A MACRO STRESS TEST APPLICATION ON THE FINANCIAL SYSTEM OF TURKEY: A CREDIT RISK PERSPECTIVE

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ABSTRACT

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Macro stress testing applications were initially introduced in 1991 with the Financial Sector Assessment Program (FSAP) launched by International Monetary Fund (IMF). Along with each economic and financial crisis, the popularity of macro stress testing increased. This study aims to investigate the financial stability of Turkey by testing it against shocks on macro variables using the Vector Error Correction model and the most up-to-date publicly available data. To this end, the banking sector as the main pillar of the financial sector was stress-tested against macroeconomic shocks using the Vector Error Correction Model based on monthly data for the period between 2005-2021. The impact of the shocks on the selected financial stability indicator, non-performing loan ratio was analyzed using Impulse Response Functions. The results showed that the banking sector was resilient to the applied shocks and the increase in non-performing loan ratio was of no significant concern. The present study also highlighted that the need for prudential oversight by conducting periodic tests and publication of the results remains of substantial importance to be prepared for possible future shocks.

Keywords: Macro Stress Testing, Vector Error Correction Model, Impulse Response Functions, Bootstrap Confidence Intervals, Piecewise Approach.

ÖZ

KREDİ RİSKİ PERSPEKTİFİ İLE TÜRKİYE'NİN FİNANSAL SİSTEMİ ÜZERİNE BİR MAKRO STRES TESTİ UYGULAMASI

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Makro stres testi uygulamaları ilk olarak 1991 yılında Uluslararası Para Fonu (IMF) tarafından başlatılan Mali Sektör Değerlendirme Programı (FSAP) ile tanıtılmıştır. Her ekonomik ve finansal krizle birlikte makro stres testlerinin popülaritesi artmıştır. Bu çalışma, Vektör Hata Düzeltme modeli ve kamuya açık en güncel veriler kullanılarak makro değişkenler üzerindeki şoklara karşı Türkiye'nin finansal istikrarını test etmeyi amaçlamaktadır. Bu amaçla, finans sektörünün temel direği olan bankacılık sektörü üzerine, 2005-2021 dönemi aylık verilere dayalı Vektör Hata Düzeltme Modeli kullanılarak makroekonomik değişkenler üzerine şoklar verilmesi ile stress testi uygulanmıştır. Şokların seçilen finansal istikrar göstergesi takipteki kredi oranı üzerindeki etkisi Etki-Tepki Fonksiyonları kullanılarak analiz edilmiştir. Sonuçlar, bankacılık sektörünün uygulanan şoklara dayanıklı olduğunu ve takipteki kredi oranındaki artışın önemli bir endişe kaynağı olmadığını göstermiştir. Mevcut çalışma ayrıca, periyodik testler gerçekleştirerek ve sonuçları yayınlayarak ihtiyatlı gözetim ihtiyacının, gelecekteki olası şoklara hazırlıklı olmak için büyük önem taşıdığını vurgulamıştır.

Anahtar Kelimeler: Makro Stres Testi, Vektör Hata Düzeltme Modeli, Etki Tepki Fonksiyonları, Bootstrap Güven Aralıkları, Parçalı Yaklaşım.

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LIST OF ABBREVIATIONS

ADF	: Augmented Dickey Fuller
ARIMA	: Autoregressive Integrated Moving Average
BASEL	: Basel Committee on Banking Supervision at the Bank for International Settlements
BCBC	: The Basel Committee on Banking Supervision
BIST	: Istanbul Stock Exchange (Borsa İstanbul)
BISTRE	: The Rate of Real Profit Created by BIST100 Index Compared to Consumer Price Index
BRSA	: Banking Regulation and Supervision Agency of Turkey (Bankacılık Denetleme ve Düzenleme Kurumu)
BSKUAOF	: Weighted Average Interest Rate of Loans Given by Banks
CPI	: Consumer Price Index
CPISA	: Consumer Price Index Seasonally Adjusted
EU	: European Union
EVDS	: Electronic Data Distribution System of Turkey (Elektronik Veri Dağıtım Sistemi)
FSAP	: The Financial Sector Assessment Program
GDP	: Gross Domestic Product
GLS	: Generalized Least Squares Regression
GNP	: Gross National Product
IMF	: International Monetary Fund
IP	: Industrial Production Index
IPSACA	: Industrial Production Index, Seasonally Adjusted, Calendar Adjusted
KPSS	: Kwiatkowski Phillips Schmidt Shin
MTM	: Mark to Market

NPL	: Non Performing Loan
OECD	: The Organisation for Economic Co-operation and Development
OLS	: Ordinary Least Squares Regression
PD	: Probability of Default
PiT	: Point in Time
RAMSI	: The Bank of England's Risk Assessment Model of Systemic Institutions
RSCI	: Real Sector Confidence Index
SME	: Small and Medium-sized Enterprises
TITISACA	: Total Industrial Turnover Index, Seasonally Adjusted, Calendar Adjusted
TTC	: Through the Cycle
TURKSTAT	: Turkish Statistical Institute (TÜİK)
TVAR	: Multivariate Threshold Autoregressive Model
UK	: United Kingdom
USA	: United States of America
USDFXI	: USD Effective Buy Exchange Rate
VAR	: Vector Autoregressive Model
VEC	: Vector Error Correction
WB	: World Bank

INTRODUCTION

The increased pace of globalization and the following integration of financial systems accelerated the spread of shocks. Each financial and economic crisis began to impact not only the point of emergence but also affected the connected markets and systems in an unprecedented manner.

In order to countervail the effects of macroeconomic and macro-financial shocks and maintain stability, International Monetary Fund (IMF) and World Bank (WB) launched the Financial Sector Assessment Program (FSAP) in 1991. Within the scope of the financial stability program, macro stress tests were introduced as instruments for detecting vulnerabilities of financial systems.

As there are more evolved and sophisticated approaches and methods in the present day, the financial systems of developed countries are being kept under continuous scrutiny by their central banks, many other regulatory bodies, and academic researchers. Although macro stress testing is not a novel area of research in Turkey, it should be better explored by reviewing the related literature on stress testing around the world and in Turkey.

This thesis mainly aims to investigate the financial stability of Turkey by testing it against shocks on macro variables using the Vector Error Correction model and the most up-to-date publicly available data.

A macro stress test focuses on the resilience of a system against applied shocks. These applied shocks must be severe enough since the purpose is to create extreme conditions to measure the level of resilience. However, they must also meet the criteria required for the test to be meaningful for real-life implications. For that reason, carefully deciding the risk exposures, scenarios, model, and measure of outcome for a macro stress test is a complex and essential task.

The risk exposures include both the institutions and relevant risks to be covered. For the purpose of testing the entire financial system, the total coverage of all financial institutions is the most ideal scenario. However, having this kind of goal brings about certain complexities and data availability issues. Given the preponderance of the banking sector in the financial system and that the sector has the greatest share compared to other financial sector actors in Turkey, the macro stress test application presented in this thesis focuses on the banking sector.

When three main approaches for scenario creation were reviewed, a probabilistic approach was utilized in this thesis. The historical simulation contains the risk of missing events that did not occur. In addition, the hypothetical approach was not preferred since the method relies on expert judgment, and making such judgments was a better fit for experts that have more outstanding expertise in the field.

In model selection, among the two main model forms used in stress testing, the reduced form was used instead of the structural model due to having better performance with regards to forecasting accuracy. The Piecewise Approach was preferred over the Integrated Approach as the latter requires greater data availability and has more issues of complexity. Hence, a Vector Error Correction model was employed, and one standard deviation shock was applied on each selected macroeconomic variable.

The selected outcome metric is the change in the non-performing loan ratio, which falls into the category of default measure models. Corollary to this metric, the measured risk type is the credit risk. Credit risk was highlighted since financing is the primary function of banks. For this reason, credit risk was considered to be the most significant one among other financial risks.

In order to connect the theoretical selection reasoning of methods, approaches, and variables of the stress testing application in the present thesis to the application side, the thesis presentation is mainly separated into two main chapters: The Literature Review and The Data and Methodology.

In The Literature Review Chapter, the framework of macro stress tests was introduced. The definition of stress testing and the relevant classifications were detailed. The structure of macro stress tests was discussed along with the advantages and the disadvantages of selecting different approaches. Following the presentation of the theoretical framework, empirical applications from the world and Turkey literature were reviewed.

In the light of the reviewed literature, The Data and Methodology Chapter presented and explained data selection and model creation.

In the Results chapter, the analysis of the impulse response functions and the variance decomposition tests were presented. The results of the robustness checks were also demonstrated in this chapter, along with the discussion of other candidate models. In Conclusion chapter, a brief summary of all findings and critical discussions were listed, including recommendations for future research.

CHAPTER I

LITERATURE REVIEW

The reviewed literature on macro stress tests will firstly be presented by discussing the framework of macro stress tests. This section will draw the theoretical framework, provide the main classification of stress tests, and discuss the advantages and disadvantages of selecting different approaches and methods. In the final section, the drawn theoretical framework will be supported by a brief discussion of empirical examples around the world and in Turkey.

1.1 THE FRAMEWORK OF MACRO STRESS TESTS

In this section, the definition of stress testing and components of the main structure of macro stress tests will be presented. In addition, the challenges and limitations will be discussed.

1.1.1 The Main Structure of Macro Stress Tests

According to the formal definition given by IMF (2012), "*Stress testing is a technique that measures the vulnerability of a portfolio, an institution, or an entire financial system under different hypothetical events or scenarios.*". Stress tests serve as quantitative tools to help estimate the impact on firms or financial systems when certain risks materialize. It is a complex process since it involves selecting risks, institutions, and scenarios to be covered.

Macro stress tests' key components are summarized by Borio (2012) as follows:

1- A collection of **risk exposures** that are subject to stress testing,
2- The macroeconomic **scenarios** which set down and fine-tune the exogeneous stress shocks,

3- The **model** that maps the effect of shocks on a measure of the outcome by entrancing the movement of the shock through the systems,
4- **A quantifier (measure) of outcome** that measures the effect of the simulated shocks on the balance sheet of the financial sector.

Alternative but similar approaches to the main structure may be found in Bunn et al. (2005), Sorge and Virolainen (2006), Summer (2007), McNeil et al. (2015) as well.

1.1.2 Risk Exposures

In general, the decision-making on risk exposure consists of a broad spectrum of options (analyzed risk types, collections of institutions, decisions on approaches to financial conglomerates, use of market or book data, etc.). It depends on both data availability and the scope of stress testing (Sorge and Virolainen 2006).

The decision-making with regards to risk exposures consists of both the selection of the collection of institutions (banking sector, insurance firms, etc.) and the selection of relevant risks and their indicators of measurement, which should be subject to stress testing. (Borio et al. 2012)

The whole financial system is preferred to be the subject matter; however, the stress test efficaciously concentrates on sub-sets, specifically the banking sector due to its importance and preponderance in the financial system and its potential role in the spill-over effect of financial shocks to the real economy (Borio et al. 2012; Drehmann 2008; Sorge and Virolainen 2006).

1.1.3 Scenarios

A critical component of stress test applications is designing the scenarios (Boss 2002). The designed scenarios must be considered from a “severe but plausible” point of view. Hence, scenario designs are generally based on adverse macroeconomic conditions such as recessions (Borio et al. 2012).

Scenario run is not possible when models’ data generating process is auto-regressive for each systematic risk factor. The main technical approaches to scenario creation were documented in several studies (ECB 2013; IMF 2012; Jobst et al. 2013). Accordingly, the first step is to establish a benchmark scenario (baseline), which gives a high probability forecast of the macroeconomic evolution. For instance, the FSAP framework uses the IMF's World Economic Outlook projections. The next step is to create an alternative adverse scenario by following the approaches listed below:

1) Historical simulation: Replicating past severe periods such as the financial crisis of 2008.

2) Probabilistic approach: Use of shock scenarios as implied by the tail of the historical distribution of risk factors ("x-standard deviation" or extreme quantiles in the distribution).

3) Hypothetical scenarios (ad-hoc expert judgment scenarios): These scenarios do not include historical background, but they have specific relevance to the vulnerability of the systems.[1]

Straightforward interpretation is another crucial advantage of historical-based scenarios in addition to being easy to implement (ECB 2012). However, the historical approach has a degree of complacency, especially in good times. This approach apparently misses events that did not occur, depending on the selected historical horizon (IMF 2012).

Although probabilistic approaches may extend the scope of historical approach, they (concentrated on unlikely tail risks) depend on the selected time period. Volatility in the selected sample may be low. Hypothetical scenarios' flexible approach may mitigate these disadvantages and be beneficial to complement general historical-based scenarios (Oura and Schumacher 2012). As previously stated, however, the plausibility of hypothetical or extremely unlikely scenarios is generally assessed against historical evolutions (Borio et al. 2013).

Although several rules and guidelines are usually applied in practice, the design of specific scenarios includes a considerable amount of expert judgment regardless of the selected approach. Additionally, even if consistent and comparable cross-country methods are helpful, scenario design should stay flexible to allow the assessment of particular vulnerabilities of the analyzed financial system (Jobst et al. 2013). Furthermore, central supervisory authorities must make a crucial trade-off between

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[1] With regards to simulating hypothetical shocks, Berkowitz (2000) carries out a conceptual classification with four types:
1) simulating shocks which are considered to occur more frequently than
historical observations suggest;
2) simulating shocks which have never occurred;
3) simulating shocks which reflect, in some circumstances, the possibility of statistical patterns
could break down;
4) simulating shocks which reflect structural breaks that could occur in the future.

plausibility and severity, particularly in turbulent times of crisis. Under those conditions, supervisory authorities may become unenthusiastic for excessively extreme scenarios since the baseline scenario is already adverse. In general, central bank stress testing results are being published. Therefore, the adoption of extreme scenarios contains the hazard of triggering crises characterized by “self-fulfilling prophecy” (IMF 2012).

Besides, country-, regional or international level stress test applications concerning re-capitalization needs of banking systems rest on a complex economic and political context (Elsinger et al. 2006).

Then again, the credibility of the procedure may be heavily threatened by compromising on severity, which may contribute to a prolonged crisis. Hence, near-crisis stress tests should not compromise severity. Instead, central authorities should take support measures to a reasonable degree to be able to mitigate the potential adverse effects of stress test findings (IMF 2012).

In several studies, the main scenario construction techniques given below were documented (IMF 2012; Jobst et al. 2013):

1. Construction of GDP shock scenarios based on standard deviations from long-term historical averages:

i. a mild adverse scenario based on one standard deviation

ii. a severe adverse scenario based on two standard deviations from historical averages. This is the standard practice in IMF’s FSAP framework, and it possesses the advantage of comparability across countries.

2. Designing a historical scenario to replicate big shocks (such as the financial crisis of 2008-2009)

As previously suggested, the above-mentioned scenarios are generally complemented by hypothetical scenarios designed in order to incorporate particular vulnerabilities of the financial system on which the financial stress test is applied.

A crucial decision in scenario design is related to the scenario time horizon. Macro financial adverse shocks usually create a lasting effect distributed over the years, and countermeasures taken by regulators are typically slow. This is why longer time horizons are more suitable. For instance, a 5-year time horizon is the usual horizon for FSAP programs. Nevertheless, extended time periods involve more uncertainty. Even though stress testing is not entirely based on forecasting, the decision is expected to be adapted to the dynamics of a given environment. The reason for selecting shorter time horizons is the rapid changes a financial system is undergoing. For instance, most FSAP applications have a time horizon of 1 to 3 years for emerging markets with less mature banking systems (IMF 2012).

A stress testing performed in the volatile environment of Eurozone countries' debt crises in 2010 had a two-year time horizon, which is in line with the argument presented above (EBA 2011).

Selecting a time horizon also has an implication on endogenous behavior and feedback modeling. If a model does not incorporate second-round effects, choosing a short-term forecast horizon would be reasonable (Elsinger 2006).

1.1.1.3 Models

In general, one of the two forms is used in macro stress testing: reduced form (parsimonious framework) or structural model (established on a macroeconomic theory) (Foglia 2009).

In the case of the structural approach, the initial point is a macroeconomic model which estimates the impact of the exogenous factor on the economy. These macro-economic models, however, do not usually embody financial variables. Hence, the output of the models is used as input on a satellite model linking macroeconomic variables to relevant variables for financial risk assessment (Borio et al. 2012; Foglia 2009).

Satellite models usually consist of credit risk models and frameworks that require the collection of asset classes and risks broadly. In basic models, the stress testing is generally limited to the "first-round effect" analysis. EU adopted a similar methodology from macroeconomic to financial variables in the past decade (EBA 2011). However, the advanced models are aimed at assessing the impact of possible feedback ("second-round effects") created by endogenous behavior response of the actors of the financial system (i.e., portfolio optimization maneuvers of actors, response of policymakers, liquidity risk, the impact of financial sector on real economy) (Drehmann 2008; IMF 2012).

Structural approaches improve the understanding of the transmission of initial shocks into the systems and thereby allow the assessment of policy trade-offs and potential conflicts. Some studies argued that parsimonious models (for instance, models that are based on vector autoregressive specifications) may perform better in terms of forecasting accuracy (Sorge and Virolainen 2006).

The objective of stress test should be taken into consideration for the model type selection. For example, transparent models are more suitable for policy assessment and communication as they accommodate storytelling property on results and methodology compared to technical reduced-form models that are preferred in decision-making where accuracy is the main objective (Drehmann 2008).

Also, a third option documented by the study is a purely statistical approach (System Risk Monitor model) that is used by the Austrian central bank. In this approach, macroeconomic and financial variables are modeled through a multivariate t-copula. This approach focuses on accuracy and is not considered suitable for communication (Boss 2002).

Apart from the technical classification above, two primary econometric modeling approaches for macro stress testing are identified: piecewise approach and integrated approach (Sorge and Virolainen 2006).

1.1.1.3.1 Piecewise Approach

This approach includes forecasting the impact of macroeconomic stress shocks on several measures of outcomes (for instance, loan losses, NPLs (non-performing loans)). The overall evaluation of financial stability is then derived by summing up the estimated impact on each indicator.

These econometric models generally estimate a direct and linear relationship between risk measures and macroeconomic variables. Typically, this approach has intuitive models that are easy to implement. However, the assumption of a linear relationship and the reduced applicability (only capturing expected losses) are the main limitations of the approach (Sorge and Virolainen 2006).

1.1.1.3.2 Integrated Approach

This approach incorporates the evaluation of multiple risk factors into an overall estimate of the probability distribution of aggregate losses.

The models using this approach estimate a conditional probability distribution of losses for the simulated macroeconomic scenarios. In general, unexpected losses (value at risk) are used as summary statistics of the estimated distribution to measure the sensitivity of the portfolio to risk sources in a single metric (Foglia 2009). In this approach, integration of other risks enables advanced modeling of the relationship between indicators of financial stability and macro variables (Sorge and Virolainen 2006).

Modeling credit risk-related default probabilities as a non-linear function of macro-economic variables based on the methodology (this was proposed for assessing the credit quality of banks’ portfolios) is a core strand of literature within this approach for evaluation of credit quality of banks’ portfolios (Wilson 1998).

Typically, a multifactor macro model is used for determining the distribution of industry-specific default rates while a reduced form model is used for forecasting the evolution of individual macroeconomic time series. The follow-up step is the construction of stress test simulation by using the estimated parameters and error terms of the models. A firm-level structural framework (Merton 1974) is an alternative to credit portfolio risk modeling (Wilson 1998).

The firm-level structural models are stated in a non-linear fashion. These models start with the response of equity prices to macroeconomic variables, and then they map asset price movements into default probabilities conditional on the macroeconomic scenario (Drehmann 2005; Sorge and Virolainen 2006).

The theoretical structural assumption is that a default occurs when asset market value decreases below the liabilities’ value (Merton 1974). This framework was also used by many other researchers. The most notable ones are a global study by Pesaran et al. (2006), a UK corporate sector by Drehmann (2005), and a German corporate loans’ automotive sector by Duellmann and Erdelmeier (2009).

It was argued that being intuitive and easy to implement are the key features of approaches based on Wilson (1998), and the advantage of the Merton (1997) approach is taking a forward-looking perspective based on equity prices and credit ratings (Sorge and Virolainen 2006).

However, several crucial assumptions of firm-level theory and related stress testing procedures are not always valid. For instance, assumptions of complete and efficient markets, the relevance of equity prices for the entire industry, and as proxies for assets fluctuations are conditionally valid assumptions (Drehmann 2005; Duellmann and Erdelmeier 2009; Pesaran et al. 2006).

Merton-based credit risk models are primarily used by banks for risk evaluation in large corporate credit portfolios while it is utilized for small- and medium-sized enterprises’ (SME) portfolios to a lesser extent.

It was also argued that constraints caused by data availability and complexity problems lead to a scarcity of fully integrated approaches (Borio et al. 2012).

Both of the aforementioned approaches may be implemented in reduced form or structural models.

1.1.1.4 A Quantifier of Outcome

Typically, outcome metrics are capital adequacy (stress testing of solvency), portfolio losses, assets quality, and market liquidity indicators (Sorge and Virolainen 2006). Choosing a particular outcome (risk indicator/variable) is a fundamental decision to be made in the stress testing procedure. In many examples, it was restricted by data availability to a great extent for the selected degree of aggregation (Ferrari et al. 2011; Foglia 2009).

The main approaches regarding the outcome measure are as follows:

1) Fundamental approach models: Fundamental approach models are predicated on a detailed analysis of financial institutions' balance sheets.

2) Default measure models: Default measure models based on financial institutions' summary default measures. In this approach, market prices (stocks, bonds, etc.) are used for the financial system as a whole.

It was argued that model choices are more limited in developing countries due to data availability or ineffective regulatory and accounting systems. Nevertheless, this constraint also brings about the advantage of having simpler financial systems in which identifying economic risks and vulnerabilities is relatively more straightforward. Implementation of simple fundamental approach stress tests with single- or multi-factor shocks is feasible in most countries that use basic supervisory data (Cihak 2007).

These two approaches complement each other since they both have some advantages and disadvantages. The strength of fundamental approach models is related to identifying the source of vulnerability in the balance sheet. This positive aspect makes them more informative and more easily applicable to developing countries where stock markets are thin. The weaknesses of these models are that they are backward-looking in nature, data-intensive, not easy to update frequently, and less suitable for capturing contagion effects. On the other hand, the advantages of market price-based models are flexibility, adaptability to incorporate portfolio effects, and market-perceived risk factors. In addition, they are easy to update. The disadvantage of these models is the difficulty of disentangling the source of vulnerabilities within them. In addition, they are too sensitive to short-term fluctuations in market perceptions, which may have a low level of connection to fundamentals. Also, they are not applicable if a given country has limited market price data or does not have any such data[2] (Foglia 2009).

Useful comparisons and general conclusions may be derived from diverse stress test results.[3] However, the primary goal of stress testing is to measure the estimated effect of shocks in a specific context of the case of the application, rather than confirming macroeconomic principles and general financial relations.

