0.3012}	{0.3432}	**{*0.1286}**	{0.7485}
D_GDP(-3)	-0.521346	-0.301411	0.21344	0.055613	-0.404689
	(-0.31141)	(-0.19813)	(-0.74869)	(-0.12986)	(-0.59797)
	[-1.67414]	[-1.52128]	[0.28508]	[0.42824]	[-0.67677]
	{*0.0986}	**{*0.1327}**	{0.7764}	{0.6698}	{0.5008}
D_GDP(-4)	-0.349108	0.775706	0.239297	0.26454	-0.325915
	(-0.33394)	(-0.21246)	(-0.80286)	(-0.13926)	(-0.64124)
	[-1.04541]	[3.65099]	[0.29805]	[1.89962]	[-0.50826]

	{0.2994}	**{***0.0005}**	{0.7665}	**{*0.0616}**	{0.6129}
D_INF(-1)	0.091892	0.009252	-0.276688	0.043017	0.085366
	(-0.10374)	(-0.066)	(-0.24941)	(-0.04326)	(-0.19921)
	[0.88577]	[0.14017]	[-1.10935]	[0.99435]	[0.42853]
	{0.3788}	{0.8889}	{0.2711}	{0.3235}	{0.6696}
D_INF(-2)	0.133932	-0.039001	-0.310022	-0.147199	-0.102376
	(-0.10082)	(-0.06414)	(-0.24239)	(-0.04204)	(-0.19359)
	[1.32843]	[-0.60802]	[-1.27903]	[-3.50113]	[-0.52882]
	{0.1884}	{0.5451}	{0.2051}	**{***0.0008}**	{0.5986}
D_INF(-3)	0.127214	0.1193	0.207043	-0.045302	-0.099235
	(-0.09932)	(-0.06319)	(-0.23877)	(-0.04142)	(-0.19071)
	[1.28091]	[1.88803]	[0.86711]	[-1.09381]	[-0.52036]
	{0.2045}	**{*0.0632}**	{0.3888}	{0.2778}	{0.6045}
D_INF(-4)	0.24955	0.002405	-0.215606	-0.120034	-0.163893
	(-0.09252)	(-0.05886)	(-0.22243)	(-0.03858)	(-0.17765)
	[2.69733]	[0.04087]	[-0.96933]	[-3.11121]	[-0.92255]
	{*0.0088}**	{0.9675}	{0.3357}	**{***0.0027}**	{0.3594}
D_I(-1)	0.241738	0.69261	1.359774	0.587593	1.499138
	(-0.568)	(-0.36138)	(-1.36557)	(-0.23686)	(-1.09067)
	[0.42560]	[1.91659]	[0.99576]	[2.48073]	[1.37452]
	{0.6717}	**{*0.0594}**	{0.3228}	**{**0.0155}**	{0.1737}
D_I(-2)	0.097263	-0.616951	-2.613825	0.13588	0.6581
	(-0.53996)	(-0.34354)	(-1.29816)	(-0.22517)	(-1.03683)
	[0.18013]	[-1.79587]	[-2.01348]	[0.60345]	[0.63472]
	{0.8576}	**{*0.0768}**	**{**0.0479}**	{0.5482}	{0.5277}
D_I(-3)	-0.187525	-0.097192	-1.547258	-0.019802	0.305265
	(-0.51314)	(-0.32648)	(-1.23369)	(-0.21399)	(-0.98534)
	[-0.36544]	[-0.29770]	[-1.25417]	[-0.09254]	[0.30981]
	{0.7159}	{0.7668}	{0.214}	{0.9265}	{0.7576}
D_I(-4)	0.150652	0.416048	2.890806	-0.302115	0.002777
	(-0.50437)	(-0.3209)	(-1.2126)	(-0.21033)	(-0.96849)
	[0.29869]	[1.29652]	[2.38398]	[-1.43639]	[0.00287]
	{0.7661}	{0.1991}	**{**0.0198}**	{0.1553}	{0.9977}
D_EGP_USD(-1)	0.056359	0.129115	0.700192	-0.091028	-0.1625
	(-0.1427)	(-0.09079)	(-0.34307)	(-0.05951)	(-0.274)
	[0.39496]	[1.42217]	[2.04097]	[-1.52972]	[-0.59306]