1.1.2 Stress Test Types Based On Risk Type

From the perspective of risk types, a general categorization of the risks that are focused on by macro stress testing may be listed as follows (Borio C. et al. 2012; IMF 2012):

- credit risk (the most significant risk for big banks, the default of borrowers)
- market risk (mainly due to interest rate and foreign exchange rate risks)
- sovereign risk (default of country)
- counterparty risk (the likelihood of counterparty's default in the transaction and as a result, failing to meet its contractual obligations)
- liquidity risk
- solvency risk

[2] A similar classification is as follows: mark to market perspective and accounting perspective.
Mark to market perspective is useful with regards to providing a long-term view of the health based on economic fundamentals of banks. Accounting perspective is suitable for evaluation purposes if there would be future liquidity or regulatory constraints. For instance, there may be significant losses in short run and sufficient profits in the long run, so capital adequacy may be threatened over a one-year horizon even if banks are fundamentally sound. It is argued that the selection of the quantifier of outcome depends on the objective. Therefore, the selection is linked to the intent of using results, whether internally or externally.

[3] Private banks focus on optimization of the trade-off between risk and return, and risk measures are in general capital adequacy or profitability in the future. Hence, the results of stress tests are also expressed in similar terms. Financial stability stress tests usually normalize losses by capital to determine whether the banking system is robust or not. This phenomenon has two challenges: 1) Banks generally make positive profits acting as the buffer against losses. That is, unless profits are stress tested, the stress testing scenario's risk is probably overestimated. 2) Banks set aside capital against all the risks (credit, operational, reputational, market). These risks affect profits and losses; however, not all of them are stress tested, which means that capital indicated buffer may be excessive. One of the other problems of financial stability stress tests is a representation of the financial system with aggregate variables. Different stress tests' results may show average capital adequacy ratios above the minimum requirements. For financial stability, the failure of a small player may be absorbed by the system while the failure of a large player may distort the system and create severe losses. Using size weighted average is a potential, albeit rarely used, solution (Drehmann 2008).

Liquidity and solvency stress tests will be explained in more detail in the following sections.

1.1.2.1 Solvency Stress Tests

When the debt of an institution is larger than its assets, the institution at stake is insolvent. Solvency depends on future cash flows, which is inherently uncertain due to its dependence on future economic and financial conditions. Being solvent is an ongoing concern for institutions. Therefore, a minimum of positive equity capital needs to be maintained to absorb potential losses in a shock.

By using profit-loss and changes in valuation estimations, a solvency test evaluates whether the institution has sufficient capital to remain solvent in a challenging environment.

Single-factor stress tests examine one source of risks while multiple-factor stress tests analyze multiple sources. If risk factors are ad hoc combined, the test is called a combined shock test. On the other hand, if a coherent macroeconomic framework is used, it is called a macro scenario test. In macro scenario stress tests, estimation of solvency ratios necessitates macro-financial models.

The empirical relationship between key risk parameters (non-performing loan ratio, probability of default ratio, loss given default ratio, etc.) and relevant macroeconomic variables (gross domestic product, unemployment rate, interest rate, etc.) is estimated with a macro-financial model. To this end, macro-econometric models should be utilized along with expert judgment.

In general, a one to three year horizon is covered for macro stress tests since risks materialize gradually. The factors affecting capital including retained earnings need to be projected, which requires using assumptions on bank behavior (dividend payment policy etc.). This increases the complexity of stress tests.

Typically, different capital ratios are used to measure solvency depending on the regulatory requirements. The ratio of Risk-Weighted Assets is one of the most commonly used ones. If the targeted capital ratio is above the threshold (also known as hurdle rate), the financial institution/system is considered to have passed the stress test. This rate may be the same as the regulatory requirement itself or a different value. The selection of the threshold is critical since capital planning may be linked to the result of stress tests (Borio et al. 2012; IMF 2012).

1.1.2.2 Liquidity Stress Tests

When the financial institution does not have enough cash inflow, that institution is considered illiquid. A liquidity test evaluates whether the institution is able to withstand cash outflows in a challenging environment characterized by sudden distress in funding. Banks and other financial intermediaries, by nature of their business, have maturity mismatches in the balance sheet. When a large number of customers withdraw their deposits, a liquidity shortage may occur regardless of the bank's solvency. The crystallization of liquidity risk is due to the endogenous behavioral response of agents. The behavior of depositors is driven by negative information (Goldstein and Pauzner 2005).

In addition to funding liquidity risk, market liquidity risk may impact the stability of the financial system as well. Market liquidity is defined as the ability to sell assets at their fair value without delay. On the other hand, funding liquidity is defined as the ability to satisfy the demand for money (Drehmann and Nikolaou 2010).

Another reason for illiquidity is the linkages between funding liquidity and market liquidity. When asset prices are volatile, institutions that take active positions in the market face liquidity crises due to margin calls and collateral needs. Also, if financial institutions are unable to generate enough cash when faced with a shock, they may experience a liquidity shortage. If a high proportion of assets consists of non-marketable loans or the market value of an asset falls sharply, the institution may not sell the assets to generate sufficient cash.

Several different thresholds may be used in liquidity stress tests, including the net cash flow position, the number of days the bank/institution can tolerate a liquidity shock in advance of a cash outflow, and the stressed liquidity ratios.

It is challenging to disentangle liquidity and solvency stress tests since they are closely interconnected. A liquidity shortage may create insolvency if assets cannot be sold or can be sold at a meager price (fire sale). When a crisis occurs, liquidity issues arise before solvency problems. This is why current stress testing practices include liquidity concerns (IMF 2012).

The Bank of England uses a framework called the Risk Assessment Model for Systemic Institutions (RAMSI). This model is quite comprehensive with regards to incorporating main risks, including liquidity risks and second-round effects (Aikman et al. 2009; Drehmann et al. 2010). Another alternative approach is focusing on the market and funding liquidity risk of banks. As in the classic example of lemons and peaches (Akerlof 1970), markets may be illiquid due to information asymmetries. In addition, market liquidity may decrease due to the behavioral responses of agents. For instance, people may withdraw their money when the funds they invested in are underperforming. Also, a negative feedback loop may occur between funding liquidity and market liquidity. Instead of embedding this spiral[4], these events are usually used in the form of historical stress tests. Nevertheless, such an approach would not reveal the underlying transmission mechanism. For this reason, it is less suitable for financial stability stress tests.

Not only assets but also liabilities, off-balance sheet items, and maturities of them need to be taken into account for financial stress tests to incorporate liquidity risk (Jenkinson 2007). This, unfortunately, increases the amount of data required. Private banks rely on their own confidential data when conducting stress tests, and these data change rapidly during times of stress. That is the reason their use is limited from a perspective of financial stability. Also, data on behavioral responses of depositors in the interbank market is not abundant. Due to these reasons, liquidity stress tests rely on rules of thumb instead of empirical relationships (Drehmann 2008).

However, incorporation of modeling of endogenous behavior is used by several central banks and initially proposed by the Central Bank of Netherlands (IMF 2012). Endogenous behavior will be further discussed in section 1.1.5.

1.1.3 Stress Test Types Based on Objective

As is the case with any other model, a stress test should be designed bearing in mind which elements are essential and which ones can be ignored. This can be achieved by understanding the objective in the first place. Stress test types based on their objective are discussed below[5] (IMF 2012).

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[4] The intuition is that when a severe drop in asset prices is assumed, this decrease induces higher margin calls. When this occurs at the same time when banks funding liquidity is constrained, the only way to satisfy higher margin calls is to sell assets. Selling assets further decreases asset prices. In addition, if the other banks are also facing the same issue, asset prices decrease even more (Drehmann 2008; Shim 2007). Hence, higher margin calls and a decrease in asset prices have a spiral relationship similar to that of air conditioners and global warming.

[5] For objective based lists, Drehmann's (2008) typology could have been presented as well. However, IMF's (2012) list is opted for since it is more comprehensive and compact. For those who are interested, Drehmann (2008) lists three ultimate objectives of stress tests: validation, decision-making, and communication. He discusses internal and external purposed stress tests depending on these ultimate objectives. For internal stress tests, the main objective is validation and/or decision-making. When the objective is validation, model accuracy is the crucial factor. If the objective is decision-making, forecast performance becomes the crucial factor. For external stress tests where the main objective is communication, transparency, and suitableness for story telling are the crucial factors.

1.1.3.1 Internal Risk Management Purposed Stress Tests

Stress testing is used as a measurement tool for managing risks in the investments of institutions. J.P. Morgan was one of the earliest examples, and they used Value-at-Risk to measure market risk. However, early examples had limits in coverage of different risk factors and exposures, and the integration with risk management and capital planning was not established properly.

1.1.3.2 Supervisory (Microprudential) Purposed Stress Tests

Basel II[6] framework made the conduct of stress tests for market risk compulsory for banks. Additional tests are also indicated for pillar one and pillar two. These tests enable supervisors to order banks to take administrative actions where necessary. There is an increase in the supervisory stress test used by banks to set capital requirements and determine capital buffers. In Basel III, the liquidity ratios are utilized as a regulatory framework.

1.1.3.3 Macroprudential (Surveillance) Purposed Stress Tests

Macroprudential stress tests are used for analyzing system-wide risks and are usually utilized by central banks. The results of such tests are usually reported in Financial Stability Reports. Since 1999, IMF has included stress tests in FSAPs as well.

1.1.3.4 Crisis Management Purposed Stress Tests

With each financial crisis, the use of crisis management stress tests has become more common and prominent. Crisis management stress tests evaluate key financial institutions with the aim of determining recapitalization needs. For example, IMF programs for banking sector distress in Ireland, Greece, and Portugal estimated bank recapitalization needs through these stress tests. As the use of stress tests became widespread, the methodologies and risk coverage developed over time. Individual institutions now use more integrated approaches covering a wide range of risk factors

[6] Basel refers to a set of regulations created by the Basel Committee on Banking Supervision (BCBS) with the aim of creating an international regulatory framework to manage market and credit risk. To this end, Basel regulations manage to ensure banks preserve adequate cash reserves to meet their financial obligations and survive in financial and economic distress. Basel I was formed in 1988, Basel II was established in 2004, and Basel III is expected to be fully implemented in 2022. (Please see "https://corporatefinanceinstitute.com/resources/knowledge/finance/basel-accords/" for further details.)

and exposures. In addition, central banks use more macro scenario tests instead of single-factor tests in macroprudential stress testing.

Necessary actions may be decided upon based on the objective of the stress test. Macroprudential tests (for example, FSAPs) are mainly designed for policy recommendations. These tests are increasingly being used in improving data collection, close monitoring, detecting the need for additional capital, and reducing specific exposures. Crisis management stress tests are usually suitable for estimating capital shortfalls and planning follow-up actions.

1.1.4 Stress Test Types Based on Approach

Based on the approach used, two types of FSAP stress tests may be listed:

1) Top-Down Approach: The main characteristic of FSAP stress tests that use a top-down approach is that the stress test is conducted by national authorities or IMF staff by acquiring each bank's individual data. A consistent set of assumptions and methodology is used in this approach. Therefore, the central authority uses its own model and complements it with individual banks' positions.

2) Bottom-Up Approach: The main characteristic of FSAP stress tests that use the bottom-up approach is that an individual financial institution conducts the test by using internal data and models it usually based on common assumptions in this approach. Generally, the central authority gives a common scenario to each bank. These individual banks use their own models to estimate the effect, and the results are then aggregated by the central authority.

In addition, a third approach may be listed as follows:

3) Combined Approach: Use of a combination of bottom-up and top-down approaches (Borio et al. 2012).

Some macroprudential stress tests contain bank-specific risks and add reverse stress tests that are based on the shocks capable of causing a financial institution to become insolvent. Most of the liquidity stress tests use a bottom-up approach since they are dependent on the liquidity strategy of banks and need to make use of granular data. Also, bottom-up liquidity tests have more room for flexibility for banks in comparison to solvency tests. Most of the FSAP tests have a top-down structure which is supplemented by a bottom-up test. Top-down tests are used to validate bottom-up test results competently. Both of the approaches are used by many national authorities (Drehmann 2008).

Communication practices may differ based on the specific stress tests that are being conducted. In general, communication is needed between:

1) banks and supervisors
2) supervisory agents in a country
3) country authorities and the FSAP teams

Nevertheless, communicating stress test results to the public is not common. However, the number of publicly communicated stress tests has increased recently, especially in crisis management stress tests.[7] Macroprudential stress tests are usually reported in financial stability reports.

In the case of the FSAPs, individual institutions are rarely identified. Customarily, the communication of stress tests to the public is a controversial topic. Some country authorities raise the concern that public communication may create unrealistic expectations, which may cause misinterpreting of results in the media. This may cause institutions to focus more on media repercussions and communication instead of the supervisory benefits of the stress test. As for the FSAPs, the majority of the countries publish the reports even though the publication of the results is voluntary. Lastly, the technical appendix is less frequently published.

1.1.5 The Challenges and Limitations

Macro stress tests have widespread use around the globe, and hence an enormous amount of research was conducted on stress testing, leading to significant progress in dealing with the inherent challenges. However, except for a rough consensus on model structure, unresolved obstacles and opposing objectives lead to a diverse number of complex methodologies recommended.

In this section, major current challenges in macro stress testing methodologies will be discussed and some solutions will be suggested (Crouhy et al. 2000; Drehmann 2008; IMF 2012; Sorge and Virolainen 2006).

[7] In the USA, the Dodd-Frank Act makes communication of Comprehensive Capital Analysis and Review (CCAR) conducted by individual banks and by the Federal Reserve Board compulsory. The Dodd-Frank Act is promulgated in order to preserve financial stability by improving accountability and transparency and end bailing “too big to fail” entities. It is enforced by The Financial Stability Oversight Council and The Consumer Financial Protection Bureau (North and Buckley 2012).

1.1.5.1 Data Availability

Data scarcity for severe stress periods is a long-standing problem with regards to financial stability stress tests. In general, there is a scarcity of data concerning severe stress events. Availability of data is a primary concern for the selection of exposures to model and the adoption of risk measures.

Also, the issue of data availability is further complicated by rapid innovation in financial markets, the emergence of new products and players.

Capturing innovations in models is almost impossible and endogenous relationships in the system along with parameters used to model the data generating process may change with innovations. It is advocated that stress tests are helpful to address these issues as long as users are aware of the assumptions made (Drehmann 2008).

The underlying problem is that standard econometric techniques require sufficient data, which are often not available for stress tests. In turn, this may lead to errors in the data generating process' econometric specification. However, hypothetical scenarios are accommodated in the framework of stress testing to be able to address these challenges (Bunn et al. 2004).

In order to deal with the challenge of data constraints that affect the robustness of the model and impose the use of several assumptions, testing the model on different assumptions is suggested (Cihak 2007). Another recommendation is the adoption of different econometric approaches such as Bayesian and non-parametric entropy models (Drehmann 2008; Segoviano and Padilla 2006). Alternatively, a simple reverse test is proposed to find the system's breaking point in order to address scarcity in the data environment (Ong et al. 2010).

1.1.5.2 Incorporating Different Risks

Incorporating different risks together is a difficult goal yet necessary because real life practices show that there is no reason to think each risk will materialize in isolation. More often than not, different risk types are related to each other and materialization of one facilitates the other ones. For this reason, incorporating all relevant risk is a challenge and succeeding in doing so by modern risk management tools is a possible solution.

Multiple risks incorporating model (market risk, credit risk, interest rate risk, etc.) is proposed based on combining modern risk management tools with a network model of interbank loans that uses credit register data (Elsinger 2006; Foglia 2009). Since this framework has a short-term horizon, it does not incorporate second-round effects. It is extended to incorporate future income and cross-border exposure risks by accommodating a forecast horizon of three-year (Boss et al. 2008).

It is stated that balance between assets and liabilities is usually overlooked with stress testing models. Therefore, a framework is proposed to incorporate credit and interest rate risk by modeling the assets, liabilities, and off-balance positions of banks concurrently to ensure accounting quality among them (Drehmann 2010).

1.1.5.3 The Endogeneity of Risk

Potential endogenous behavioral reactions of market participants including policymakers and banks faced with stress conditions cause second-round effects, which is called the endogeneity of risk (Drehmann 2008). The endogeneity of risk in financial systems may occur due to several reasons. The most important challenge in risk management and stress tests is developing models that can capture the endogeneity of risk. The standard tools are not adequate when the risk is endogenous (Danielsson 2002).

The difficulties in trying to model such behaviors create unresolved challenges of macro stress tests. Models estimated on historical data may have structural breaks caused by severe shocks, which leads to parameter instability. Reduced-form models are particularly vulnerable to this phenomenon (Sorge and Virolainen 2006). In the absence of the feedback mechanism’s specific structural modeling, the feedback will be following historical patterns based on the implicit assumption. However, this assumption is not always valid, and it restricts the objective of stress testing, making it difficult to assess various policy options (Drehmann 2008).

In the aftermath of severe shocks, market participants attempt to optimize risks and hedge their portfolios. Due to the aforementioned reactions, however, it is not easy to implement stress testing models that assume exogenous portfolio evolution where the behavioral response is excluded, and losses are caused solely by shocks.

Some suggested solutions are as follows: A rule of thumb to partially incorporate this exogenous effect, which is based on the assumption that private banks and depositors should be passive, meaning that they continue to invest in the same assets as before. Even if it is not optimal, this is proposed as the first step in the modelling of endogenous behavior (Drehmann 2007).

Another one is a parsimonious model which associates credit supply and demand with the macroeconomic state and hence includes an adjustment for the balance sheet in a reduced form (De Bandt and Oung 2004).

In addition, it is emphasized that endogeneity of risk can facilitate macro feedback from the financial system to the real sector and generate liquidity risk (Drehmann 2008).

In standard stress tests, the only way of modifying exposures is either through default or market value changes. Private banks are assumed to stick with their initial portfolio allocation without changing their portfolio or trying to hedge losses during the stress event. This method is evidently not realistic considering a one to three year time horizon. Even though most modelers acknowledge the issue, the structure of the model conceals this problem.

The endogeneity of behavior problem should be addressed when the maturity structure of private banks is taken into account. Complete portfolio optimization would be taken into account by an ideal model, and this is realized by operations research literature which discusses stochastic programming models for dynamic asset and liability management. However, these kinds of modeling exercises are only aimed at tradable assets which are funded with a simple cash account (Jobst 2006).

An essential point is the policymakers in endogenous behavior discussions. Data generating process already includes the average central bank response if the model of the systematic risk drivers is reduced form. If the events of 2007-2008 are assumed to be executed as a historical stress test scenario using the observed changes in market prices to visualize this phenomenon, the result will include not only stress events but also central bank’s liquidity interventions. Nevertheless, if the stress test is to be conducted by a central bank to evaluate the robustness of the system, including and excluding the policy interventions, the problem remains unresolved.

A similar problem regarding interest rates in reduced form macro models which represent data generating progress is that when a macro model is used in order to capture macro risk factors’ dependence, it mostly relies on an estimated Taylor rule for behavior (which means that central banks set interest rates to minimize deviations in inflation and output is assumed). For instance, the UK housing crisis in the 1990s showed that house price falls could be concurrent with the increase in interest rates. In that case, a stress test that uses the Taylor rule for behavior would be problematic since a severe shock to the housing market means a reduction in the interest rates. In addition, a scenario creation of interest rate rise-house price fall would be very difficult without additional shocks to inflation (Drehmann 2008). Even if there is no easy answer to modeling endogenous behavior, taking both private banks' and policymakers' behavior into consideration is a focal point.

1.1.5.4 Macro Feedback

There exists a broad theoretical and empirical support for feedback from the financial sector to the real economy (Sorge and Virolainen 2006). However, as documented by Drehmann (2008) and Foglia (2009), only a small number of models have explicitly incorporated this effect since large-scale macro-structural models involving financial variables are at an emerging level.

For instance, a study on the Italian banking system used a vector autoregression model that incorporated credit supply and banks' capital adequacy variables to test transmission channels (Marcucci and Quagliariello 2008).

The reduced form models, on the other hand, were not developed in a particular context of macro stress testing. Hence, modeling of macro feedback is still a significant concern for future academic research and practice (IMF 2012).

The studies show that system-wide liquidity and solvency crises in the banking system lead to a significant loss in GDP (Hoggarth et al. 2005). However, establishing a link between the real and financial sectors is difficult. The financial sector is both the source of many shocks and an amplification mechanism in the financial accelerator (Bernanke 1999).

Moreover, not only the whole financial system but also different heterogeneous actors in the financial system should be modeled to unmask important relationships. For instance, different private banks may take different risks, and the ones bearing the highest risk would be the first to fail, as is the case with Demirbank.

In addition, funding liquidity conditions are set by central banks. As long as no policy mistake is made, the level of aggregate liquidity is not expected to cause a crisis. Nevertheless, considering the allocation of liquidity across institutions, an institution being short of liquidity results in a failure. Failed institutions may trigger a contagion effect. From this aspect, large-scale VAR models are considered the most successful approaches to link the financial sector to the real economy (Aspaches et al. 2006; De Graeve et al. 2007; Hoggarth et al. 2005; Jacobsen et al. 2005).

1.1.5.5 Non-Linearity

A consensus seems to be reached on Wilson (1998) and Merton (1974) based credit risk models in their capability to capture the non-linearity of the relationship between the financial system and macroeconomic shocks (Foglia 2009). As stated by Drehmann (2008), however, such specification may still overlook some of the non-linearity attributes across the system. Gradually, increased attempts to incorporate non-linear dependencies into macro stress testing models are observed (IMF 2012).

Mathematically, a model has non-linearities if the impact of a three standard deviation shock is not simply three times the impact of one standard deviation shock. Drehmann (2008) and Haldane et al. (2007) point out that the occurrence of non-linearities is frequently argued by policymakers during stress periods.

Non-linearities are the result of endogenous behavioral responses and are difficult to be captured due to misspecification errors. Standard parametric econometrics generally imposes a log-linear specification on the model of the data generating process.[8] This is also carried out for macroeconomic models. Given that their objective is to forecast the mean outcome around the equilibrium, results may be acceptable as mistakes may not be too serious. The same cannot be expected for extreme stress events. Therefore, Drehmann (2006) and Pesaran et al. (2006) emphasize that stress testing modelers have to assess the point where significant non-linearities may arise.

1.1.6 Lessons from the Global Financial Crisis and the European Sovereign Debt Crisis

The conduct of stress tests and results use are heavily impacted by the global financial crisis and European sovereign debt crisis. These crises turn the spotlight on the weaknesses of pre-existing approaches. It is argued that these pre-existing approaches failed to detect important vulnerabilities (Haldane 2009).

Moreover, a significant rise is observed in the use of crisis management stress tests in the aftermath of these crises. In addition, the crisis management stress test signifies the controversial topic of greater transparency arguments.

[8] A log-linear specification, mathematically, is a first order Taylor approximation of the true data generating process. For severe stress events in the tail of the distribution, such an approximation cannot hold (Drehmann 2008; Jorda 2005).

The narrowness of institutional perimeter was the main reason pre-crisis stress tests were not successful in detecting vulnerabilities that are later materialized (IMF 2012). This is because shadow banking (money market funds, credit insurance written by insurance firms, etc.) was not covered in stress tests. Hence, originating or transmitting shocks was not appropriately covered due to the exclusion of shadow banking.

Cross exposures amplify shocks. However, this interconnectedness among financial institutions was not covered (for example, Lehman Brothers), and second-round feedback between the financial sector and real economy was not incorporated into pre-existing stress tests.

Because of a common stress factor or contagion, markets and countries are impacted by a systemic shock. Missing specific risk factors was an underlying reason for pre-existing stress tests' failure (BCBS 2009).

A posteriori analyses showed that the stress tests shocks were less severe than the actual ones for some cases. Also, tail risks were not examined to a great extent due to the lack of long data series to reflect time-varying correlation and extreme market risks (Rosch and Scheule 2008). Another reason was not including many shocks such as severe liquidity risks or sovereign default risk in advanced economies, and this was because those risks were considered unthinkable and too implausible to materialize.

Recent stress-test designs are being developed in order to address the lessons learned from the crises and deficiencies detected.

1.1.7 Best Practice Principles of IMF for Stress Testing Practices

Best practice principles are stated in the IMF (2012) paper on stress testing. The principles have been suggested for solving deficiencies in pre-existing stress tests and improving the stress testing procedure for future implementations. These principles are designed to tailor operationally feasible stress tests, maintain minimum standards for comparability purposes, and can be used in a variety of countries.

Most of the time, stress testing practices have been unsystematic and mainly depending on trial and error and constrained by technical and data capabilities. The principles suggested by IMF (2021) are primarily for macroprudential stress tests, however, they are applicable to other kinds of stress tests to a great extent as well.

The principles listed by IMF are as follows:

1. Define the institutional perimeter appropriately for the tests.

2. Identify all relevant channels of risk propagation.
3. Include all material risks and buffers.
4. Make use of the investors' viewpoint in the design of stress tests.
5. Focus on tail risks.
6. When communicating stress test results, speak smarter, not just louder.
7. Beware of the black swan.

The first principle is choosing the institutions to include in the stress test. For system tests, this refers to the selection of some institutions and leaving out the rest. Hence, the financial institutions that are systemically important must be decided carefully. Systemic importance refers to the capability of triggering and amplifying systemic risk. The criteria used for evaluating systemic importance are *"size, substitutability, complexity, and interconnectedness"* (IMF 2012).

The second principle is identifying sources of risk propagation and network effects. Some prominent examples of these other sources are given below:

- The feedback between solvency and liquidity risks
- The feedback from finance to the real economy
- Policy feedback

The third principle is including all material risks and buffers to obtain reliable results. Pre-global financial crisis stress tests usually focus on credit and market risk from customer loans and marketable securities. With the crisis, however, it is realized that this scope was not sufficiently encompassing, and sovereign risk, funding risk, systemic liquidity risk, and counterparty risks should also have been included in the stress testing. Unless these risks are included, it is not possible to capture potential vulnerabilities to the whole extent.

The fourth principle highlights taking investors' viewpoints into consideration. Market perceptions of asset values and solvency are essential in stress tests. This phenomenon is better understood in the post-crisis period. In order to apply this principle, the suggested methods are as follows:

- Under the baseline and adverse scenarios in the valuation of all banks assets and liabilities, adoption of mark to market (MTM) methodology.
- Instead of statutory capital, using economic capital as the basis for the stress test.

The underlying economic value of a bank is captured by economic capital and that may be different from statutory capital. For example, if asset prices decline substantially, security holdings of banks may carry unrealized losses that may not be reflected in regulatory and accounting capital to a full extent.

- Use of Point in Time parameters[9] in expected and unexpected loss measurement.
- Stressing appetite of market risk. When designing stress test scenarios, market risk appetite can be stressed explicitly.

The fifth principle is associated with tail risks. If they are correlated, modest shocks can cause a breakdown in the system even if they are not individually severe. Extreme outcomes may occur if the correlation is not taken into consideration. Given all the plausible scenarios, not only individual risk factors but also the dependence of risk factors should be taken into account for stress tests reliability. Moreover, it must be noted that the risk which would not be correlated under normal conditions may be correlated in stress conditions.

The sixth principle is related to communicating results. The public awareness of risks increases with public disclosures of stress test methodologies, assumptions, underlying exposures, and results. Therefore, pricing can become more realistic and market discipline can be strengthened. The probability of investors' sudden reversals in the future reduces, and fruitful financial stability discussions may be in place with intelligent communication.

The last principle is about unthinkable risks. Despite the coverage and robustness of stress tests, there is always the danger of black swans.[10] The black swan principle is connected with the context and proper use of stress tests rather than design and implementation mechanisms.

1.2 LITERATURE REVIEW OF APPLIED MACRO STRESS TESTS

In the previous sections, the terminology of macro stress tests was detailed to present the comprehensive framework of the various types of stress tests involved. In this section, applied research literature will be briefly discussed.

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[9] Normally, Through the Cycle (TTC) parameters are used for capital measurement which is more of a regulatory approach. Using Point in Time parameters may be a better choice to reflect investors' evaluation of economic capital (IMF 2012).

[10] This term was first used to indicate highly improbable events that have a major impact (Nassim 2004).

1.2.1 Macro Stress Test Applications on Developed and Developing Countries

One of the earliest applications of stress testing in the literature was a credit risk model conducted for Australia’s banking system by Kalirai and Scheicher (2002) using the data between 1990-2001, where the capital ratio of the simulations was at an acceptable level compared to the actual ratios. Boss (2002) also used default rates to stress-test the Australian economy using the data between 1965-2001 from a perspective of credit portfolio. These two studies demonstrated that the Australian banking system was resilient.

Later Drehmann (2005) used the Merton model systematic risk factors to model default rates in the UK banking sector. The stress test findings showed that the banking sector was not prone to a crisis when faced with undesirable conditions. It was also found out that systematic factors had unsymmetrical and nonlinear effects on credit risk. Hoggarth et al. (2005) used a VAR model to stress-test the UK banking sector against macroeconomic shocks and focused on write-offs to loans ratio. An adverse output shock was increasing write-offs. The results of this study also showed that the UK banking sector was resilient to applied shocks.

On the other hand, Pesola (2005) used panel data of Nordic countries, Germany, Belgium, UK, and Greece between 1980-2002 for a regression analysis to unveil the macroeconomic factors that affect credit loss. The results indicated that income and real interest rate shocks were the most prominent macroeconomic factors contributing to banking sector distress.

Another stress test application focusing on credit loss was conducted by Wong et al. (2006) using quarterly data between 1994-2006 on Hong Kong banks. They applied some shocks that are similar to those of the Asian Financial Crisis, and the results pointed out that credit risk remained at a normal level even in the most extreme scenario.

Comparative research on Germany and the Check Republic was conducted by Jakubik and Schmieder (2008) by using the data between 1994-2006 to create a Meron type one factor credit risk model. The analysis included sectoral and individual levels and focused on non-performing loans. The results showed that the German economy was more resilient to GDP and inflation shocks compared to the Check Republic economy.

A stress test application on the Slovakian banking sector was conducted by Zeman and Jurca (2008) using the data between 1995-2006 and creating a VEC model.

The impact of interest rate and exchange rate shocks on non-performing loans was analyzed. The results concluded that the Slovakian banking sector was resilient to these macroeconomic shocks.

Girault (2008) adopted an integrated approach and used a VAR model to stress-test the Argentinian economy. Vazquez et al. (2011) also used a VAR model to stress-test the Brazilian economy and applied scenario analysis using the data between 2001-2009. In both of these stress tests, the non-performing loan ratio was selected to be the dependent variable, and macroeconomic variables such as GDP growth, credit growth, and interest rate were independent variables. The results showed a significant negative relationship between GDP and non-performing loans.

Dovern et al. (2010) also stress-tested the German banking sector, however, they used a Bayesian VAR model. As in most other stress test applications, GDP, interest rate, and inflation were selected to be the macroeconomic variables. Instead of non-performing loans, write-offs rates and return on equity were the dependent variables. Another Bayesian VAR application on the UK, USA, and EU was conducted by Aikman et al. (2009) by modeling first- and second-round effects using 24 domestic and 22 foreign variables.

Some other notable stress test applications using vector autoregressive models include Jacobsen et al. (2005) on the Swiss banking sector, Andersen et al. (2008) on the Norwegian banking sector, De Graeve et al. (2008) on the German banking sector, and Kattai (2010) on the Estonian banking sector. All of these studies use VAR models and apply shocks on macroeconomic variables such as GDP, interest rate, inflation, and exchange rate to analyze the effects on default rates.

Stress tests were applied not only for the banking sector but also for the corporate sector. Virolainen (2004) stress-tested the corporate sector of Finland by estimating industry-specific macroeconomic index. A Seemingly Unrelated Regression model was used to calculate the probability of default for six industries using the data between 1986-2003. The results showed that macroeconomic variables such as GDP and interest rates were significantly related to default rates. Avouyi-Dovi et al. (2009) used a logistic function to estimate a VAR model for the corporate sector of France using macroeconomic variables including GDP, interest rate, and the borrowing speed of firms.

These two studies are highlighted since they focused on the default risk of firms, which is the counterparty risk for credit risk of banks. The corporate sector default risk was low in both of these studies.

1.2.2 Macro Stress Test Applications on Turkey

Macro stress test applications on Turkey may be best described as scattered if not limited. Unlike most of The Organisation for Economic Co-operation and Development (OECD) countries, no regular macro stress test is being conducted by the central bank.[11] Banking Regulation and Supervision Agency (BRSA) conducts official stress tests based on the Basel criteria. In addition to BRSA provided scenarios, banks create their internal scenarios and use these for capital and liquidity planning and risk appetite calculations. The BRSA coordinated bank-specific test results and the aggregated sector results are not officially published. Hence, most of the studies presented in this section are of independent researchers.[12]

In parallel to BRSA demanded stress tests, independent stress tests also focus on the banking sector and credit risk. Most of this independent research started in the 2000s. Two of the earliest studies by Uzer (2002) and Tuncer (2006) merely consisted of Basel II discussions and did not include a stress test application with data from Turkey.

In the research paper of Kucukozmen and Yuksel (2006), a sectoral evaluation of resilience of the banking sector to external shocks was investigated by using Autoregressive Integrated Moving Average (ARIMA) models. Eight OLS regression for various sectors was run to uncover the determinants of non-performing loans and a credit risk proxy. The selected macroeconomic indicators were banking sector total loans, current account balance, GNP, exchange rate, interest rate, inflation, and unemployment. Stress tests were conducted using historical shocks, and portfolio losses were calculated. Then, banking systems' risk resilience was analyzed using

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[11] Since macro stress testing is a method to measure the vulnerability of the financial system, instead of conducting macro level stress tests, the central bank publishes "Financial Stability Report" which presents a macroeconomic outlook of the country using indexes such as Macrofinancial Outlook Index (The latest report available at the time of the writing of this thesis is "TCMB Finansal İstikrar Raporu, Kasım 2021 Sayı:33", and it can be accessed at "https://www.tcmb.gov.tr/wps/wcm/connect/TR/TCMB+TR/Main+Menu/Yayinlar/Raporlar/Finansal+Istikrar+Raporu/")

[12] BRSA is part of Basel Committee and official stress tests in Turkey are demanded and supervised by BRSA. The tests are banking sector-specific, and individual stress tests of the banks are augmented by BRSA to measure resilience against stress scenarios. Please refer to https://www.bddk.org.tr/ContentBddk/dokuman/duyuru_0541_01.pdf for further details.

expected and unexpected losses calculated based on the loss distributions with specific assumptions. Their results showed that loss levels could be absorbed by profits and allocated capital.

Another study focusing on the banking sector was conducted by Bese (2007). The researcher analyzed the sensitivity of NPL ratio and financial stability index against shocks on different macro variables. The NPL ratio was affected most by a shock on country risk premium, whereas the financial stability index was affected most by shocks on inflation and exchange rate.

Instead of focusing on the entire financial sector, Aktan (2007) investigated the risk exposure of a selected number of commercial banks' foreign exchange portfolio between 2001-2003 using the Monte Carlo simulation method. Monte Carlo simulation was applied 2000 times, and the simulation results were compared to the internal scenario results. The study was notable for emphasizing various methods aimed at calculating Exposure at Default (EAD).

In another research by Tokatlı (2011), the credit portfolio approach was used to develop models to investigate relations between macroeconomic factors and sector-specific non-performing loan ratios. The forecasts of the study suggested that the banking sector in Turkey was capable of absorbing losses since expected and unexpected losses did not exceed 3% with respect to credit portfolio and 7% with respect to equity capital.

In another study by Yüksel (2011), Merton's one-factor credit risk model was used. Instead of selecting the total non-performing loan ratio, household and corporate non-performing loans were separately tested. The selected macroeconomic variables were exchange rate, deposit interest rate, growth, industrial production index, export growth, unemployment rate, BIST 100 index, and credit volume to GDP ratio. Shocks were applied at the levels of 10% and 20%. The results showed that the post-2008 crisis period was more sensitive to shocks.

Another macro stress test was conducted by Iskender (2012) on the banking sector for a two-year horizon. The applied shocks were a decrease in GDP, increase in interest rates, and increase in crude oil prices. Furthermore, two micro econometric models were used to estimate the capital adequacy ratio. The capital adequacy ratio at the end of the two-year horizon was calculated to be around 15% and considered resilient since it was above both the legal and the target ratios (8% and 12%, respectively).

Another banking sector stress test was conducted in the same year by Altıntas (2012) using the data between 2003-2010. The chosen dependent variable was an index series created with the logistic transformation of the total default ratio as a representation of credit risk. Independent variables were GDP, nominal interest rate, consumer price index, and exchange rate. VAR method was used, and the results demonstrated that a decrease in GDP; increase in nominal interest rate and inflation rate, and a depreciation of domestic currency caused an increase in default ratio.

In the research carried out by Başarır (2013), NPL ratios of the banking sector between 1999-2004 were utilized to develop a macroeconomic credit risk model by using Wilson's credit risk portfolio approach. The same model was used to develop a satellite model for the NPL ratios of the three biggest banks. Historical scenario analysis was used to estimate the effect of shocks on sector NPL ratio and bank-specific NPL ratios for the 2013-2014 period. The reactions of the NPL ratio were compared with historical data. The results indicated that the banking sector, as a whole, was resistant to applied shocks, but three investigated banks showed different levels of sensitivity.

In another study by Çakmak (2014), a set of complementary models were used. The first model was aimed at linking financial stability to macroeconomic stability and the second model was designed for employing static and dynamic panel data techniques which regress non-performing loans to macro variables. While the study mainly focused on comparing linear and non-linear model performances, the findings of the applied alternative scenario tests suggested that the banking sector was resilient to the shocks on industrial production and sudden stop in credit growth. This was because the non-performing loans did not exceed 5%, and capital adequacy ratio did not fall below 15%.

In another research by Gümüş and Nalbantoğlu (2015), banking sector was stress-tested by choosing 12 representative banks and dividing them into four groups: public banks, local private banks, foreign banks, and participation banks. They only used the data from 2014. Three ratios were tested: capital adequacy ratio, liquidity ratio, and foreign exchange net general position to regulatory capital ratio. In this paper, three levels of shocks were applied on provisions: 3%, 5%, and 10%. The results showed that public banks were the most resilient while the participation banks were more prone to the effects of shocks on the selected ratios.

In another research by Güneş (2016), the effect of financial stress on growth was investigated. Linear VAR and non-linear Multivariate Threshold Autoregressive (TVAR) models were employed. The used variables were industrial production index, a financial stress index (developed within the scope of the study by using three methods: principal component analysis, equal variance weighting, and portfolio theory), credit growth ratio of banks, consumer price index, and purchasing managers' index. Industrial production reacted approximately 1.5% to a shock on the financial stress index in VAR and 2.5% in TVAR. The study concludes by highlighting industrial production's sensitivity to periods of stress.

In another research by Akkuş (2017), three participation banks were selected and stress-tested for the period between 2005-2016. The non-performing loan ratios of the banks were selected to be dependent variables, and GDP, 3-month average profit-sharing yield (which corresponds to the interest rate for participation banks), petroleum price, exchange rate, and inflation were independent variables. Credit portfolio view and VAR method were employed for modeling. In addition, the expected and unexpected loss distributions were estimated by using the Monte Carlo Simulation method. The result of the study suggested that the selected participation banks were resilient since they had the required capital adequacy ratios against possible shocks.

In another study by Gülhan (2018), banks were liquidity stress-tested by using net stable funding. Seven models were created using the system generalized moments method using the data between 2003-2016. This study is particularly notable since most of the stress tests conducted on Turkey find the system to be resilient. However, this liquidity-oriented study concludes that the banking sector is unable to realize the net stable funding rate in the relevant stress conditions. The determinants of liquidity buffers were asset size, profitability, capital adequacy, non-performing loans, GDP, and inflation. On the other hand, only 21 banks were selected, and the banking sector as a whole was not tested, which may be a limitation of the study.

In a recent study by Karaaslan and Sayılır (2019), a macro-economic credit risk model was created by using the credit portfolio view of Wilson in order to estimate expected and unexpected losses and defaults in the banking sector by using the data between 2010-2018. In this study, Monte Carlo simulations and scenario analyses were used. Default ratio was chosen to be the dependent variable and unemployment rate, interest rate, money supply, inflation, and GDP were the independent variables. It was emphasized that banks compensate expected losses from their reserves and unexpected losses from provisions and equity capital. The study focused on the estimation of default levels according to various stress test scenarios (20%, 30%, and 40% shocks). It was concluded that the banking sector in Turkey is resilient to shocks on macroeconomic variables, and the effect on the default ratio was not high. However, as shocks on multiple macroeconomic variables co-occur for an extended period, the default ratio was expected to reach a considerably higher level.

CHAPTER II

THE DATA AND METHODOLOGY

This thesis aims to conduct an applied macroeconomic stress test using the relevant data for Turkey. The previous chapter prepared the foundation on which the results of the empirical application can be based by demonstrating the theoretical stress test framework and a concise summary of previous applied studies.

In this chapter, data selection, model, and methodology will be detailed. The empirical findings of the stress test will be illustrated. The application details will pave the way towards the discussion of the interpretation of the results and related policy implications.

2.1 DATA

For financial stability stress tests, the initial point is to evaluate the most significant risks for the financial system. A common practical approach for financial stability stress tests is starting with the banking system since the banking system assumes a prominent role in transforming savings into investments. The banking sector is the central pillar of the financial sector, and it has a tremendous potential to transfer financial shocks to the real economy. Due to this potential, the selection of the banking sector to measure financial stability is a good approximation (ECB 2013; Pesaran et al. 2006).

When the banking sector is selected to test financial stability, probability of default (credit loss) distribution is required for the estimation of expected and unexpected losses under the stressed condition for typical probability levels (Foglia 2009). Since PDs are not publicly available, however, a key credit risk indicator used in order to reflect PD is the Non-performing Loan ratio in practice.

Despite the worthwhile advance in evaluating and incorporating other risks' effects, as argued by Borio et al. (2012), the heart of the analysis remains to be the credit risk. Due to the aforementioned reasons, the banking sector was focused on in this application and the NPL ratio was chosen to be the focused risk indicator. As the NPL ratio is considered a major financial stability indicator in addition to being primarily a credit risk indicator, the stress test application in this thesis may be regarded both a credit stress test and a financial stability stress test. Also, the Non-Performing Loan ratio was focused on since it is one of the main indicators[13] used by IMF to evaluate financial soundness.

In most of the stress testing exercises in Turkey and other countries, the NPL ratio was the most commonly used one since it is considered the predominant indicator of the banking sector's credit risk. Given that the banking sector is the backbone of the financial system in most of the countries, including Turkey, the NPL ratio was selected for both representativeness and comparability reasons.

The non-performing loan ratio is calculated as the banking sector's total non-performing loans divided by banking sector's total loans. This calculation does not include the foreign branches of the banks. The data of the banking sector's total non-performing loans and banking sector's total loans were obtained from The Central Bank of the Republic of Turkey Electronic Data Distribution System (EVDS) and the calculation was performed by the author of this study.

The non-performing loan ratio of Turkey between January 2005 and August 2021 is presented in Figure 1. The NPL ratio is decreasing until mid-2011, most plausibly due to the fading impact of the global financial crisis of 2008. Following a long period of stability where the ratio remained approximately around 3% between 2011-2018, the NPL ratio started to rise due to Turkey's foreign exchange and debt stress, further impacted by the recent Covid-19 pandemic and the response of regulatory institutions.[14]

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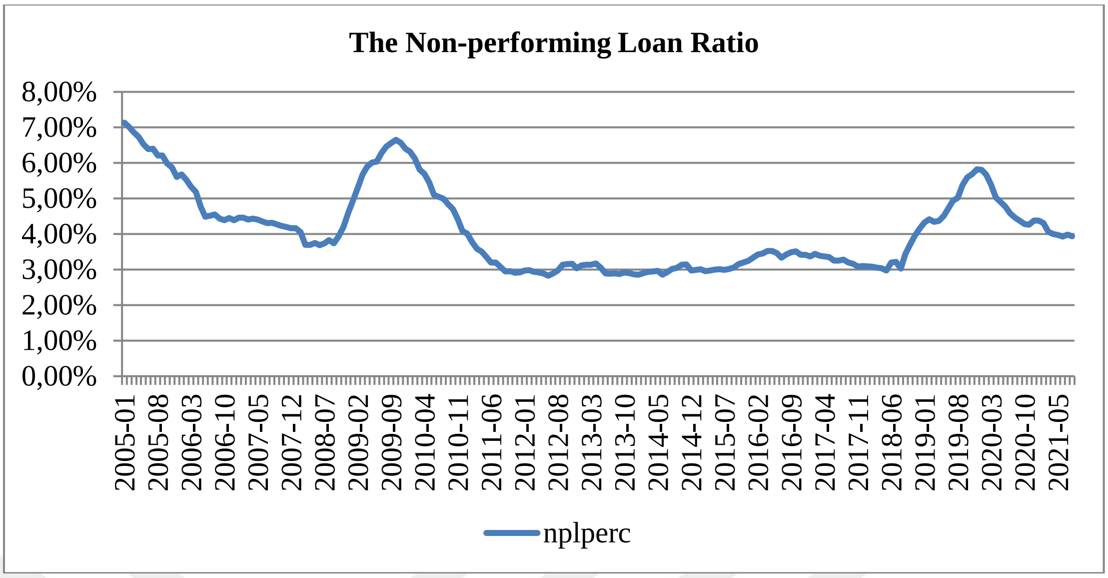
[13] The other key financial soundness indicators used by IMF are as follows: capital to assets, regulatory capital to risk weighted assets vs. regulatory tier 1 capital to risk weighted assets, return on assets vs. return on equity). Please refer to "https://data.imf.org/?sk=51B096FA-2CD2-40C2-8D09-0699CC1764DA" for details.