	{0.6941}	{0.1594}	**{**0.045}**	**{*0.1306}**	{0.5551}
D_EGP_USD(-2)	0.117389	0.155849	0.20077	0.018483	-0.106306
	(-0.15069)	(-0.09587)	(-0.36229)	(-0.06284)	(-0.28936)
	[0.77901]	[1.62556]	[0.55417]	[0.29414]	[-0.36739]
	{0.4386}	**{*0.1085}**	{0.5812}	{0.7695}	{0.7144}
D_EGP_USD(-3)	-0.064568	0.041406	0.401426	0.180086	-0.197475
	(-0.15598)	(-0.09924)	(-0.375)	(-0.06505)	(-0.29951)
	[-0.41396]	[0.41724]	[1.07047]	[2.76863]	[-0.65933]
	{0.6802}	{0.6778}	{0.2881}	**{***0.0072}**	{0.5118}
D_EGP_USD(-4)	-0.097806	-0.207587	-0.310613	-0.08769	-0.411479
	(-0.17678)	(-0.11247)	(-0.42501)	(-0.07372)	(-0.33946)
	[-0.55326]	[-1.84565]	[-0.73083]	[-1.18949]	[-1.21217]
	{0.5818}	**{*0.0692}**	{0.4673}	{0.2383}	{0.2295}
C	-0.002667	-0.005432	-0.001922	0.002211	-0.003378
	(-0.00915)	(-0.00582)	(-0.02199)	(-0.00381)	(-0.01757)
	[-0.29154]	[-0.93330]	[-0.08737]	[0.57963]	[-0.19228]
	{0.7715}	{0.3539}	{0.9306}	{0.564}	{0.8481}
R-squared	0.576772	0.964984	0.81782	0.879496	0.512172
Adj. R-squared	-0.02784	0.914962	0.557563	0.707348	-0.184726
Sum sq. resids	0.033864	0.013708	0.19574	0.005889	0.124864
S.E. equation	0.049182	0.031291	0.118243	0.02051	0.09444
F-statistic	0.953954	19.29099	3.142354	5.108952	0.734931
Log likelihood	71.80007	87.6269	41.09771	102.4122	48.96504
Akaike AIC	-2.902861	-3.807251	-1.14844	-4.652129	-1.598002
Schwarz SC	-1.969652	-2.874043	-0.215232	-3.71892	-0.664793
Mean dependent	-0.000286	-0.000548	0.000115	-0.001032	0.000833
S.D. dependent	0.048512	0.107304	0.177766	0.037913	0.086765
Determinant resid covariance (dof adj.)		3.72E-14			
Determinant resid covariance		3.81E-16			
Log likelihood		373.0234			
Akaike information criterion		-15.31562			
Schwarz criterion		-10.64958			
Number of coefficients		105			

Table 11. Descriptive statistics of the residuals.

	RESID01	RESID02	RESID03	RESID04	RESID05
Mean	-3.37E-18	1.17E-17	-2.93E-17	-1.83E-17	-3.87E-17
Median	0.007860	-0.002745	-0.007824	-0.000148	-0.003891
Maximum	0.045972	0.041629	0.221117	0.027129	0.226019
Minimum	-0.063951	-0.047009	-0.195093	-0.024407	-0.133603
Std. Dev.	0.031560	0.020079	0.075875	0.013161	0.060601
Skewness	-0.358808	-0.046922	0.281479	0.403119	0.991855
Kurtosis	2.198029	3.150023	4.657252	2.602029	7.167546
Jarque-Bera	1.688940	0.045666	4.467467	1.178916	31.06766
Probability	0.429785	0.977426	0.107128	0.554628	0.000000
Sum	-9.71E-17	4.06E-16	-9.58E-16	-6.28E-16	-1.35E-15
Sum Sq. Dev.	0.033864	0.013708	0.195740	0.005889	0.124864
Observations	35	35	35	35	35

Table 12. Correlation matrix of the residuals.