[14] The economic impact of Covid-19 on the Turkish economy along with the global economy is a matter that should be explored in greater detail due to sui generis nature of this worldwide pandemic. The general slowdown in economies due to nationwide lockdowns, curfews, and travel restrictions among many other measures to prevent the spreading of the disease can be further dissected by analyzing its peculiar impact on certain most affected sectors and businesses. For instance, due to the impact on tourism and airline transportation sectors, BRSA (Banking Regulation and Supervision Agency) enforced additional measures to monitor possible delinquencies regarding these sectors. However, a rough calculation of NPL ratio is non-performing loans divided by total loans given, and it must be also noted that while Covid-19 has an increasing effect on the nominator of the ratio, the response of the regulatory institution BRSA (the feedback effect) to ease contraction of the economy was opting to

Figure 1: The non-performing loan ratio of Turkey, 2005-2021



Source: The Central Bank of the Republic of Turkey, EVDS data

Macroeconomic models are computationally cumbersome, and they are excessively complex for stress testing purposes since they are designed as tools for monetary policy decisions. Vector auto-regressive approaches are argued to be providing a more optimal trade-off among computational complexity, story-telling, and forecast performance for stress tests by Drehmann (2008). After selecting the NPL ratio as the risk indicator, the rest of the macroeconomic variables were chosen based on the literature of applied studies using VAR and VECM approaches reviewed in Chapter I. Furthermore, data availability and frequency are other reasons to choose the selected variables among similar other variables.[15] Among similar variables, variables being in monthly frequency are selected over the non-monthly ones in order to obtain an adequate number of observations for estimation of VECM and capture short-term dynamic changes.

The other selected macro-economic variables are presented below:

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choose release of credit by encouraging public banks to facilitate conditions, a decrease of the interest rate for mortgages, and increasing legal default date from 90 days past due to 180 days past due in addition to making payment postponement, holiday, and restructuring options more available, which had a decreasing pressure on to the NPL ratio by either decreasing the nominator or increasing the denominator. BRSA regulations can be found on its official website: “https://www.bddk.org.tr/Mevzuat”. Since the investigation of Covid-19 impact is not the main topic of this study, the related discussion will be presented only where necessary within the scope of the thesis.

[15] For example, regulatory tier 1 capital to risk weighted assets could also have been chosen as financial soundness indicator instead of non-performing loan ratio, however, acquiring the data would be more problematic.

- Industrial Production Index: IP (as the indicator for real economy)
- Consumer Price Index: CPI (as the indicator for inflation)
- Weighted Average Interest Rate of Loans Given by Banks: BSKUAOF (as the indicator for interest rate)
- USD Effective Buy Exchange Rate: USDFXI (as the indicator for exchange rate)
- The Rate of Real Profit Created by BIST100 Index compared to CPI: BISTRE (as the indicator of the stock exchange)

The above listed variables were obtained from The Central Bank of the Republic of Turkey Electronic Data Distribution System (EVDS) and Turkish Statistical Institute (TURKSTAT). The overall number of monthly observations is 200 from January 2005 to August 2021.

The graphs of the unadjusted data of the selected macroeconomic variables are presented below:

Figure 2: Industrial Production Index, 2005-2021

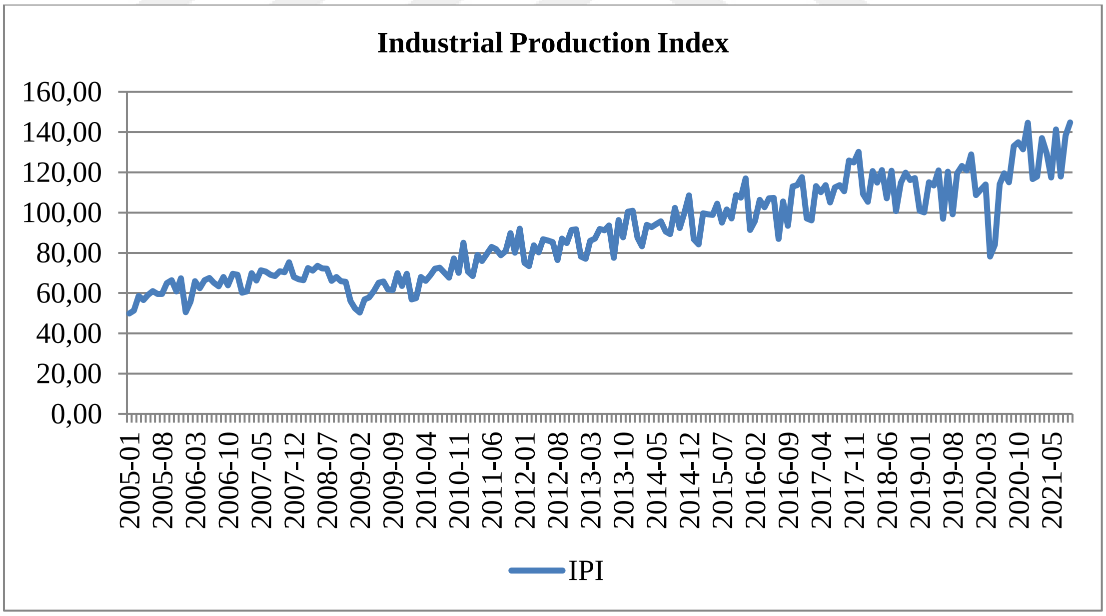


Figure 3: Consumer Price Index, 2005-2021

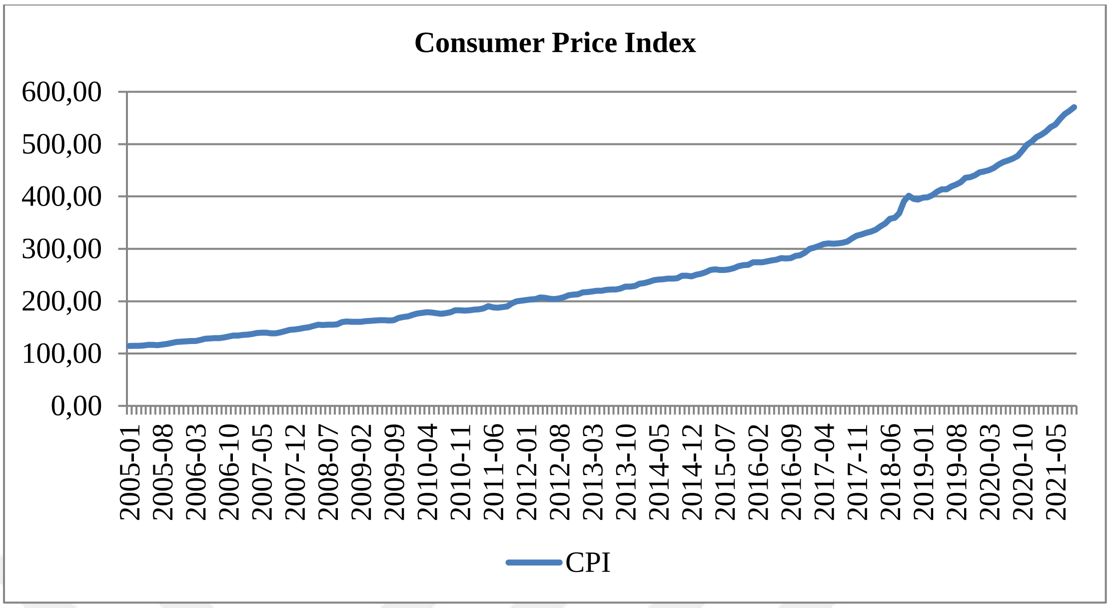


Figure 4: The Weighted Average Interest Rate of Loans Given by Banks, 2005-2021

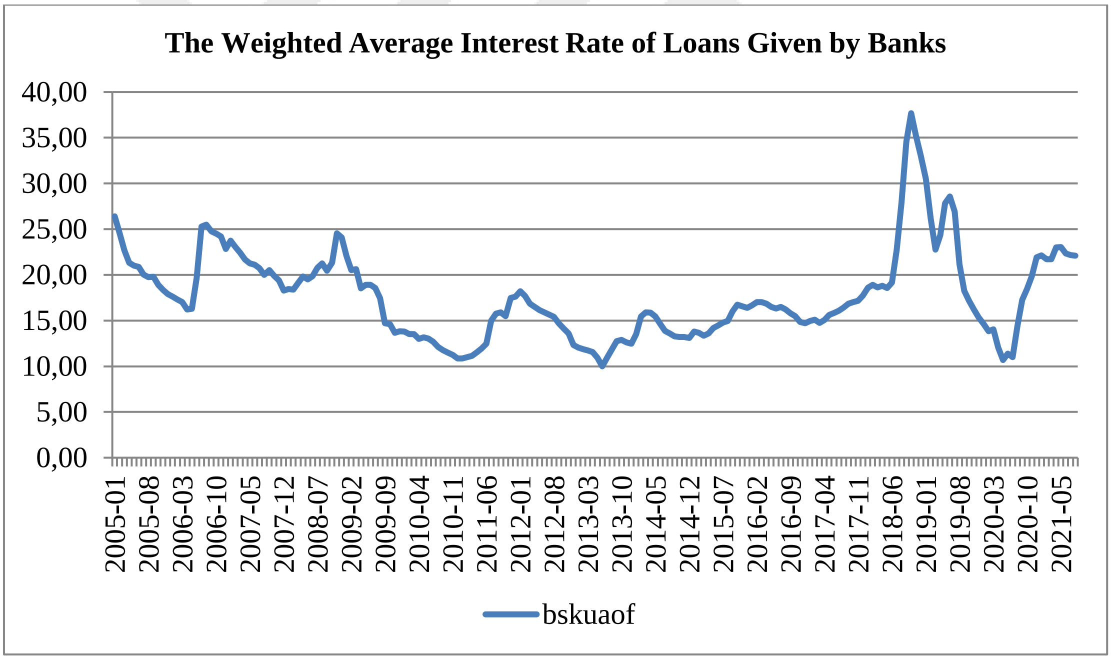


Figure 5: USD Effective Buy Exchange Rate, 2005-2021

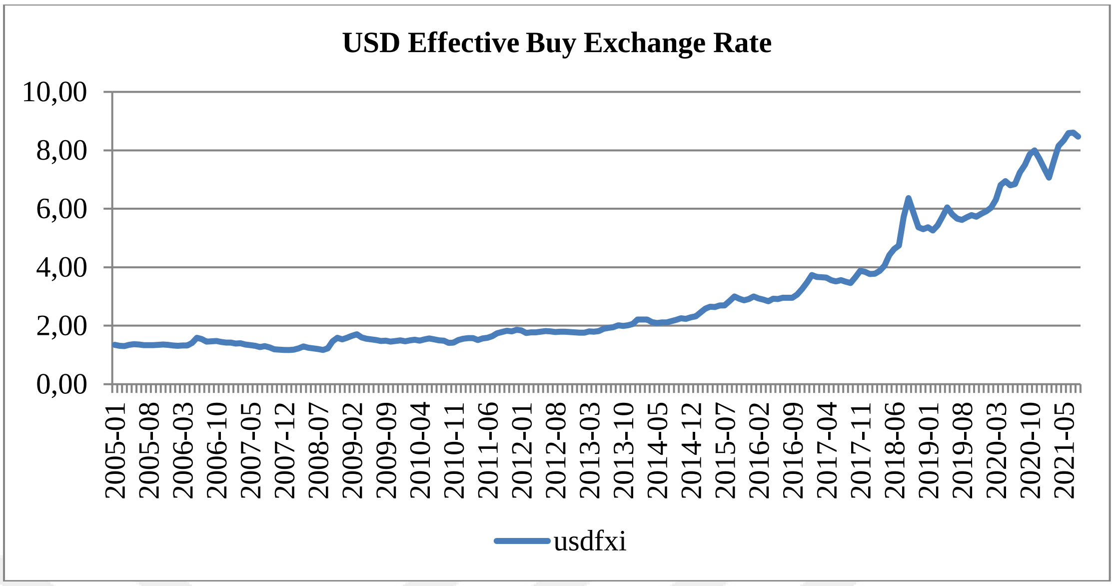
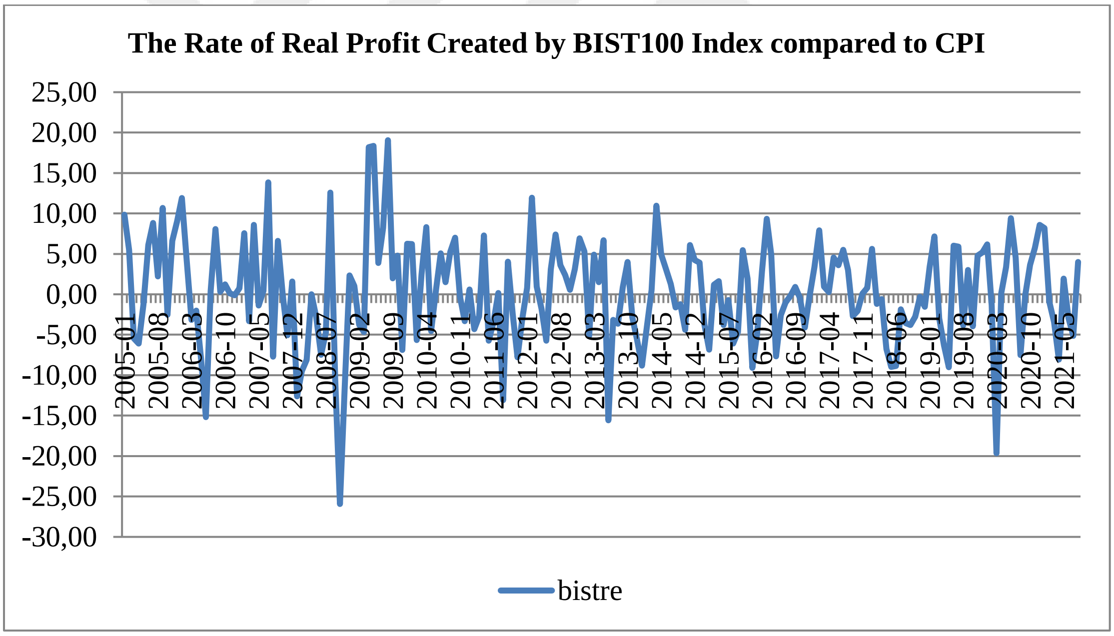


Figure 6: The Rate of Real Profit Created by BIST 100 Index compared to CPI, 2005-2021



Due to seasonality concerns, Industrial Production Index and Consumer Price Index were not used in the unadjusted form. Instead, seasonally and calendar-adjusted Industrial Production Index and seasonally adjusted Consumer Price Index were used to prevent non-constant variance and regression fallacy problems and to obtain a more parsimonious model. The graphs of the adjusted series are presented below:

Figure 7: Seasonally and Calendar Adjusted Industrial Production Index, 2005-2021

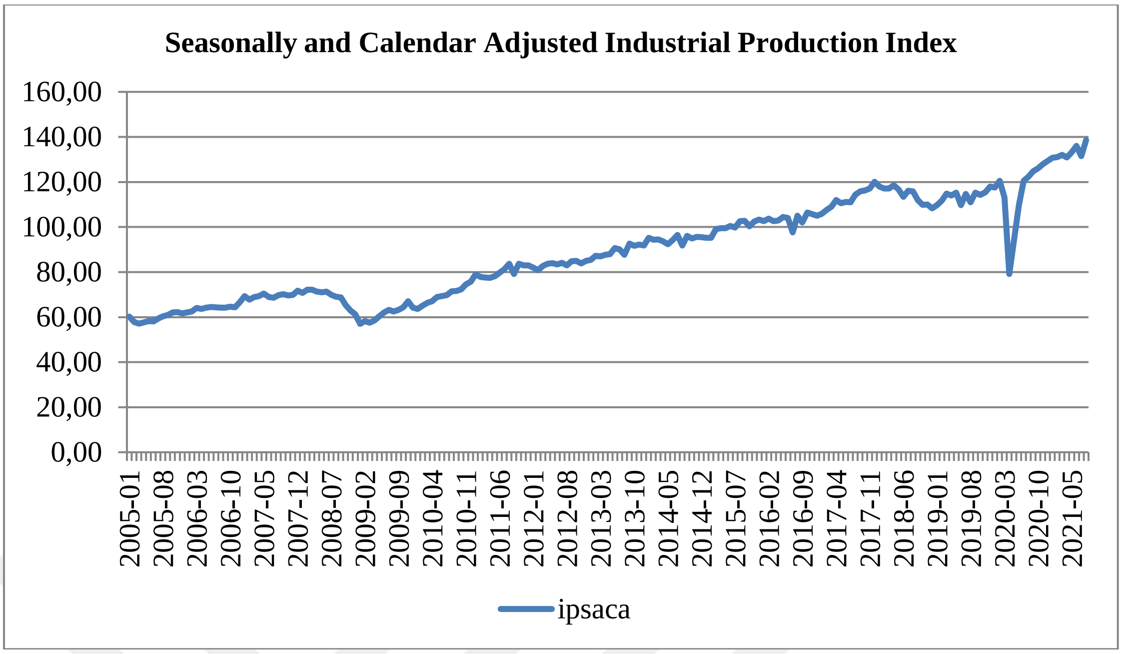
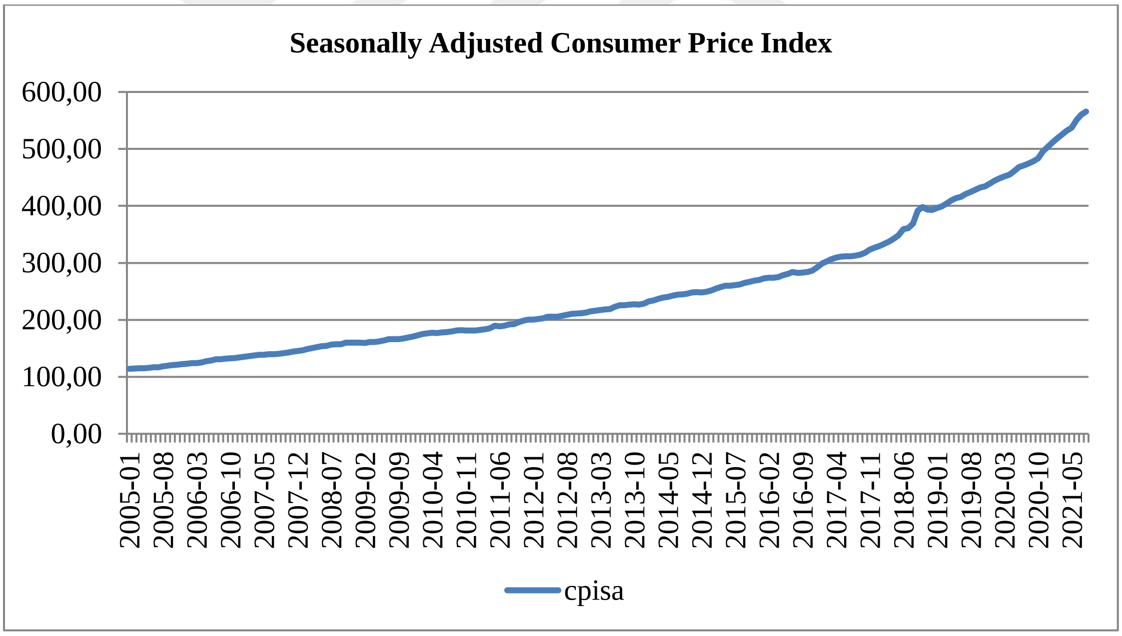


Figure 8: Seasonally Adjusted Consumer Price Index, 2005-2021



In the below tables, the descriptive statistics of variables as level form and first difference form are presented:

Table 1: The Descriptive Statistics of Variables, Level

	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
Mean	0.0411	89.3482	252.4425	17.6630	2.8903	0.2911
Median	0.0388	87.4261	218.5316	16.7850	1.8475	0.4400
Maximum	0.0713	138.5604	565.5949	37.6825	8.6069	19.0600
Minimum	0.0282	57.0014	114.0440	9.9950	1.1696	-25.9300
Srd. Dev.	0.0113	21.9216	115.9768	4.8770	1.9895	6.4607
Skewness	0.8220	0.2483	0.9435	1.1534	1.3613	-0.2585
Kurtosis	2.6088	1.8707	2.9344	4.9912	3.6969	4.3826
Sum	8.228	17869.640	50488.500	3532.617	578.076	57.940
Sum Sq. Dev.	0.026	95630.910	2676671.000	4733.295	787.668	8264.865
Observations	200	200	200	200	200	200

Table 2: The Descriptive Statistics of Variables, First Difference

	NPLPERC1	IPSACA1	CPISA1	BSKUAOF1	USDFXI1	BISTRE1
Mean	-0.0024	0.0048	0.0081	0.0013	0.0099	-1.0719
Median	-0.0030	0.0056	0.0075	-0.0101	0.0040	-0.6410
Maximum	0.1328	0.1921	0.0621	0.3076	0.2068	30.4318
Minimum	-0.0890	-0.3009	-0.0122	-0.2137	-0.0829	-143.5000
Srd. Dev.	0.0324	0.0360	0.0071	0.0693	0.0382	12.8829
Skewness	0.5574	-1.9364	2.3586	1.3612	1.4687	-7.9865
Kurtosis	4.6171	32.2935	18.6875	7.5446	8.5771	83.9674
Sum	-0.4901	0.9735	1.6127	0.2763	1.9842	-211.1677
Sum Sq. Dev.	0.2088	0.2591	0.0101	0.9531	0.2893	32530.1600
Observations	199	199	199	199	199	199

2.2 METHODOLOGY

In this section, the selected Vector Error Correction Model and the methodology will be detailed.

2.2.1 Preliminary Checks

General inference procedures become inapplicable if the series contains a unit root and is not stationary. For that reason, it was of utmost importance to verify the stationarity properties of the series before using them in stress testing.

Augmented Dickey-Fuller (1979) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS 1992) tests were applied to check for unit roots and determine the order of differencing operations necessary to make the used series stationary.

The null and alternate hypotheses of the ADF test are;

H_0: A unit root is present

H_1: The time series is stationary

The null and alternate hypotheses of the KPSS test are;

H_0: The time series is stationary

H_1: A unit root is present

After the application of ADF and KPSS tests, series are tested for potential cointegration by Johansen Cointegration Test. When multiple time series have a long-run equilibrium, the linear combination of the time series is a stationary series, or there is an underlying common stochastic trend for these series. In that case, this phenomenon implies cointegration.[16]

By using the E-views software, Johansen Cointegration Test (1991; 1995) was applied to detect multiple cointegration relationships. The created VAR equation[17] for the Johansen Cointegration Test to be applied can be shown as follows:

$NPLPERC_{t+1}=\Gamma+\sum_{i=0}^{k} \phi_i Z_{t-1}+\varepsilon_{NPLPERC,t+1}$ where;

- NPLPERC shows the non-performing loan ratio (level);
- Γ shows intercepts;

[16] For a simple step by step cointegration guide, you may refer to “https://www.aptech.com/blog/a-guide-to-conducting-cointegration-tests/”

[17] For details of VAR equations, you may refer to the below web address: “http://www.eviews.com/help/helpintro.html#page/content%2FVAR-Vector_Autoregressions_(VARs).html%23”.

- Z_t shows the vector of lagged values of NPLPERC and the vector of macro variables (level);
- Φ shows coefficients of variables;
- $\varepsilon_{NPLPERC,t+1}$ shows white noise shocks.

The order of variables in VAR approach is, in general, from the most endogenous to the most exogenous. As observed in several studies of Beşe (2007), Stock and Watson (2001), Enders (2004), and based on Granger Causality test and economic theory, the order of variables from the most endogenous to the most exogenous is NPLPERC, IPSACA, CPISA, BSKUAOF, USDFXI, and BISTRE. Lag order of the VAR was selected according to Schwarz Information Criterion and Hannan-Quinn Information Criterion.

After the creation of VAR, Johansen Cointegration test is applied for all of the five trend assumptions below to determine the number of cointegrating relationships:

1. No deterministic trend in level data and no intercepts in cointegrating equations
2. No deterministic trend in level data, but cointegrating equations have intercepts
3. Level data have linear trends, but cointegrating equations have only intercepts
4. Level data and the cointegrating equations have trends
5. Level data have quadratic trends, and cointegrating equations have linear trends

Practically, assumption of trend one and assumption of trend five are rarely used. Assumption one is advised to be used if all of the series are known to have zero mean and, assumption five is advised to be used for a good fit in-sample. Assumption one was not focused on since none of the means is zero. Assumption five was not focused on because of the risk of producing implausible forecasts out-of-sample. Among the remaining assumptions, assumption four is advised to be used if some of the series are believed to be trend stationary. According to the conducted unit root tests, it is observed that the series were difference stationary instead of trend stationary. Therefore, assumption four was not focused on. Assumption two is advised if none of the series appear to have a trend but this assumption is considered to be less realistic because most of the economic time series exhibit trend most of the time.[18]

[18] For a brief introduction to unit roots and details of the assumptions please see below website: "https://faculty.washington.edu/ezivot/econ584/notes/unitroot.pdf".

Accordingly, the most suitable assumption was assumption three and this assumption was focused on since all trends are considered to be stochastic.

The Maximum Eigenvalue test and the trace test are similar to each other but the alternate hypothesis of them are different.[19] An eigenvalue is a non-zero vector and changes by a scalar vector when a linear transformation is applied to it. The null hypothesis of the third trend assumption with both the maximum eigenvalue and the trace test is that there are no cointegrating equations.

H_0: r = k

where;

r= the number of cointegration relationships

k= the number of variables

However, the alternate hypothesis is stated different in the trace test and the maximum eigenvalue test. The alternate hypothesis of the trace test is:

H_1: r > k

The alternate hypothesis of the maximum eigenvalue test is:

H_1: r = k+1

Due to this difference, the trace test statistic and the maximum eigenvalue statistic may show different results. For assumption three, the result of the maximum eigenvalue test instead of the result of the trace test was selected to be used since the maximum eigenvalue test was argued to be more advantageous in situations further away from the null hypothesis and this test was observed to have smaller size distortions than the trace test (Lütkepohl 2000).

2.2.2 Model

The piecewise approach was endorsed in this thesis due to its suitableness for communication purposes, calculation clarity, intuitiveness, and comparability to most of the stress testing applications on Turkey in the reviewed literature.

However, as stated before, the piecewise approach may result in overlooking some impacts other than expected losses (Sorge and Virolainen 2006). In order to address this challenge, Vector Auto Regressive context was chosen for the stress test application in this chapter. Vector Auto Regressive context is frequently used for interrelated time series and in analyzing impacts of random disturbances on the system

[19] For the hypotheses of the maximum eigenvalue and the trace tests please see: “https://studfile.net/preview/4375525/page:101”

of variables. Since it treats each endogenous variable as a lagged value of all endogenous variables in the system, it helps to circumvent the need for structural modeling. This approach is also considered to be the most successful method to link the financial sector to the real economy in several other studies (Aspaches et al. 2006; De Graeve et al. 2007; Hoggarth et al. 2005; Jacobsen et al. 2005).

Vector Auto Regressive context enables the impact of the shock on the macroeconomic variables onto the financial sector in Turkey to be evaluated, and the feedback effects and interactions among macro variables to be taken into consideration. For instance, the impact of the shock on the consumer price index onto the non-performing loan ratio can be evaluated while concurrently calculating the impact on the interest rate as well.

The model was specified as a vector error correction model because of the two main reasons[20]:

1) As it is presented in the next chapter, the series of macroeconomic variables are not stationary in their levels but were stationary in their first difference.

2) Johansen cointegration test results show that the variables are cointegrated.

Cointegration indicates that an error correction model is needed to connect through the series of macro variables. The danger of not properly modeling cointegrated variables is biased estimates. In addition to serving the purpose of preventing this risk, VEC models are suitable for understanding long-run dynamics due to the following reasons:

- Long-run equilibrium relationships of the variables are better reflected in VEC models.
- The inclusion of short-run dynamic adjustment mechanisms in VEC models helps to describe the adjustment of out of equilibrium variables.
- The adjustment coefficients are used to measure the forces which push the relationship of the variables towards long-run equilibrium.

Since this stress testing is on a vector autoregressive context, the implied VECM is:

$$\Delta NPLPERC_{t}=\Phi D_{t}+\Pi NPLPERC_{t-1}+\Gamma_{1}\,\Delta NPLPERC_{t-1}+\ldots+\Gamma_{p-1}\,\Delta NPLPERC_{t-p+1}+\varepsilon_{t}$$

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[20] Please refer to below web addresses for further details on VEC models: "http://www.eviews.com/help/helpintro.html#page/content/coint-Johansen_Cointegration_Test.html" "http://www.eviews.com/help/helpintro.html#page/content/VAR-Vector_Error_Correction_(VEC)_Models.html"

- Π is the long-run impact matrix. It contains the cointegrating relationships and captures the adjustments towards the long-run equilibrium. $\Pi = \Pi_1 + \Pi_2 + \ldots + \Pi_p - I_n$
- Γ_k is the short-run impact matrix. It is constructed from $-\sum_{j=k+1}^{p} \Pi_j$ and short-run deviations from the equilibrium are captured by this term.
- $D_t = u_0 + u_1 t$, and it is the deterministic term where u_0 is the constant component, and $u_1 t$ is the trend component.

In addition, monthly seasonality dummies were used with the exception of January to prevent collinearity and redundancy. The number of lags is two based on the lag order selection test result presented in the next chapter. The results of the VECM estimation are presented in Appendix 2.

In order to ensure model stability, stability was checked according to the inverse roots of the characteristic AR polynomial test.

As a next step, since it is important to measure the extent to which two or more variables move in relation to each other to be aware of a possible misleading statistical relationship between the variables, the correlation presence was analyzed using the Residual Correlation Matrix and Serial Correlation LM test. Serial Correlation LM Test is a variant of Breusch-Godfrey test which tests for correlation at higher orders, for lags 1 to h, and in the case of stress testing, for lags one to three since the selected number of lags is two. The following hypotheses are used in this test:

H_0 : There is no serial correlation at any order less than or equal to h.

H_A : There exists serial correlation at some order less than or equal to h.

In order to apply a normality test, Jarque-Bera test statistic was used. Jarque-Bera is a test statistic for determining whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution.

The covariance presence was analyzed using the Residual Covariance Matrix and VECM Residual Heteroskedasticity Test. VECM Residual Heteroskedasticity Test is run by regressing each cross product of the residuals on the cross products of the regressors and testing the joint significance of the regression. No cross-term option was selected since the number of observations is not high. White Heteroskedasticity test is similar to Breuch-Pagen test but it is considered to be more general since it does not rely on the normality assumption.

In the next chapter, the results will be presented and discussed in detail.

CHAPTER III

THE RESULTS

In this chapter, the results of the preliminary checks, the stability and the residual checks, the impulse response functions and the variance decomposition test are presented. The results of this thesis are discussed in comparison to other related studies where applicable.

3.1 THE RESULTS OF THE PRELIMINARY CHECKS

ADF and KPSS test results of the level and first difference variables are presented below:

Table 3: Unit Root Test Results

	Level		First Difference	
Variables	**ADF Unit Root Test**	**KPSS Unit Root Test**	**ADF Unit Root Test**	**KPSS Unit Root Test**
NPLPERC	-3.115037	0.240706***	-4.152394***	0.049271
IPSACA	-2.636158	0.145187*	-14.84405***	0.047977
CPISA	4.659594	0.395932***	-10.67969***	0.194223**
BSKUAOF	-2.973175	0.255097***	-8.040504***	0.024019
USDFXI	0.292244	0.411128***	-11.07787***	0.022046
BISTRE	-5.177180***	0.222200***	-14.08271***	0.040585

Note: *** denotes significant at 1%; ** denotes significant at 5%; * denotes significant at 10%.

When the results of ADF and KPSS tests were evaluated together, testing the series for potential cointegration by Johansen Cointegration Test is observed to be required.

For lag order selection, due to NPLPERC reacting to shocks with lags, two is selected as the number of lags according to Schwarz Information Criterion and Hannan-Quinn Information Criterion. The table of VAR lag order selection criteria[21] is presented below:

Table 4: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2291.9350	NA	3251.1950	25.1140	25.2192	25.1566
1	-597.6588	3258.9350	4.38e-05	6.9908	7.7274	7.2893
2	-463.0127	250.1621	1.49e-05	5.9127	7.2067*	6.4672*
3	-417.6037	81.3889	1.35e-05	5.8098	7.8092	6.6203
4	-375.6736	72.0246	1.28e-05*	5.7474*	8.3781	6.8138
5	-357.6736	30.2664	1.56e-05	5.9417	9.2038	7.2640
6	-328.8351	46.0155	1.72e-05	6.0200	9.9135	7.5982
7	-289.4020	60.3470	1.69e-05	5.9825	10.5073	7.8166
8	-244.2800	66.0803*	1.57e-05	5.8828	11.0390	7.9729

Notes: * indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike Information Criterion

SC: Schwarz Information Criterion

HQ: Hannan-Quinn Informaiton Criterion

Even though assumption three was focused on, Johansen Cointegration test was applied for all of the assumptions. As it may be observed from the below presented table of results, when maximum eigenvalue test is considered, not only assumption three but also assumption two, assumption four and assumption five results also show four cointegrating relationships. Accordingly, the results below showed that the first non-rejection of the null hypothesis at a significance level of 5% was 4. The detailed results are presented in Appendix 1.

[21] Since critical values reported by E-views software do not account for exogenous variables, seasonal dummies were excluded in order not to affect the mean and the trend of the level series.

Table 5: Johansen Cointegration Test Results Summary

Date: 12/05/21 Time: 00:11
Sample: 2005M01 2021M08
Included observations: 193
Series: NPLPERC IPSACA CPISA BSKUAOF USDFXI BISTRE
Lags interval: 1 to 2

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	3	5	6	4	4
Max-Eig	3	4	4	4	4

*Critical values based on MacKinnon-Haug-Michelis (1999)

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	-561.0402	-561.0402	-550.0144	-550.0144	-535.2664
1	-517.4501	-516.8800	-512.9524	-511.4499	-498.8378
2	-482.1951	-481.5744	-481.0112	-479.2289	-474.1419
3	-462.9433	-460.9538	-460.6470	-457.6244	-453.9438
4	-455.0487	-447.2635	-446.9601	-437.4633	-435.3813
5	-451.4373	-440.3408	-440.1142	-430.6151	-428.5986
6	-451.3444	-436.8213	-436.8213	-426.4239	-426.4239
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	6.560002	6.560002	6.507922	6.507922	6.417269
1	6.232643	6.237098	6.248211	6.243005	6.164122
2	5.991659	6.005952	6.041567	6.043822	6.032559
3	5.916511	5.926983	5.954891	5.954657	5.947604
4	5.959053	5.919829	5.937411	5.880449	5.879599*
5	6.045983	5.982806	5.990821	5.944198	5.933664
6	6.169372	6.081050	6.081050	6.035480	6.035480
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	7.777171	7.777171	7.826522	7.826522	7.837300
1	7.652674	7.674034	7.769673	7.781371	7.787015
2	7.614551*	7.662655	7.765890	7.801956	7.858313
3	7.742265	7.803452	7.882076	7.932557	7.976220
4	7.987669	8.016065	8.067457	8.078116	8.111076
5	8.277460	8.298809	8.323729	8.361632	8.368003
6	8.603710	8.616820	8.616820	8.672681	8.672681

3.2 THE RESULTS OF THE STABILITY AND RESIDUAL CHECKS

VECM Stability Condition Check Table is presented below. The number of endogenous variables minus the number of cointegrating relations must equal to the number of unit roots. Since the result equals to two, the condition is confirmed. [22]

Table 6: VECM Stability Condition Check

Roots of Characteristic Polynomial
Endogenous variables: NPLPERC IPSACA CPISA BSKUAOF USDFXI BISTRE
Exogenous variables: M2 M3 M4 M5 M6 M7 M8 M9 M10 M11 M12
Lag specification: 1 2
Date: 11/14/21 Time: 20:10

Root	Modulus
1.015258	1.015258
1.000000	1.000000
1.000000	1.000000
0.882748 - 0.112730i	0.889917
0.882748 + 0.112730i	0.889917
0.139325 + 0.631497i	0.646684
0.139325 - 0.631497i	0.646684
0.605433 - 0.059982i	0.608397
0.605433 + 0.059982i	0.608397
0.399091 - 0.450322i	0.601718
0.399091 + 0.450322i	0.601718
0.141884 + 0.470278i	0.491215
0.141884 - 0.470278i	0.491215
-0.057258 - 0.346727i	0.351423
-0.057258 + 0.346727i	0.351423
-0.324315	0.324315
-0.116873 - 0.112542i	0.162250
-0.116873 + 0.112542i	0.162250

VEC specification imposes 2 unit root(s).

The Residual Correlation Matrix and the results of the Serial Correlation LM Tests are presented in below tables.

[22] The endogenous variables are: nplperc ipsaca cpisa bskuaof usdfxi bistre. The number of cointegrating relationships is four based on the Johansen Cointegration Test in the previous section.

Table 7: The Residual Correlation Matrix

	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
NPLPERC	1	0.1504	0.0910	0.1314	-0.3291	0.1758
IPSACA	0.1504	1	0.0495	0.2647	-0.1249	0.0324
CPISA	0.0910	0.0495	1		0.3648	-0.1663
BSKUAOF	0.1314	0.2647	0.2223	1	0.2139	-0.1535
USDFXI	-0.3291	-0.1249	0.3648	0.2139	1	-0.3902
BISTRE	0.1758	0.0324	-0.1663	-0.1535	-0.3902	1

Since the resulting p-values are less than 0.05 the null hypothesis is rejected and it can be concluded that serial correlation exists among the residuals at order less than or equal to three.[23]

Table 8: VECM Residual Serial Correlation LM Tests

VEC Residual Serial Correlation LM Tests
Date: 11/14/21 Time: 20:11
Sample: 2005M01 2021M08
Included observations: 193

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	60.42046	36	0.0066	1.710319	(36, 683.4)	0.0066
2	72.17273	36	0.0003	2.060475	(36, 683.4)	0.0003
3	39.43197	36	0.3191	1.099404	(36, 683.4)	0.3194

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	60.42046	36	0.0066	1.710319	(36, 683.4)	0.0066
2	114.0955	72	0.0012	1.626033	(72, 816.5)	0.0012
3	134.5953	108	0.0424	1.265513	(108, 826.7)	0.0434

*Edgeworth expansion corrected likelihood ratio statistic.

The results of the applied Jarque-Bera test is presented below and show that the series are non-normal:

[23] The found serial correlation assumed to be pure serial correlation. Pure serial correlation means the error in one period is correlated with the other periods and model is correctly specified. Pure serial correlation is assumed due to the absence of reasons for model misspecification.

Table 9: VECM Residual Normality Tests

VEC Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: Residuals are multivariate normal
Date: 11/14/21 Time: 20:14
Sample: 2005M01 2021M08
Included observations: 193

Component	Skewness	Chi-sq	df	Prob.*
1	-0.271139	2.364771	1	0.1241
2	-4.179761	561.9646	1	0.0000
3	0.871881	24.45232	1	0.0000
4	0.390306	4.900218	1	0.0269
5	0.795804	20.37129	1	0.0000
6	-0.162891	0.853489	1	0.3556
Joint		614.9067	6	0.0000

Component	Kurtosis	Chi-sq	df	Prob.
1	4.066371	9.144553	1	0.0025
2	42.08024	12281.76	1	0.0000
3	6.308294	88.01452	1	0.0000
4	5.638668	55.99065	1	0.0000
5	6.659906	107.7174	1	0.0000
6	3.987011	7.834125	1	0.0051
Joint		12550.46	6	0.0000

Component	Jarque-Bera	df	Prob.
1	11.50932	2	0.0032
2	12843.72	2	0.0000
3	112.4668	2	0.0000
4	60.89087	2	0.0000
5	128.0887	2	0.0000
6	8.687613	2	0.0130
Joint	13165.36	12	0.0000

*Approximate p-values do not account for coefficient estimation

According to the results of the Residual Covariance Matrix, the VECM Residual Heteroskedasticity Test was applied to better check for heteroscedasticity.

Table 10: The Residual Covariance Matrix

	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
NPLPERC	8.8834	0.0004	0.0001	0.0001	-3.6482	0.0009
IPSACA	0.0004	11.9247	0.3008	0.8373	-0.0507	0.6748
CPISA	0.0001	0.3008	3.0956	0.3584	0.0754	-1.7648
BSKUAOF	0.0001	0.8373	0.3584	0.8390	0.0230	-0.8481
USDFXI	-3.6482	-0.0507	0.0754	0.0230	0.0138	-0.2768
BISTRE	0.0009	0.6748	-1.7648	-0.8482	-0.2768	36.3712

The VECM Residual Heteroskedasticity Test results presented below show that the series contain heteroskedastic properties.

Table 11: VECM Residual Heteroskedasticity Tests (Levels and Squares) (White Heteroskedasticity)

VEC Residual Heteroskedasticity Tests (Levels and Squares)
Date: 11/14/21 Time: 20:14
Sample: 2005M01 2021M08
Included observations: 193

Joint test:

Chi-sq	df	Prob.
1369.268	903	0.0000

Individual components:

Dependent	R-squared	F(43,149)	Prob.	Chi-sq(43)	Prob.
res1*res1	0.314563	1.590221	0.0221	60.71063	0.0386
res2*res2	0.643438	6.253018	0.0000	124.1836	0.0000
res3*res3	0.766193	11.35530	0.0000	147.8752	0.0000
res4*res4	0.400808	2.317868	0.0001	77.35600	0.0010
res5*res5	0.375458	2.083140	0.0006	72.46348	0.0033
res6*res6	0.194960	0.839164	0.7445	37.62734	0.7029
res2*res1	0.607761	5.369077	0.0000	117.2978	0.0000
res3*res1	0.528179	3.879020	0.0000	101.9386	0.0000
res3*res2	0.438954	2.711060	0.0000	84.71821	0.0002
res4*res1	0.437607	2.696268	0.0000	84.45825	0.0002
res4*res2	0.583727	4.859027	0.0000	112.6593	0.0000
res4*res3	0.538434	4.042192	0.0000	103.9178	0.0000
res5*res1	0.370668	2.040906	0.0009	71.53892	0.0041
res5*res2	0.611596	5.456295	0.0000	118.0379	0.0000
res5*res3	0.394216	2.254932	0.0002	76.08359	0.0014
res5*res4	0.325203	1.669937	0.0130	62.76426	0.0261
res6*res1	0.276289	1.322867	0.1125	53.32378	0.1345
res6*res2	0.243512	1.115415	0.3105	46.99785	0.3121
res6*res3	0.326230	1.677763	0.0123	62.96244	0.0251
res6*res4	0.300662	1.489734	0.0422	58.02773	0.0627
res6*res5	0.355047	1.907553	0.0024	68.52416	0.0079

When the results of the residual check tests were reviewed, the bootstrap method was selected for response standard errors to provide better statistical inference. According to the relevant literature (Abadir et al. 1999; Brüggemann et al. 2016; Efron 1979; Gon-calves and Kilian 2004; Hafner and Herwartz 2009; Ji and Kim 2005; Kilian 1999; Mammen 1993), the bootstrap method provides improved statistical inference for the impulse response analysis compared to the asymptotic method. Since conventional asymptotic inference is based on a normal approximation, the bootstrap method was proven to provide more meaningful inference when the sample size is small, and the data has non-normal and heteroskedastic properties. Therefore, bootstrap method was selected in impulse response functions in this study to obtain an improved statistical inference even in the presence of non-normality and conditional heteroscedasticity.

3.3 THE RESULTS OF THE IMPULSE RESPONSE FUNCTIONS

In order to evaluate the results of the model from a perspective of macro stress tests, the impulse response functions are created.[24] The reaction of NPLPERC to the other macroeconomic variables involved is analyzed over 24 months horizon[25] when the innovation of a macro variable was shocked at time zero.

A shock to one of the variables not only affects the relevant variable but also relates to other variables' effect on each other due to the dynamic nature of vector autoregressiveness of VEC model.

In the response function of NPLPERC to the shock on NPLPERC, it is observed that initially, a shock to NPLPERC increases NPLPERC in the short run as expected. In the long run, as banks are more conservative in credit decisioning, NPLPERC returns to its initial level. After the 12th month, the interpretation would not be healthy since the confidence interval intersects with the x-axis.

Similarly, Hoggarth (2005), Amediku (2006), and Beşe (2007), based on their analysis on the UK, Ghana, and Turkey respectively, noted that response of non-performing loans to a shock on non-performing loans has an increasing effect in the short run.