	D_NPL	D_GDP	D_INF	D_I	D_EGP_USD
D_NPL	1	0.1470	-0.3758	-0.3991	0.0804
D_GDP	0.1470	1	0.4050	0.1903	0.4207
D_INF	-0.3758	0.4050	1	0.2539	0.1664
D_I	-0.3991	0.1902	0.2539	1	0.4760
D_EGP_USD	0.0804	0.4207	0.1664	0.4760	1

Figure 4. Plot of the residuals.

Figure 5. Impulse to innovations in NPL ratio.

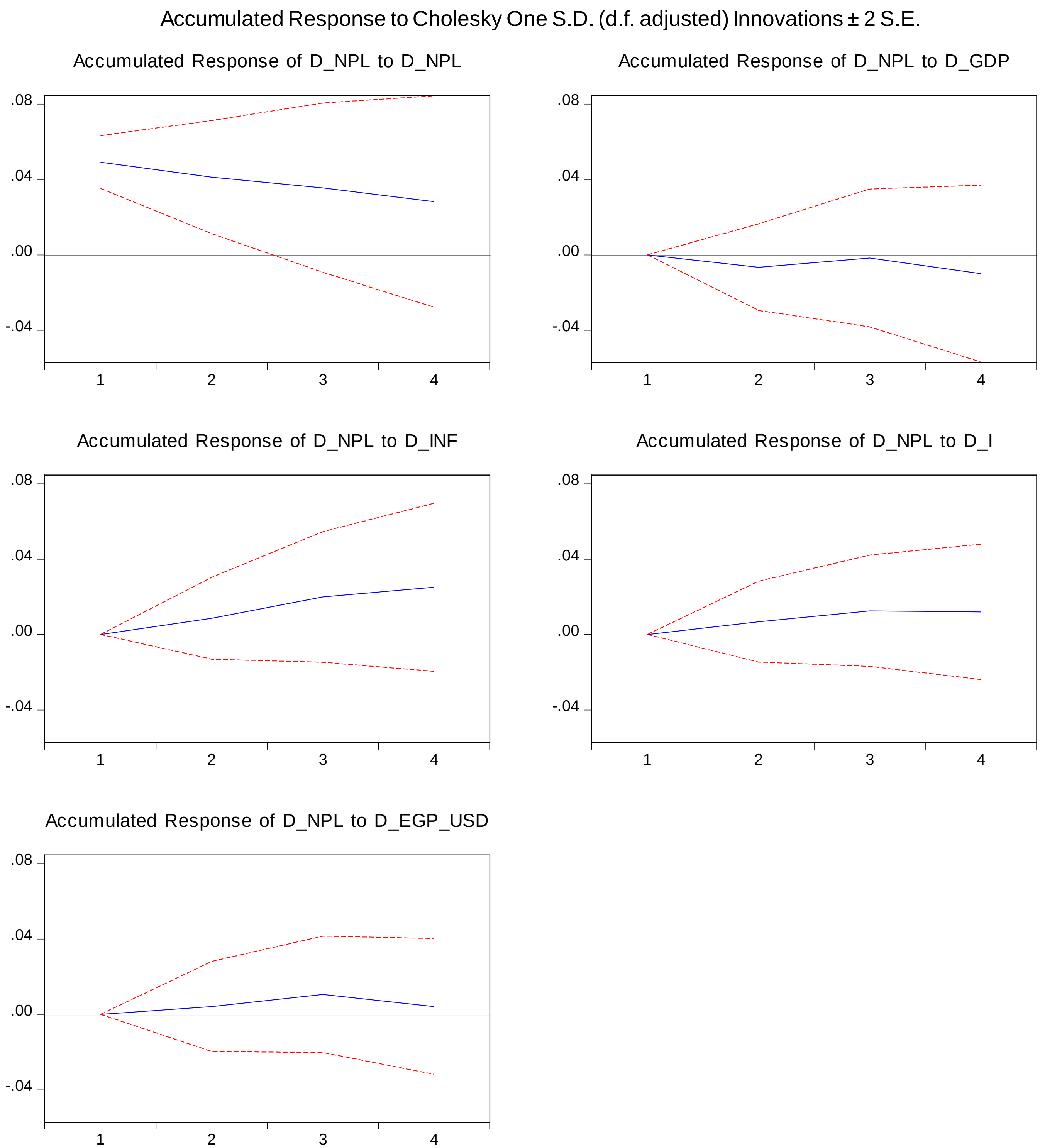

Figure 6. Impulse to innovations in GDP.