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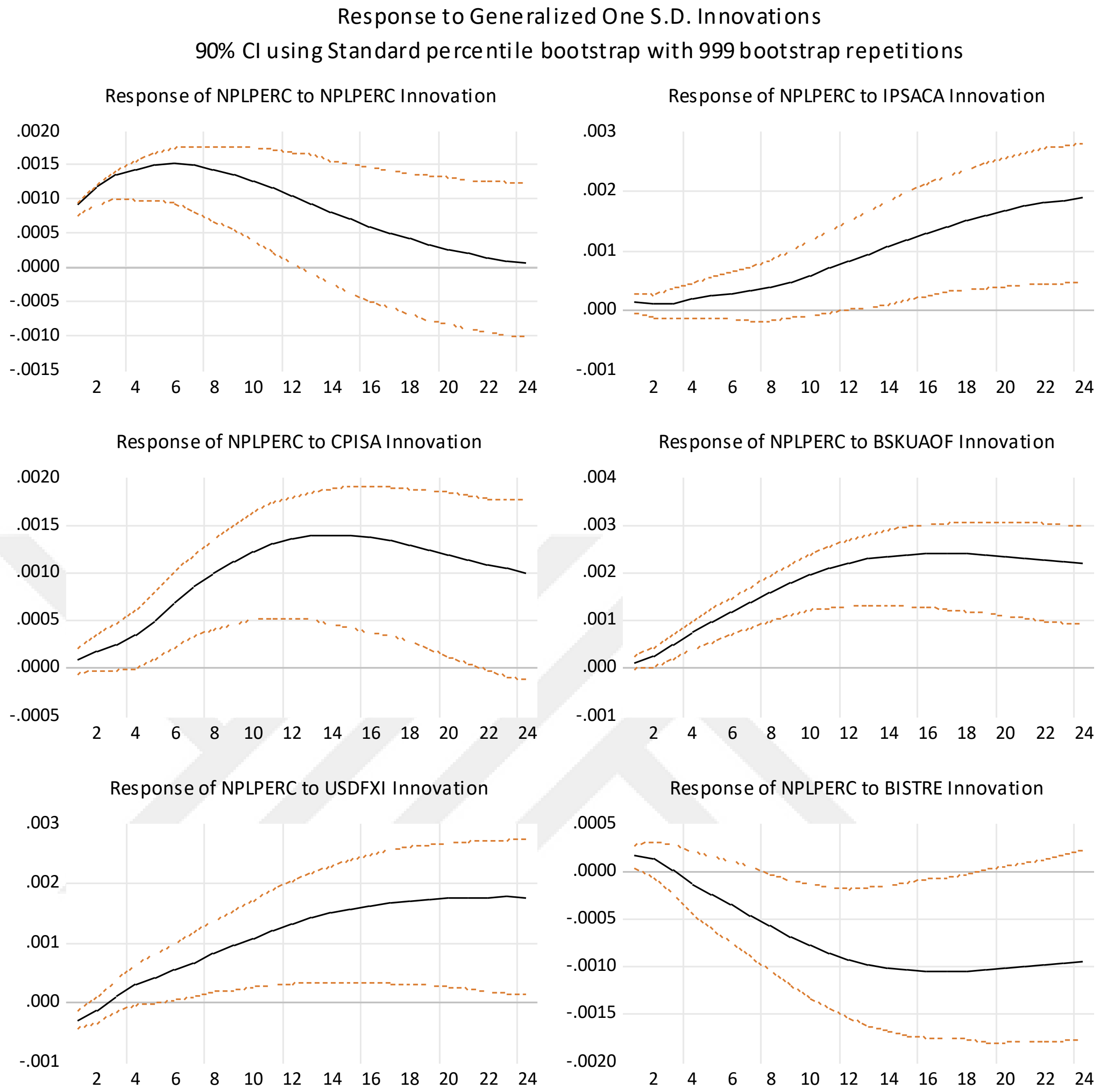
[24] The question regarding the horizon of interest is of utmost importance in stress tests. Early financial stability stress tests used one year horizon when it is identified that risk losses take time to spread through the system, central banks started to opt for longer years of horizon. Since, in essence, the selected horizon necessitates a trade-off between the required time for a vulnerability to crystalize and the modeled behavioral responses of policy makers' and market participants' realism in times of stress, the duration of 2 years which is in the range of recommended one to three year horizon by Drehmann (2008) and IMF (2012) is chosen.

[25] Impulse response functions of all variables were presented in Appendix 4. The black line represents impulse response while the red dotted lines represent response standard errors.

Figure 9: Impulse Response Functions of Non-Performing Loan Ratio, 90% CI



Since the response function of NPLPERC to shock on NPLPERC means the variable's reaction to shocks on itself, it is predictable to observe that the reaction overlaps with the existing expectations. On the other hand, a disjunctive interpretation of the behavior of NPLPERC would be that the banking sector takes quick actions in case of an increase in credit defaults. This responsiveness is highly likely to result from the legacy of increased regulation of the financial sector in the aftermath of the financial crisis of 2001 to prevent any possible crises in the future. In the response function of NPLPERC to shock on IPSACA, it is observed that the response can be interpreted as meaningful between the 12th month to 24th month. Accordingly, NPLPERC gives a lagged response to IPSACA. A positive shock on IPSACA increases NPLPERC in this period. This response mainly contradicts the expectations.

This is because IPSACA is an indicator of growth and the good performance of the economy is mainly associated with lower default rates instead of higher ones. Based on the theoretical anticipation, NPLPERC would typically decrease as economic conditions improve, and bank customers' creditworthiness would be expected to increase along with an improvement in their ability to repay loans.

In addition, when growth slows down, wages of households and income of firms decrease, and the repayment of loans becomes difficult, which is discussed in several studies by Salas and Saurina (2002), Girault (2008), Jakubik and Schmieder (2008), Zeman and Jurca (2008), Altıntaş (2011), Çakmak (2014).

The main point to be highlighted in this response is that the reaction is given in the second half of the two-year horizon. This lagged response may be interpreted as the second-round effect of IPSACA increase. During the bust, due to regulations in place for the financial sector and the risk-averse behavior of individual banks in Turkey, NPLPERC is curbed by financial actors' more cautious behavior. Banks' credit decisioning criteria become stricter in busts, causing NPLPERC to stabilize if not fall. It should be remembered that, in the banking sector, the state sets the minimum thresholds to be followed in credit decisioning, but it is ultimately decided based on the individual banks' internal regulation. They can implement stricter criteria than the bare minimum set by the state in their credit-giving decisions where applicable. In bust periods, banks are concerned that state-mandated minimum standards for credit giving are too lax, and they have begun to implement stricter versions. As a corollary, during booms, banks exhibit greater risk appetite and loosen their internal credit giving criteria, making it converge to the state-mandated minimum since the economy grows. The reaction of NPLPERC to a positive shock on IPSACA was also in line with the studies of Beck et al. (2013) and Çakmak (2014) where they found that NPLPERC was also increasing against a positive shock on growth indicator.

In this thesis, NPLPERC was calculated for the entire banking sector. If it had been calculated for public banks and private banks separately, the expectation according to this rationale would be a stabilization or decrease of private banks' NPLPERC during busts due to more conservative behavior as opposed to an increase of public banks' NPLPERC due to the mission assigned to them by governments to act as a countering force to economic contraction. A recent example of this phenomenon is the Covid-19 slow-down in Turkey's economy. During the initial dire environment of Covid-19, banks were encouraged by the government to ease their credit giving criteria to support reviving the economy. Where public banks implemented this instruction, the private banks' response remained conservative.

As for the response of NPLPERC to a shock on CPISA, the response can be interpreted as meaningful between the 5^{th} month to 21^{st} month. Accordingly, NPLPERC gives a lagged response to CPISA. A positive shock on CPISA increases NPLPERC until the 13^{th} month, to the 16th, NPLPERC is stable and starts to slowly decrease after the 16th month.

The consumer price index is an indicator of inflation. Theoretically, an increase in inflation may increase or decrease the ability to repay loans by two opposing effects, which is also discussed by Çakmak (2014) and Zeman and Jurca (2008). On the one hand, an increase in inflation reduces the real value of existing loans, and this effect facilitates repayment. On the other hand, it reduces the real income, making repayment more difficult. For countries with high inflation such as Turkey, empirical research shows that real wages fall sharply when prices increase (Braumann 2004). Rising poverty during periods of high inflation curbs the ability to pay credit debts by the real decrease of disposable income and increase in defaults follows. This phenomenon is in line with NPLPERC's response between the 5^{th} and 13^{th} months. Afterward, as is the case with IPSACA, banks' behavioral response of replacing existing credit decisioning criteria with stricter versions stabilizes and decreases NPLPERC. Altıntaş (2012) also found out that an inflation increase led to an initial increase in non-performing loans. Despite acknowledging permanent inflation's detriments to the economy, Jakubik and Schmieder (2008) determined that an increase in inflation decreased corporate defaults in their study. Hoggarth (2005) suggested a weak relationship between credit loss and inflation, where an unexpected increase in inflation also increased credit loss. On the other hand, Kalirai and Scheicher (2002) established no material relationship between provisions and inflation.

In the response function of NPLPERC to a shock on BSKUAOF, it is observed that the response can be interpreted as meaningful starting from the 2^{nd} month. A positive shock on BSKUAOF increases NPLPERC until the 13^{th} month. From the 13^{th} month onwards, NPLPERC seems to have a stabilized trend. NPLPERC is stable until the 16^{th} month and starts to decrease slowly after the 16^{th} month. An increase in interest rates leads to an increase in the direct cost of borrowing and worsens the possibility of repaying loans by both firms and households, which is stated by Jakubik and Schmieder (2008). Zeman and Jurca (2008) point out that an increase in interest rates affects banks negatively due to a decrease in the price of banks' assets. The price of banks' assets decreases since the volume of assets with long-term interest rate fixation exceeds the volume of liabilities with long-term interest rate fixation. Moreover, Hoggarth (2005) and Girault (2008) found that the loss of banks escalated with the increases in interest rate.

Accordingly, the reaction of NPLPERC to BSKUAOF shock can be explained as follows: As also pointed out by Beşe (2005) and Jakubik and Schmieder (2008), when interest rates increase, firms whose debt has a high impact on their balance sheet are affected first since the increase makes it difficult for them to pay their debts. In addition, the ones who apply for loans with higher interest rates tend to be more risky customers. Hence, delinquencies stemming from such loans have an increasing impact on the non-performing loan ratio. Furthermore, due to higher interest rates, demand for loans decreases. Shrinking of loans means the denominator of NPLPERC to decrease and NPLPERC to increase. As is the case with other shocks to other variables, the behavioral response of banks stabilizes NPLPERC and decreases the ratio from the 13th month onwards. The results align with several studies where non-performing loans, credit losses, and provisions increase with interest rate increases (Altıntaş 2012; Başarır 2013; Beşe 2007; Çakmak 2014; Hoggarth et al. 2005; Karaaslan and Sayılır 2019; Jimenez and Saurina 2005; Kalirai and Scheicher 2002).

In the response function of NPLPERC to a shock on USDFXI, the response can be interpreted as meaningful starting from the 5th month. Accordingly, NPLPERC gives a lagged response to USDFXI shock. A positive shock on USDFXI increases NPLPERC until the 20th month. From the 20th to the 24th month, NPLPERC is stable. The Appreciation of USD means the depreciation of the Turkish Lira. The cost of imported raw materials and intermediate goods increases with Turkish lira depreciation. This inflationary effect, along with having debts in foreign currency, makes firms experience a decrease in their capability to pay their debt. In addition, consumers generally experience a decrease in purchasing power, and their ability to pay their debt decreases with the devaluation of the Turkish Lira. Filosa (2007), Altıntaş (2012), and Başarır (2013) also found an increase in the non-performing loans ratio in case of an exchange rate shock.

In the response of NPLPERC to a shock on BISTRE innovation between the 9th and 16th month, a positive shock to BISTRE was decreasing NPLPERC. This response is aligned with the conventional expectation of default rates falling in periods of a stock market boom, which is also discussed by Zeman and Jurca (2008). However, a more detailed analysis is needed to further investigate the relationship between stock exchange shocks and the non-performing loan ratio. This is because the confidence interval in which a meaningful interpretation of the shock can be made was extremely narrow. Due to stock price fluctuations' possible effects on financial stability, future studies on this topic are expected to provide more comprehensive insight.

3.4 THE RESULTS OF THE VARIANCE DECOMPOSITION TESTS

The variance decomposition analysis is conducted to show how much of the forecast error variance of NPLPERC can be explained by shocks to macro variables26. The results are presented below.

When the results are reviewed, BSKUAOF has the most impact on explaining the forecast error variance of NPLPERC in the 19th month with 35%. BSKUAOF is followed by USDFXI and IPSACA with 17% in the 24th month. The next variable is CPISA with 16% in the 18th month.

Accordingly, the interest rate was the most prominent factor in explaining the non-performing loan ratio. The effect of BISTRE remained minimal since it did not go above 2% during the 24-month horizon.

[26] Variance decomposition of other variables is presented in Appendix 5.

Table 12: Variance Decomposition Using Cholesky d.f. adjusted Factors

Variance Decomposition of NPLPERC:

Period	S.E.	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
1	0.000943	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.001541	96.78468	0.277151	0.207185	0.490775	2.229887	0.010321
3	0.002151	89.61277	0.290452	0.480677	2.680878	6.921746	0.013472
4	0.002750	82.43595	0.193904	0.907082	5.845822	10.51565	0.101596
5	0.003336	76.68391	0.134654	1.863340	8.940976	12.11425	0.262869
6	0.003903	71.42804	0.117587	3.419014	11.92197	12.67627	0.437116
7	0.004459	66.05110	0.135717	5.252421	15.05878	12.89241	0.609571
8	0.005012	60.54912	0.219077	7.090291	18.35798	12.99654	0.786993
9	0.005566	55.13410	0.417589	8.861249	21.57833	13.04966	0.959072
10	0.006117	49.98759	0.767016	10.53951	24.49670	13.10256	1.106626
11	0.006662	45.22055	1.280699	12.05507	27.02250	13.20010	1.221083
12	0.007196	40.89030	1.962782	13.33540	29.14748	13.35973	1.304315
13	0.007719	37.01203	2.812637	14.35194	30.88634	13.57719	1.359863
14	0.008228	33.56982	3.820597	15.11423	32.26255	13.84278	1.390021
15	0.008724	30.53063	4.967400	15.64603	33.30993	14.14853	1.397476
16	0.009205	27.85552	6.228423	15.97414	34.06873	14.48703	1.386156
17	0.009673	25.50518	7.577374	16.12760	34.57950	14.84992	1.360425
18	0.010126	23.44208	8.987681	16.13707	34.88035	15.22859	1.324221
19	0.010567	21.63120	10.43332	16.03214	35.00693	15.61556	1.280842
20	0.010994	20.04053	11.89003	15.83933	34.99226	16.00482	1.233029
21	0.011409	18.64126	13.33649	15.58155	34.86610	16.39158	1.183011
22	0.011812	17.40780	14.75484	15.27824	34.65450	16.77211	1.132518
23	0.012203	16.31763	16.13069	14.94552	34.37974	17.14359	1.082818
24	0.012583	15.35113	17.45299	14.59640	34.06061	17.50408	1.034796

3.5 THE RESULTS OF ROBUSTNESS CHECKS

Four different models are estimated for analyzing the robustness of the results. The main model described in previous sections was the selected one among these four models.[27] As is the case with the main model, the bootstrap method was used in all impulse response functions' confidence intervals for all candidate models in order to mitigate heteroskedasticity and non-normality problems.

Candidate Model One was estimated using NPLPERC, TITISACA, RSCI, BSUAOF, USDFXI macroeconomic variables using the data between January 2007 and August 2021. No exogenous seasonal dummies or crisis dummies were used. The descriptive statistics and the residual checks results of Candidate Model One are presented in Appendix 6.

The two new variables introduced in this model compared to the main model were: TITISACA (Total Industrial Turnover Index, Seasonally adjusted, Calendar Adjusted) and RSCI (Real Sector Confidence Index). Similar to the industrial production index, TITISACA was selected to be an indicator of growth, and RSCI was

[27] The unselected candidate models will be referred to as candidate model one, candidate model two, and candidate model three.

a confidence indicator. According to ADF and KPSS test results, the variables were integrated of order one. The unit root test results are presented in Appendix 7. The applied cointegration test showed three cointegrating relations. The test results are presented in Appendix 8. The estimation results and the lag length selection table are presented in Appendix 9 and Appendix 10, respectively.

The impulse response functions of NPLPERC, BSKUAOF, and USDFXI were similar to those of the main model. The confidence interval for TITISACA innovation contained zero. Hence, a meaningful inference could not be drawn. A positive shock to RSCI resulted in an initial decrease in NPLPERC and a stabilization after the 16th month. As the confidence in the economy increases, the number of given loans increases due to the loose criteria of credit giving, causing the denominator of the loan to increase and the overall ratio to decrease. The impulse response functions are presented in Appendix 11.

Candidate Model Two was estimated using NPLPERC, IPSACA, CPISA, BSKUAOF, USDFXI macroeconomic variables using the data between January 2005 and December 2016. In addition, seasonal dummies and crisis dummies were introduced. Economic/financial crisis and the Covid-19 slowdown were dummied as one, and the rest of the periods were dummied as zero. The descriptive statistics and the residual checks results of Candidate Model One are presented in Appendix 12. According to ADF and KPSS test' results, the variables were integrated of order one. The unit root test results are presented in Appendix 13.

The applied cointegration test showed one cointegrating relation. The test results are presented in Appendix 14. The estimation results and the lag length selection table are presented in Appendix 15 and Appendix 16, respectively.

The impulse response functions of CPISA, BSKUAOF, and USDFXI were similar to those of the main model. The response of NPLPERC was also similar to that of the main model, however, the confidence interval contained zero starting from the 8th month. The impulse response of IPSACA was meaningful from the 5th month to the 24th. A positive shock to IPSACA initially decreases NPLPERC, and the ratio stabilizes afterward. This response is aligned with the conventional expectation of default rates falling in periods of economic boom. The impulse response functions are presented in Appendix 17.

Candidate Model Three was estimated using NPLPERC, IPSACA, CPISA, BSKUAOF, USDFXI, BISTRE macroeconomic variables using the data between

January 2005 and December 2016. Seasonal dummies and crisis dummies were also introduced in this model. The descriptive statistics and the residual checks results of Candidate Model One are presented in Appendix 18.

According to ADF and KPSS test' results, the variables were integrated of order one. The unit root test results are presented in Appendix 19.

The applied cointegration test showed two cointegrating relations. The test results are presented in Appendix 20. The estimation results and the lag length selection table are presented in Appendix 21 and Appendix 22, respectively.

The impulse response functions of Candidate Model Two and Candidate Model Three were highly similar. Candidate Model Two did not have BISTRE as a variable. The impulse response of BISTRE in Candidate Model Three is significant from the 6^{th} month to the 24^{th}. A positive shock to BISTRE, similar to IPSACA result, initially decreases NPLPERC, and then the ratio stabilizes. This response is also aligned with the conventional expectation of default rates falling in periods of stock market boom. The impulse response functions are presented in Appendix 23.

When all models are compared, the impulse response functions showed mainly similar results except TITISACA and RSCI variables. The impulse of IPSACA and CPISA were meaningful in a wider horizon than those of TITISACA and RCSI. Furthermore, IPSACA and CPISA are more commonly used macroeconomic variables in stress tests compared to TITISACA and RSCI. Due to these inference and research comparability reasons, Candidate Model One was eliminated first in the main model selection process. Compared to the remaining models, the main model was selected since it has the largest sample size and widest horizon range for inference of impulse response functions.

CONCLUSION

Financial stability heavily depends on the strength of the financial sector. As is the case in many countries, the financial sector is identified chiefly with the banking sector in Turkey too. The banking sector assumes the role of financial stability bearer not just because of having the largest balance sheet size compared to other sectors' shares in the financial sector but also due to being the most assuring bridge between savings and investments within a country.

Due to these reasons, the banking sector's resilience to shocks in macroeconomic factors in turbulent times is vital. Because of the significance of the banking sector's resilience, regular and systematic measurements have a prominent role in sustaining financial stability.

Especially since the early 2000s, stress testing has been a widely used method to measure the stability of the banking sector against different scenarios of risky circumstances. However, there is no official stress testing publication from the Central Bank of the Republic of Turkey to provide public transparency.

In response to this shortcoming, this thesis tests the resilience of the Turkish banking sector by building a Vector Error Correction model using the data between 2005-2021. Vector autoregressive context is preferred due to its proven success in linking the financial sector to the real economy. Error correction is applied based on the established cointegration among macroeconomic variables. The non-performing loan ratio is selected due to being one of the main financial soundness indicators recognized by IMF. Also, it is the most commonly selected variable in stress testing literature reviewed for this thesis.

Undoubtedly, the disadvantages of the selection of the non-performing loan ratio are acknowledged. It is a lagged, retrospective indicator of loan performance and does not show current asset quality. In addition, there are variations in loan provisioning rules across jurisdictions and across time within a jurisdiction. However, for the purposes of this thesis, the advantage of being the most commonly used financial soundness indicator was outweighing the listed disadvantages. Therefore, non-performing loan ratio was selected.

The macro variable selection was also conducted in line with the world and Turkey literature. The industrial production index as an indicator of growth, the consumer price index as an indicator of inflation, interest rate, exchange rate, and the stock exchange rate profits as an indicator of the stock market were the significant variables that have been selected. This variable selection provided an embracing coverage of key economic indicators and enabled the thesis to be comparable to other research conducted in the macro stress test literature.

Due to seasonality concerns, seasonal and calendar-adjusted versions of the industrial production index and consumer price index, and seasonal dummies were used.

The stress test application was conducted by using a VEC model based on the piecewise approach and falls into the category of macroprudential (surveillance) stress tests due to its purpose. The scenario selection method is a probabilistic approach. Even though VAR use was more common in stress testing literature, the VEC model was selected because of variables' being integrated of order one and the presence of cointegration relations. Also, long-run equilibrium relationships of the variables are better reflected in VEC models. The main model was selected among four different candidate models. The details of these other models were elaborated in The Results of Robustness Checks section.

The main contribution to the existing stress testing literature with regards to modeling is the use of the Vector Error Correction Model and bootstrap method in impulse responses with up-to-date data. World literature on stress testing involves several VEC model applications, however, a lack of VEC model use was observed in stress testing literature in Turkey. In this regard, the selection of vector autoregressive context in modeling provided a dynamic specification to identify all relationships among macro variables thanks to treating each endogenous variable as a lagged value of all endogenous variables in the system. With error correction, the risk of not properly modeling cointegrated variables is avoided, and long-run equilibrium relationships of the variables are better reflected.

When the main VEC model was created, the bootstrap method was used rather than the asymptotic method to provide more meaningful statistical inference thanks to its proven success in cases of small sample size, non-normal and heteroskedastic data sets.

The non-performing loan ratio's response to shocks on itself, industrial production index, consumer price index, interest rate, exchange rate, and stock market profits were analyzed. The Non-performing loan ratio's response to shocks on itself was an increase in the non-performing loan ratio in the short run. Shortly after the increase, the ratio was decreasing. This response was interpreted as the banking sector taking quick action to curb increasing non-performing loan ratios, particularly after the lessons learned from the financial crisis of 2001.

The Non-performing loan ratio's response to shocks on industrial production was a lagged increase in the non-performing loan ratio. This response was contradicting conventional expectations since defaults were expected to decrease in economic booms. As the responses were lagged, however, it is interpreted as the second-round effect of industrial production increase. When the economy faces dire conditions, banks implement stricter credit giving standards as a precautionary behavioral response. On the other hand, in economic booms, the risk appetite of banks increases, and they tend to loose the standards, which causes an increasing effect in defaults.

The non-performing loan ratio's response to shocks on inflation was also a lagged increase in the non-performing loan ratio. This is in line with the expectations since a rise in inflation is anticipated to decrease the ability to pay debts due to real income reduction. In addition, behavioral response, as is the case with industrial production shock, may also be present since the ratio stabilizes and starts to decrease afterward.

The non-performing loan ratio's response to shocks on interest rate was a lagged increase in non-performing loan ratio and the following stabilization. Since the interest rate increase brings about an increase in the direct cost of borrowing, debt repayment becomes more difficult for existing floating interest rate loan holders. In addition, the new borrowers who are willing to take loans with the increased interest rate tend to be riskier and tend to default more. Furthermore, the number of given loans decreases due to lower demand for loans with higher interest rates, which in turn lowers the ratio.

The non-performing loan ratio's response to shocks on the exchange rate was also a lagged increase in the non-performing loan ratio and stabilization at the end of the two-year horizon. Depreciation of the Turkish lira means both an inflationary effect on imports and difficulty in paying foreign currency debts. For this reason, the results are again in line with the expectations.

The non-performing loan ratio's response to shocks on the stock market profits was a lagged increase in the non-performing loan ratio in the mid-run, which is in line with expectations since default rates were anticipated to fall in stock market booms. Due to confidence intervals, it was not possible to interpret most of the periods in the two-year horizon. Further research may provide better insight into the stock market and non-performing loan ratio relationship.

When all of the impulse response functions were reviewed based on each applied shock, the increase in the non-performing loan ratio was non-concerning. Since the selected macro variables involve leading economic indicators, it can be concluded that according to this applied stress test, the financial system of Turkey was resilient to macroeconomic shocks.

Even though the increases in the non-performing loan ratio are minimal and mostly remain only in the short run due to the behavioral response of actors having a stabilizing effect, the possible vulnerability of the financial system of Turkey against simultaneous shocks should further be investigated to measure the level of resilience more profoundly. In that regard, instead of an aggregate non-performing loan ratio, impact on different ratios like corporate vs. household non-performing loan ratio and public banks vs. private banks non-performing loan ratio can be investigated to obtain more detailed results.

Furthermore, the inclusion of shadow banking in stress test applications of Turkey was considered to provide more accurate predictions for the riskiness of the financial system against macroeconomic shocks.

It should be considered that the risk of actual shocks being more severe than the stress test shocks is a possibility for each stress testing. For transparency and surveillance purposes, periodic macro stress testing applications using detailed systematic by regulatory bodies and regular publication of the results to the public are highly recommended.

The overall results in this thesis showed that no severe concern has arisen for the resilience of the financial sector, and current regulations and past crisis experiences are observed to provide the necessary measures for the financial institutions. However, it should be kept in mind that the behavioral responses of the actors may create unforeseen consequences, and the danger of actual shocks being more severe than the stress test shocks is always a possibility. Due to these considerations, the need to stay vigilant by financial authorities and actors will continue to be critical to ensure financial stability and resilience.

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APPENDICES

Appendix 1: Johansen Cointegration Test Results, Assumption 3, Linear Data, Intercept, No Trend

Sample (adjusted): 2005M04 2021M08
Included observations: 193 after adjustments
Trend assumption: Linear deterministic trend
Series: NPLPERC IPSACA CPISA BSKUAOF USDFXI BISTRE
Lags interval (in first differences): 1 to 2

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.318911	226.3862	95.75366	0.0000
At most 1 *	0.281792	152.2621	69.81889	0.0000
At most 2 *	0.190249	88.37974	47.85613	0.0000
At most 3 *	0.132234	47.65128	29.79707	0.0002
At most 4 *	0.068484	20.27754	15.49471	0.0088
At most 5 *	0.033548	6.585788	3.841465	0.0103

Trace test indicates 6 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.318911	74.12410	40.07757	0.0000
At most 1 *	0.281792	63.88235	33.87687	0.0000
At most 2 *	0.190249	40.72845	27.58434	0.0006
At most 3 *	0.132234	27.37375	21.13162	0.0058
At most 4	0.068484	13.69175	14.26460	0.0614
At most 5 *	0.033548	6.585788	3.841465	0.0103

Max-eigenvalue test indicates 4 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
-32.13724	-0.048008	0.033073	0.165455	-1.056943	0.250915
38.48899	0.024980	-0.000593	0.013852	0.481826	-0.168826
-8.423812	0.101628	-0.092828	-0.333868	4.756055	0.036937
164.1707	0.114799	0.017385	0.024559	-2.177915	-0.004630
-1.908358	0.134798	-0.044070	0.129787	1.168122	0.007205
20.19979	-0.030966	-0.015616	0.059746	1.089855	0.003105

Unrestricted Adjustment Coefficients (alpha):

D(NPLPERC)	3.16E-05	-5.80E-06	-0.000202	-0.000261	0.000126	4.71E-05
D(IPSACA)	0.544843	-0.275814	0.419512	-0.857477	-0.483615	-0.030225
D(CPISA)	0.503482	0.563106	0.382994	-0.103185	0.191928	-0.076106
D(BSKUAOF)	-0.254193	-0.119116	0.163295	-0.155022	0.069856	-0.086716
D(USDFXI)	0.006938	0.024625	-0.006784	0.006461	-0.001709	-0.018929
D(BISTRE)	-2.199865	1.968516	-0.224014	-0.542832	-0.254072	0.614263

1 Cointegrating Equation(s):	Log likelihood	-512.9524			

Normalized cointegrating coefficients (standard error in parentheses)

NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
1.000000	0.001494	-0.001029	-0.005148	0.032888	-0.007808
	(0.00061)	(0.00037)	(0.00136)	(0.01790)	(0.00099)

Adjustment coefficients (standard error in parentheses)

D(NPLPERC)	-0.001016
	(0.00244)
D(IPSACA)	-17.50974
	(7.90554)
D(CPISA)	-16.18054
	(4.31615)
D(BSKUAOF)	8.169074
	(2.15603)
D(USDFXI)	-0.222967
	(0.27946)
D(BISTRE)	70.69758
	(14.9563)

2 Cointegrating Equation(s):	Log likelihood	-481.0112			

Normalized cointegrating coefficients (standard error in parentheses)

NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
1.000000	0.000000	0.000763	0.004592	-0.003130	-0.001758
		(0.00039)	(0.00228)	(0.02390)	(0.00177)
0.000000	1.000000	-1.199929	-6.520084	24.11152	-4.049705
		(0.35208)	(2.04176)	(21.4331)	(1.58462)

Adjustment coefficients (standard error in parentheses)

D(NPLPERC)	-0.001239	-1.66E-06
	(0.00381)	(4.1E-06)
D(IPSACA)	-28.12555	-0.033046
	(12.2912)	(0.01327)
D(CPISA)	5.492831	-0.010105
	(6.39501)	(0.00690)
D(BSKUAOF)	3.584404	0.009228
	(3.33417)	(0.00360)
D(USDFXI)	0.724842	0.000282
	(0.42615)	(0.00046)
D(BISTRE)	146.4638	0.154783
	(22.1385)	(0.02389)

3 Cointegrating Equation(s):	Log likelihood	-460.6470			

Normalized cointegrating coefficients (standard error in parentheses)

NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
1.000000	0.000000	0.000000	-0.003298	-0.052073	-0.011071
			(0.00210)	(0.00717)	(0.00231)
0.000000	1.000000	0.000000	5.882226	101.0452	10.58899
			(4.02058)	(13.7324)	(4.42878)
0.000000	0.000000	1.000000	10.33587	64.11520	12.19964
			(4.46082)	(15.2360)	(4.91371)

Adjustment coefficients (standard error in parentheses)

D(NPLPERC)	0.000463	-2.22E-05	1.98E-05
	(0.00378)	(8.6E-06)	(7.3E-06)
D(IPSACA)	-31.65945	0.009588	-0.020759
	(12.3610)	(0.02799)	(0.02396)
D(CPISA)	2.266563	0.028818	-0.019234
	(6.31917)	(0.01431)	(0.01225)
D(BSKUAOF)	2.208842	0.025823	-0.023495
	(3.32345)	(0.00753)	(0.00644)
D(USDFXI)	0.781990	-0.000407	0.000845
	(0.43135)	(0.00098)	(0.00084)
D(BISTRE)	148.3508	0.132017	-0.053130
	(22.4326)	(0.05080)	(0.04348)

4 Cointegrating Equation(s): Log likelihood -446.9601

Normalized cointegrating coefficients (standard error in parentheses)

NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
1.000000	0.000000	0.000000	0.000000	0.020356	-0.015468
				(0.00626)	(0.00202)
0.000000	1.000000	0.000000	0.000000	-28.11866	18.43140
				(7.66090)	(2.46944)
0.000000	0.000000	1.000000	0.000000	-162.8432	25.97981
				(16.6570)	(5.36925)
0.000000	0.000000	0.000000	1.000000	21.95833	-1.333238
				(2.77149)	(0.89337)

Adjustment coefficients (standard error in parentheses)

D(NPLPERC)	-0.042404	-5.22E-05	1.53E-05	6.62E-05
	(0.01233)	(1.2E-05)	(7.2E-06)	(2.7E-05)
D(IPSACA)	-172.4320	-0.088850	-0.035666	-0.074794
	(40.3044)	(0.03813)	(0.02347)	(0.08763)
D(CPISA)	-14.67347	0.016973	-0.021028	-0.039299
	(21.3188)	(0.02017)	(0.01241)	(0.04635)
D(BSKUAOF)	-23.24117	0.008027	-0.026190	-0.102033
	(11.0560)	(0.01046)	(0.00644)	(0.02404)
D(USDFXI)	1.842689	0.000334	0.000957	0.003913
	(1.45567)	(0.00138)	(0.00085)	(0.00317)
D(BISTRE)	59.23374	0.069700	-0.062567	-0.275250
	(75.5049)	(0.07143)	(0.04396)	(0.16417)

5 Cointegrating Equation(s): Log likelihood -440.1142

Normalized cointegrating coefficients (standard error in parentheses)

NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
1.000000	0.000000	0.000000	0.000000	0.000000	-0.020281
					(0.00243)
0.000000	1.000000	0.000000	0.000000	0.000000	25.07874
					(3.16774)
0.000000	0.000000	1.000000	0.000000	0.000000	64.47645
					(8.52553)
0.000000	0.000000	0.000000	1.000000	0.000000	-6.524256
					(0.91255)
0.000000	0.000000	0.000000	0.000000	1.000000	0.236403
					(0.04919)

Adjustment coefficients (standard error in parentheses)

D(NPLPERC)	-0.042644	-3.52E-05	9.71E-06	8.26E-05	-0.000281
	(0.01223)	(1.5E-05)	(7.8E-06)	(2.8E-05)	(0.00039)
D(IPSACA)	-171.5091	-0.154040	-0.014353	-0.137561	2.589052
	(39.8252)	(0.04894)	(0.02534)	(0.09166)	(1.27077)
D(CPISA)	-15.03974	0.042844	-0.029487	-0.014389	2.009631
	(21.1771)	(0.02602)	(0.01347)	(0.04874)	(0.67573)
D(BSKUAOF)	-23.37448	0.017443	-0.029268	-0.092967	1.407136
	(11.0202)	(0.01354)	(0.00701)	(0.02536)	(0.35164)
D(USDFXI)	1.845949	0.000104	0.001032	0.003691	-0.043800
	(1.45559)	(0.00179)	(0.00093)	(0.00335)	(0.04645)
D(BISTRE)	59.71860	0.035452	-0.051370	-0.308225	3.093646
	(75.4390)	(0.09270)	(0.04799)	(0.17363)	(2.40715)

Appendix 2: Vector Error Correction Model Results (Main Model)

Vector Error Correction Estimates
Date: 11/14/21 Time: 20:10
Sample (adjusted): 2005M04 2021M08
Included observations: 193 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	CointEq2	CointEq3	CointEq4
NPLPERC(-1)	1.000000	0.000000	0.000000	0.000000
IPSACA(-1)	0.000000	1.000000	0.000000	0.000000
CPISA(-1)	0.000000	0.000000	1.000000	0.000000
BSKUAOF(-1)	0.000000	0.000000	0.000000	1.000000
USDFXI(-1)	0.027509	-109.3657	-260.9616	11.89603
	(0.00569)	(12.0171)	(23.7971)	(2.01582)
	[4.83661]	[-9.10081]	[-10.9661]	[5.90134]
BISTRE(-1)	-0.012575	-8.178923	-11.86226	-2.980936
	(0.00195)	(4.12332)	(8.16524)	(0.69167)
	[-6.44366]	[-1.98358]	[-1.45278]	[-4.30979]

Error Correction:	D(NPLPERC)	D(IPSACA)	D(CPISA)	D(BSKUAOF)	D(USDFXI)	D(BISTRE)
CointEq1	-0.023414	-20.37950	-7.268546	10.87335	0.283836	112.0973
	(0.00557)	(20.4071)	(10.3976)	(5.41330)	(0.69504)	(35.6399)
	[-4.20365]	[-0.99865]	[-0.69906]	[2.00864]	[0.40838]	[3.14528]
CointEq2	-1.82E-05	-0.050244	0.045934	0.043903	-0.000944	0.086319
	(1.3E-05)	(0.04691)	(0.02390)	(0.01244)	(0.00160)	(0.08193)
	[-1.42244]	[-1.07108]	[1.92187]	[3.52818]	[-0.59055]	[1.05363]
CointEq3	1.20E-05	0.025048	-0.027245	-0.022924	0.000450	-0.044134
	(7.0E-06)	(0.02553)	(0.01301)	(0.00677)	(0.00087)	(0.04459)
	[1.71731]	[0.98095]	[-2.09417]	[-3.38449]	[0.51701]	[-0.98968]
CointEq4	9.96E-05	0.067669	-0.004178	-0.060561	0.000502	-0.246945
	(2.3E-05)	(0.08520)	(0.04341)	(0.02260)	(0.00290)	(0.14880)
	[4.28377]	[0.79423]	[-0.09624]	[-2.67958]	[0.17307]	[-1.65958]
D(NPLPERC(-1))	0.388178	-424.0966	-330.8121	-43.55926	-24.51824	292.1263
	(0.07968)	(291.930)	(148.740)	(77.4387)	(9.94270)	(509.839)
	[4.87178]	[-1.45274]	[-2.22409]	[-0.56250]	[-2.46595]	[0.57298]
D(NPLPERC(-2))	0.226405	-161.2085	264.6607	-16.73596	17.37250	638.9290
	(0.07832)	(286.968)	(146.213)	(76.1226)	(9.77373)	(501.174)
	[2.89059]	[-0.56176]	[1.81011]	[-0.21986]	[1.77747]	[1.27486]
D(IPSACA(-1))	-2.66E-06	-0.080806	0.030234	0.032282	0.005427	-0.148368
	(2.3E-05)	(0.08603)	(0.04384)	(0.02282)	(0.00293)	(0.15025)
	[-0.11323]	[-0.93923]	[0.68972]	[1.41452]	[1.85195]	[-0.98745]
D(IPSACA(-2))	6.61E-06	-0.110696	-0.067555	-0.018805	0.003291	-0.075267
	(2.3E-05)	(0.08315)	(0.04237)	(0.02206)	(0.00283)	(0.14522)
	[0.29136]	[-1.33129]	[-1.59458]	[-0.85257]	[1.16193]	[-0.51832]

D(CPISA(-1))	-4.13E-05	0.090197	0.176765	0.002186	-0.024696	-0.014436
	(4.4E-05)	(0.16089)	(0.08197)	(0.04268)	(0.00548)	(0.28098)
	[-0.94008]	[0.56061]	[2.15635]	[0.05122]	[-4.50693]	[-0.05138]
D(CPISA(-2))	1.59E-06	-0.109140	-0.065996	0.185941	0.014931	-0.460271
	(4.5E-05)	(0.16573)	(0.08444)	(0.04396)	(0.00564)	(0.28944)
	[0.03511]	[-0.65853]	[-0.78156]	[4.22951]	[2.64522]	[-1.59021]
D(BSKUAOF(-1))	-3.98E-05	-0.166265	-0.030932	0.463319	0.006163	0.519106
	(8.0E-05)	(0.29263)	(0.14910)	(0.07762)	(0.00997)	(0.51106)
	[-0.49876]	[-0.56818]	[-0.20746]	[5.96879]	[0.61838]	[1.01575]
D(BSKUAOF(-2))	1.12E-05	-0.403039	0.115677	-0.168398	-0.012409	-0.049628
	(7.4E-05)	(0.27194)	(0.13855)	(0.07214)	(0.00926)	(0.47492)
	[0.15144]	[-1.48210]	[0.83488]	[-2.33446]	[-1.33978]	[-0.10450]
D(USDFXI(-1))	0.003007	-3.303912	8.106571	3.979872	0.673857	-9.361607
	(0.00074)	(2.69450)	(1.37287)	(0.71475)	(0.09177)	(4.70578)
	[4.08823]	[-1.22617]	[5.90485]	[5.56816]	[7.34284]	[-1.98938]
D(USDFXI(-2))	0.000867	4.351027	-2.923409	-2.465563	-0.294766	8.927775
	(0.00078)	(2.84269)	(1.44837)	(0.75407)	(0.09682)	(4.96460)
	[1.11725]	[1.53060]	[-2.01841]	[-3.26969]	[-3.04453]	[1.79829]
D(BISTRE(-1))	-1.62E-06	0.019945	0.028746	0.018656	0.001755	0.076132
	(1.7E-05)	(0.06284)	(0.03202)	(0.01667)	(0.00214)	(0.10975)
	[-0.09463]	[0.31737]	[0.89780]	[1.11912]	[0.81984]	[0.69368]
D(BISTRE(-2))	3.54E-07	-5.14E-05	0.006176	0.026290	0.001765	-0.026903
	(1.3E-05)	(0.04896)	(0.02494)	(0.01299)	(0.00167)	(0.08550)
	[0.02649]	[-0.00105]	[0.24758]	[2.02445]	[1.05851]	[-0.31466]
M2	-0.000718	0.374157	-0.102548	-0.502804	-0.033377	-2.245130
	(0.00028)	(1.03073)	(0.52516)	(0.27342)	(0.03511)	(1.80011)
	[-2.55386]	[0.36300]	[-0.19527]	[-1.83897]	[-0.95078]	[-1.24722]
M3	-0.001331	0.390375	0.114740	-0.142418	0.063104	-4.385835
	(0.00028)	(1.01599)	(0.51766)	(0.26951)	(0.03460)	(1.77437)
	[-4.79894]	[0.38423]	[0.22165]	[-0.52844]	[1.82363]	[-2.47177]
M4	-0.000490	-1.320665	-0.667751	-0.677496	-0.035967	1.552832
	(0.00028)	(1.04026)	(0.53002)	(0.27594)	(0.03543)	(1.81675)
	[-1.72735]	[-1.26956]	[-1.25986]	[-2.45520]	[-1.01516]	[0.85473]
M5	-0.000934	0.371034	-0.264097	0.027630	0.027489	-3.190094
	(0.00029)	(1.04874)	(0.53434)	(0.27819)	(0.03572)	(1.83157)
	[-3.26297]	[0.35379]	[-0.49425]	[0.09932]	[0.76959]	[-1.74173]
M6	-0.000998	0.774978	-0.127613	-0.294546	-0.042788	-2.870100
	(0.00028)	(1.04333)	(0.53158)	(0.27676)	(0.03553)	(1.82211)
	[-3.50590]	[0.74280]	[-0.24006]	[-1.06427]	[-1.20415]	[-1.57515]
M7	0.000157	0.709606	-0.306313	0.338505	-0.028994	1.122461
	(0.00029)	(1.04782)	(0.53387)	(0.27795)	(0.03569)	(1.82996)
	[0.54780]	[0.67722]	[-0.57376]	[1.21787]	[-0.81246]	[0.61338]
M8	-0.000367	0.687114	-0.517965	-0.160814	0.054365	-1.941647
	(0.00028)	(1.04311)	(0.53147)	(0.27670)	(0.03553)	(1.82173)
	[-1.28949]	[0.65872]	[-0.97459]	[-0.58119]	[1.53025]	[-1.06583]
M9	-0.000515	1.598217	-0.185282	-0.211748	-0.018592	-0.348330
	(0.00028)	(1.02393)	(0.52170)	(0.27161)	(0.03487)	(1.78823)
	[-1.84320]	[1.56087]	[-0.35515]	[-0.77960]	[-0.53313]	[-0.19479]
M10	-0.000472	0.419417	-0.815367	-0.007921	0.004005	-3.886246
	(0.00028)	(1.03898)	(0.52937)	(0.27560)	(0.03539)	(1.81452)
	[-1.66563]	[0.40368]	[-1.54027]	[-0.02874]	[0.11318]	[-2.14175]
M11	-0.000763	1.071570	-0.411538	-0.209537	-0.025278	-2.758723
	(0.00028)	(1.04178)	(0.53079)	(0.27635)	(0.03548)	(1.81940)
	[-2.68165]	[1.02860]	[-0.77533]	[-0.75824]	[-0.71243]	[-1.51628]
M12	-0.000737	0.587222	-0.439072	-0.328459	-0.027578	-1.224886
	(0.00029)	(1.05136)	(0.53567)	(0.27889)	(0.03581)	(1.83613)
	[-2.56859]	[0.55854]	[-0.81966]	[-1.17775]	[-0.77016]	[-0.66710]

R-squared	0.620908	0.227092	0.660810	0.618238	0.503058	0.485341
Adj. R-squared	0.561533	0.106034	0.607684	0.558444	0.425224	0.404732
Sum sq. resids	0.000147	1979.509	513.8765	139.2891	2.296200	6037.626
S.E. equation	0.000943	3.453224	1.759444	0.916019	0.117612	6.030858
F-statistic	10.45726	1.875896	12.43851	10.33945	6.463197	6.020912
Log likelihood	1085.310	-498.4988	-368.3569	-242.3827	153.7783	-606.1120
Akaike AIC	-10.96694	5.445584	4.096963	2.791531	-1.313765	6.560746
Schwarz SC	-10.51050	5.902022	4.553401	3.247970	-0.857326	7.017184
Mean dependent	-0.000146	0.419080	2.309605	0.007565	0.037598	0.148549
S.D. dependent	0.001423	3.652282	2.809036	1.378515	0.155132	7.816688

Determinant resid covariance (dof adj.)	6.74E-06
Determinant resid covariance	2.73E-06
Log likelihood	-406.8633
Akaike information criterion	6.143661
Schwarz criterion	9.288015
Number of coefficients	186

Appendix 3: The Results of VECM Lag Exclusion Test

The results of VECM Lag exclusion test are presented below. The Wald statistic for the joint significance of all macro variables at that lag is reported for each equation separately and jointly (last column) for each lag.