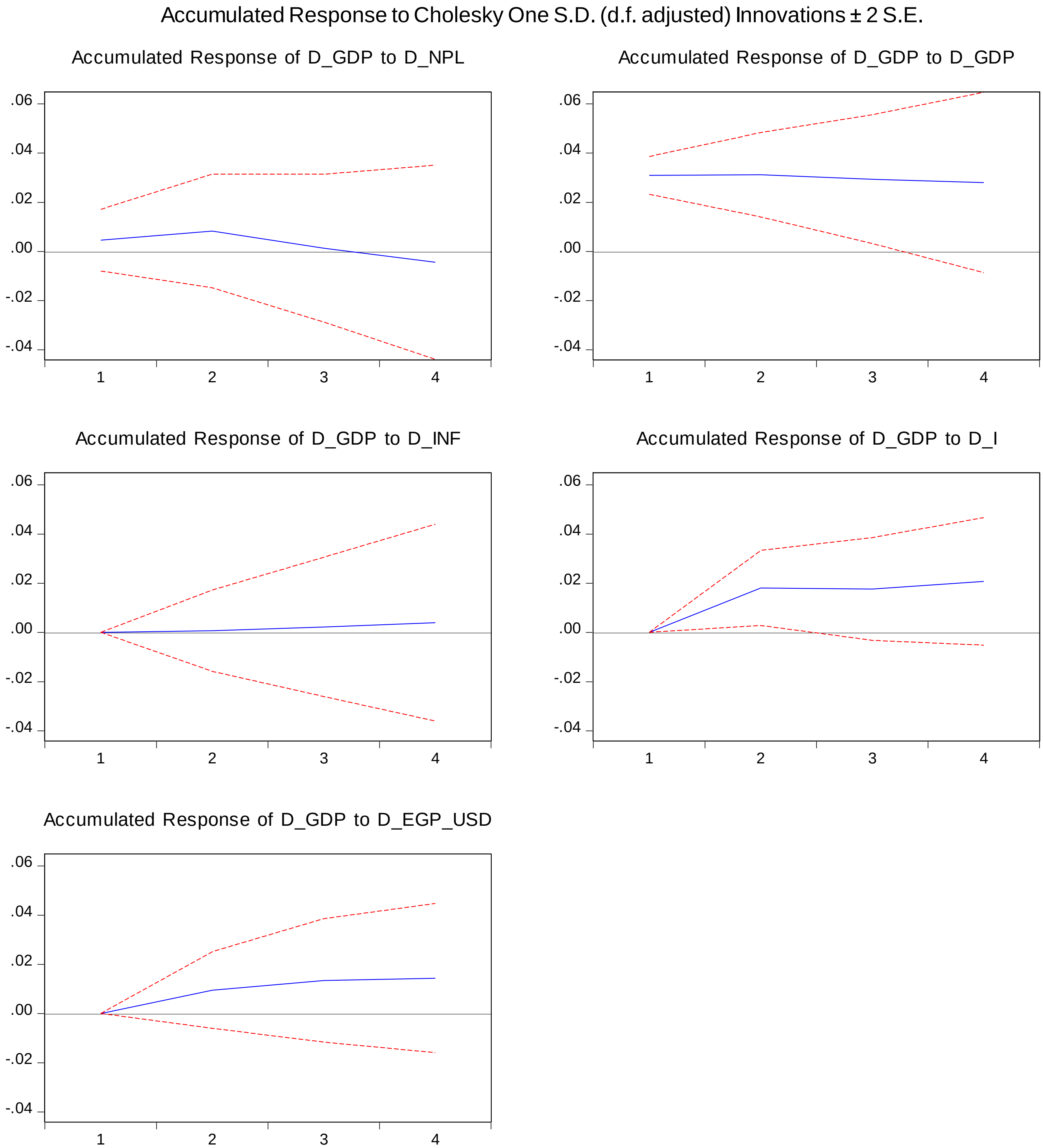

Figure 7. Impulse to innovations in CPI.

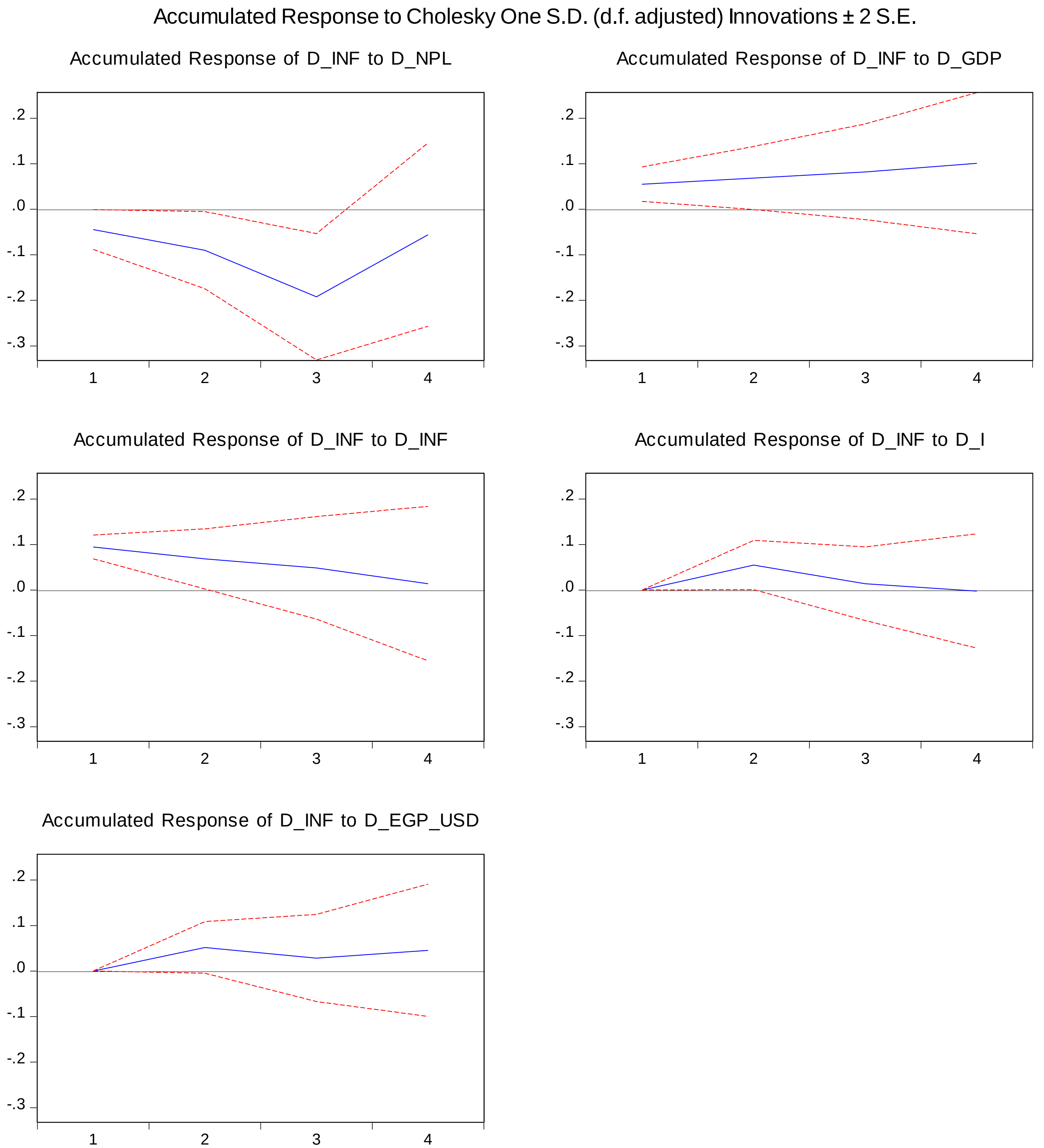

Figure 8. Impulse to innovations in lending interest rate.

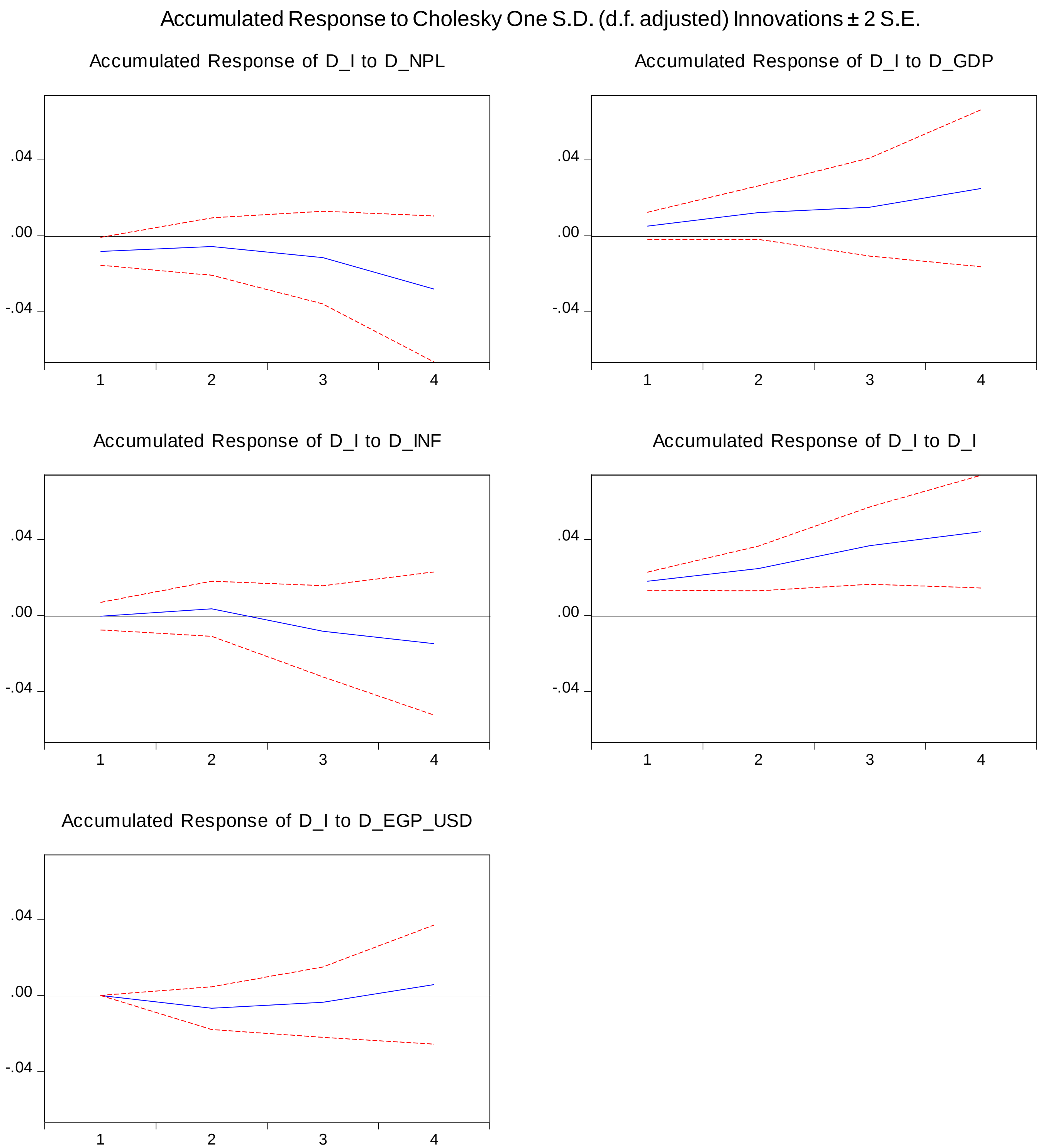

Figure 9. Impulse to innovations in foreign exchange rate.