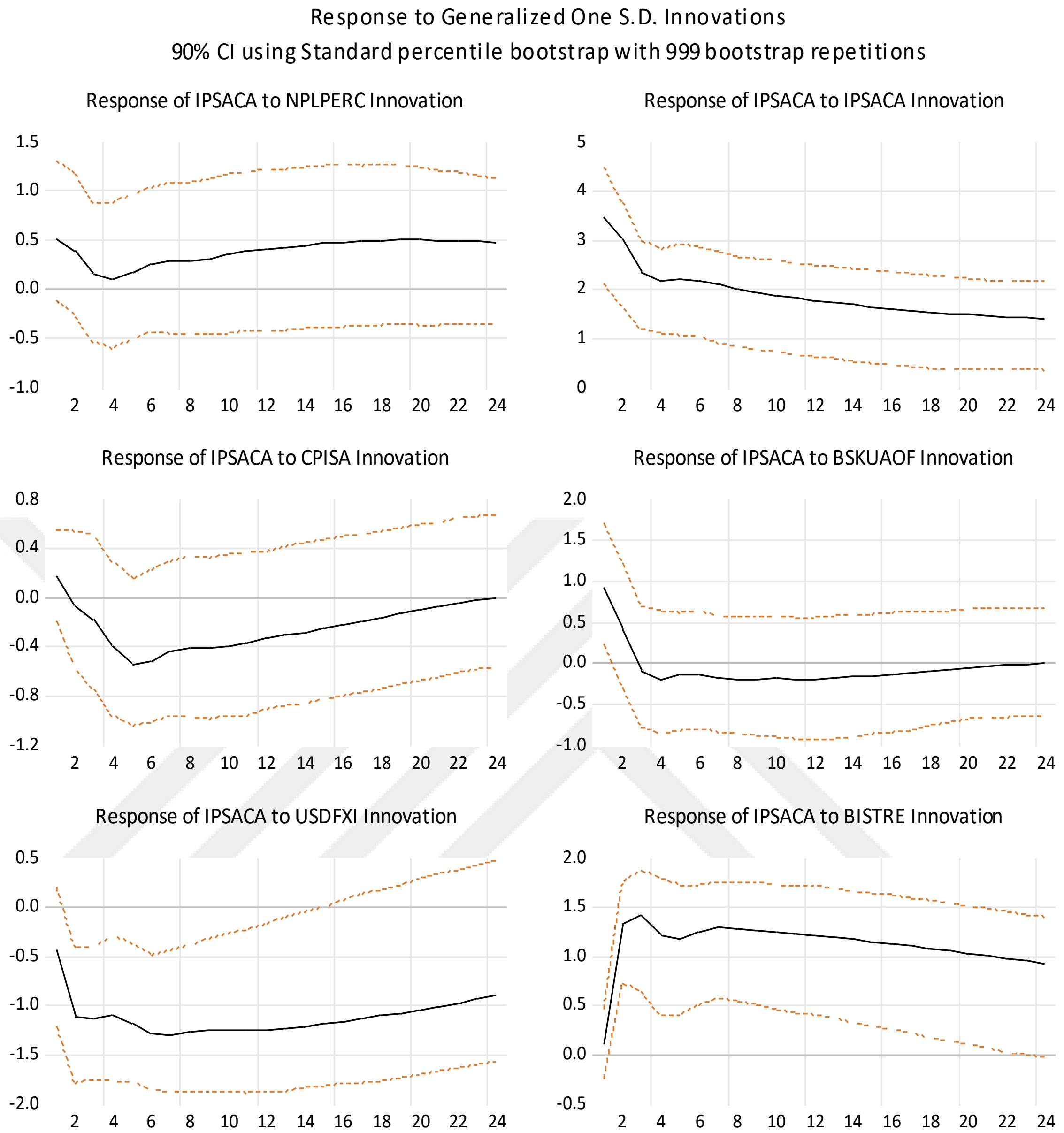
VECM Lag Exclusion Wald Test

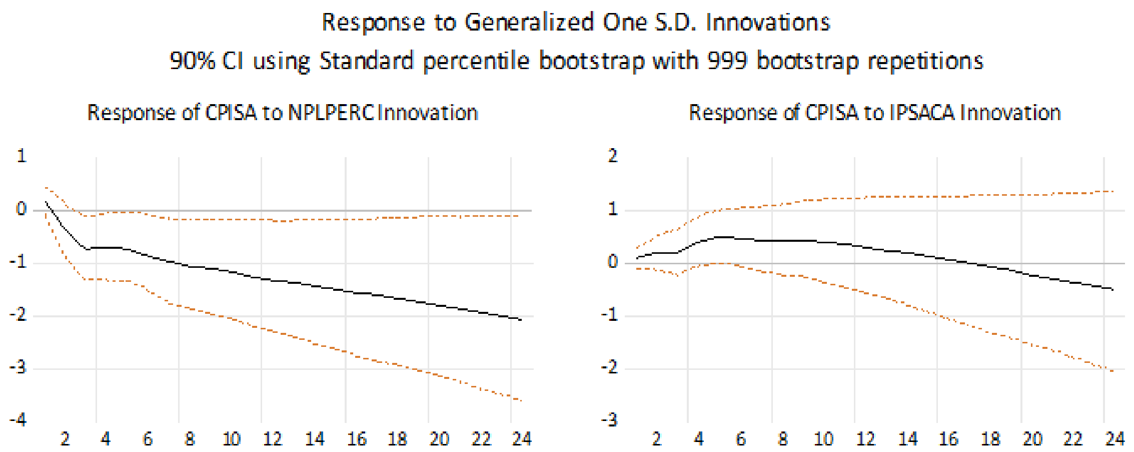
VEC Lag Exclusion Wald Tests
Date: 11/14/21 Time: 20:12
Sample (adjusted): 2005M04 2021M08
Included observations: 193 after adjustments

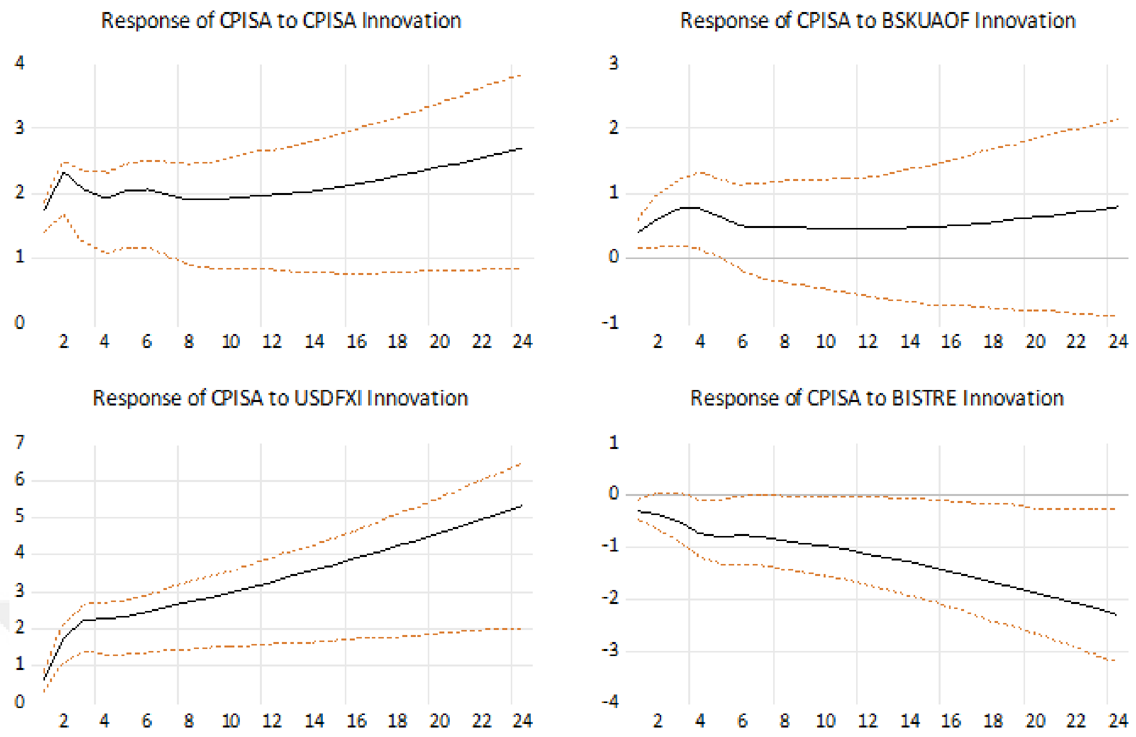
Chi-squared test statistics for lag exclusion:
Numbers in [ ] are p-values

	D(NPLPERC)	D(IPSACA)	D(CPISA)	D(BSKUAOF)	D(USDFXI)	D(BISTRE)	Joint
DLag 1	35.46910	5.355878	64.26398	101.2633	86.53824	6.329579	288.9985
	[0.0000]	[0.4990]	[0.0000]	[0.0000]	[0.0000]	[0.3873]	[0.0000]
DLag 2	10.56457	8.829147	11.18883	26.09531	26.93070	5.765462	96.49025
	[0.1028]	[0.1834]	[0.0827]	[0.0002]	[0.0001]	[0.4500]	[0.0000]
df	6	6	6	6	6	6	36

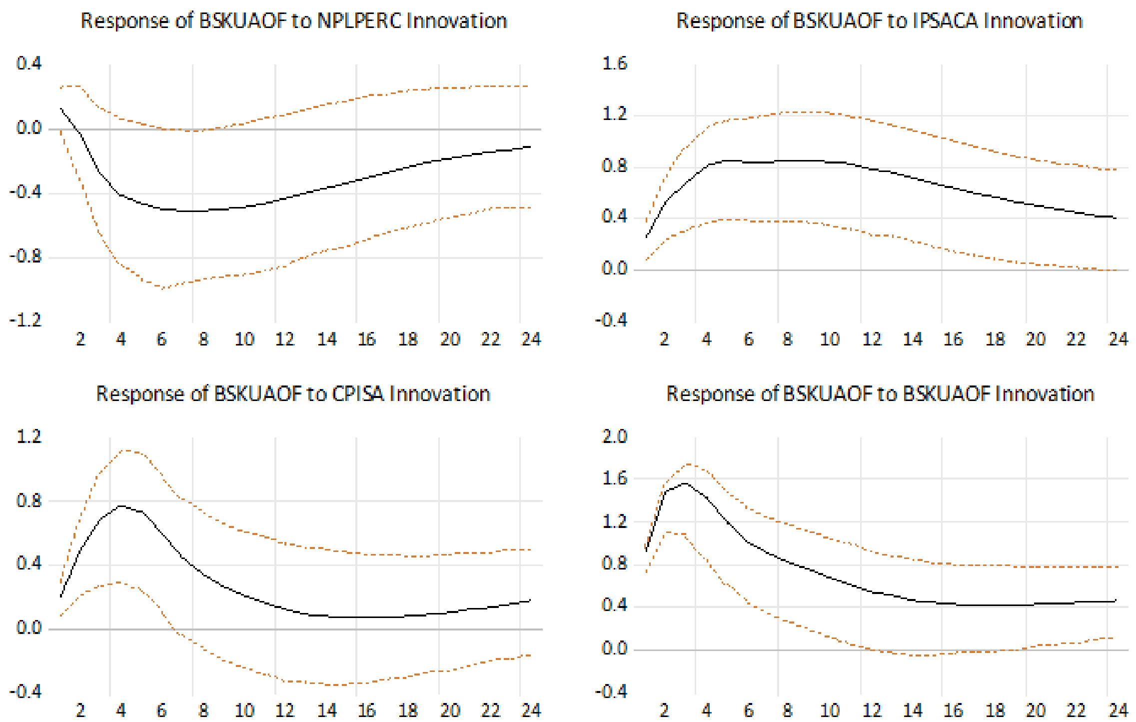
Appendix 4: Impulse Response Functions (Main Model)

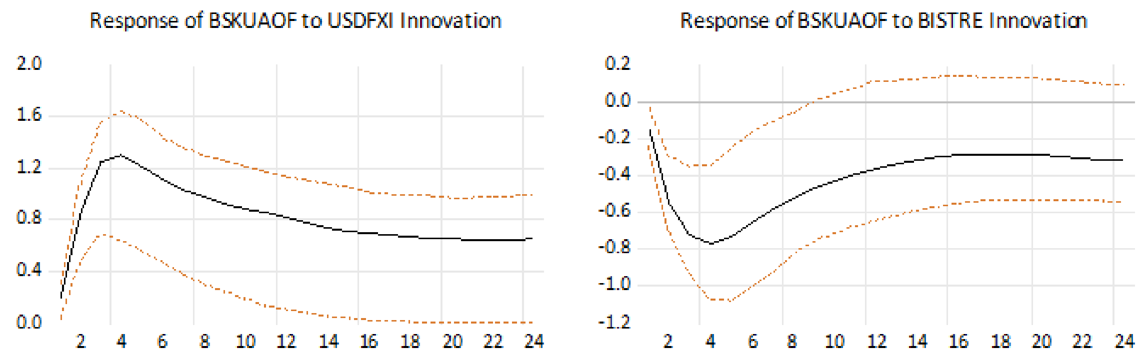




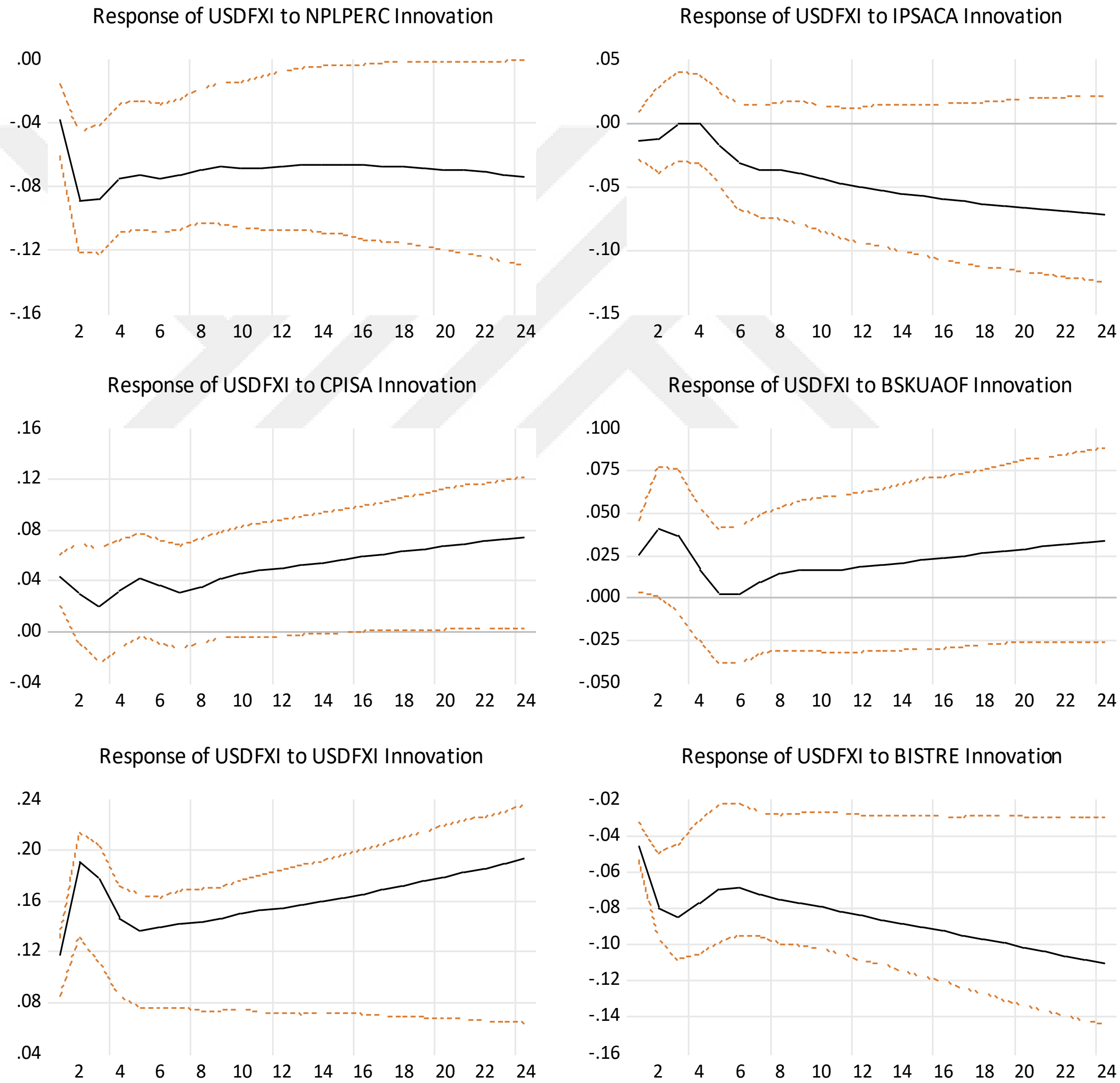


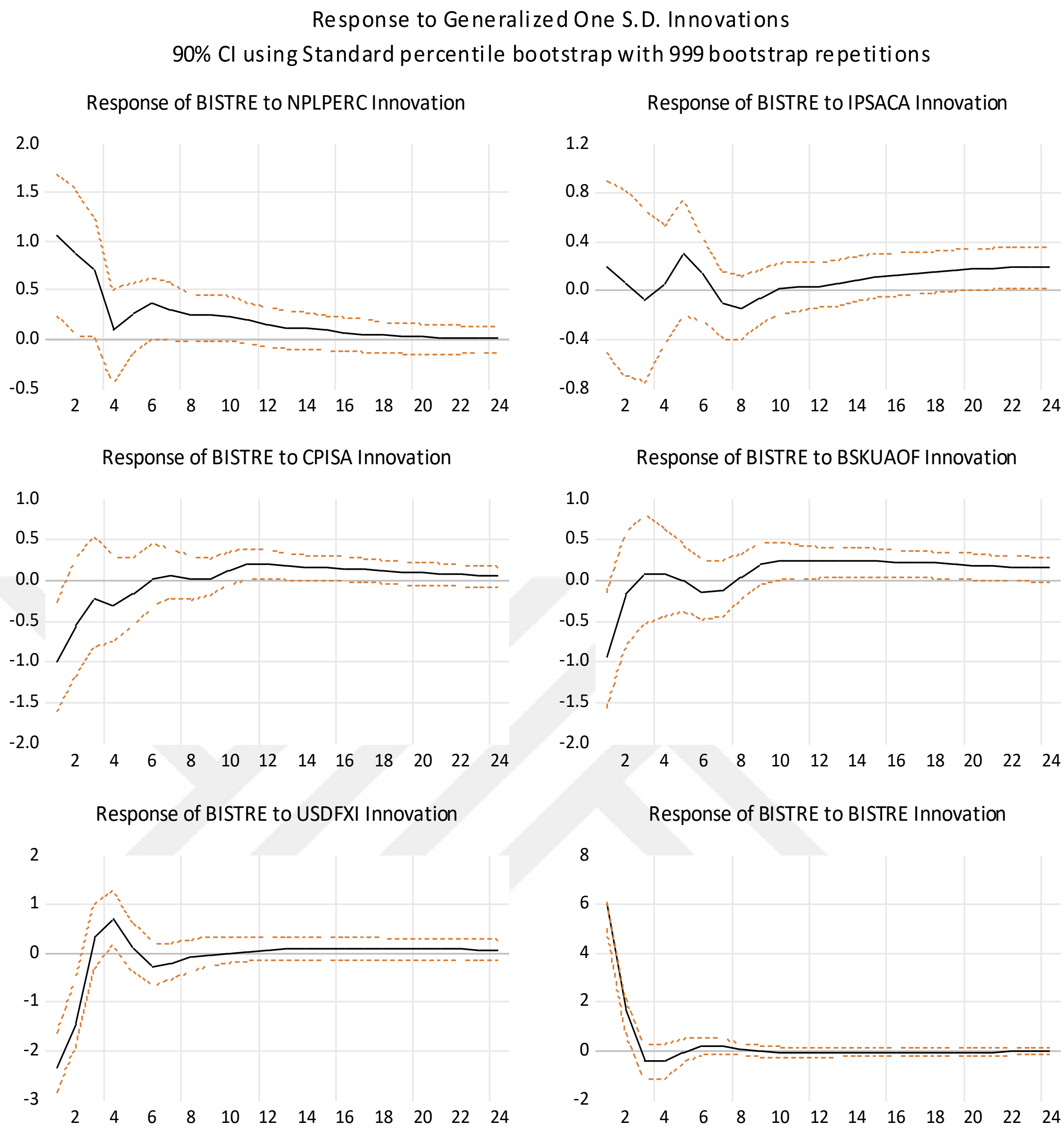
Response to Generalized One S.D. Innovations
90% CI using Standard percentile bootstrap with 999 bootstrap repetitions





Response to Generalized One S.D. Innovations
90% CI using Standard percentile bootstrap with 999 bootstrap repetitions




Response to Generalized One S.D. Innovations
90% CI using Standard percentile bootstrap with 999 bootstrap repetitions
Response of BISTRE to NPLPERC Innovation
Response of BISTRE to IPSACA Innovation
Response of BISTRE to CPISA Innovation
Response of BISTRE to BSKUAOF Innovation
Response of BISTRE to USDFXI Innovation
Response of BISTRE to BISTRE Innovation

Appendix 5: Variance Decomposition Functions (Main Model)

Variance Decomposition of NPLPERC:

Period	S.E.	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
1	0.000943	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.001541	96.78468	0.277151	0.207185	0.490775	2.229887	0.010321
3	0.002151	89.61277	0.290452	0.480677	2.680878	6.921746	0.013472
4	0.002750	82.43595	0.193904	0.907082	5.845822	10.51565	0.101596
5	0.003336	76.68391	0.134654	1.863340	8.940976	12.11425	0.262869
6	0.003903	71.42804	0.117587	3.419014	11.92197	12.67627	0.437116
7	0.004459	66.05110	0.135717	5.252421	15.05878	12.89241	0.609571
8	0.005012	60.54912	0.219077	7.090291	18.35798	12.99654	0.786993
9	0.005566	55.13410	0.417589	8.861249	21.57833	13.04966	0.959072
10	0.006117	49.98759	0.767016	10.53951	24.49670	13.10256	1.106626
11	0.006662	45.22055	1.280699	12.05507	27.02250	13.20010	1.221083
12	0.007196	40.89030	1.962782	13.33540	29.14748	13.35973	1.304315
13	0.007719	37.01203	2.812637	14.35194	30.88634	13.57719	1.359863
14	0.008228	33.56982	3.820597	15.11423	32.26255	13.84278	1.390021
15	0.008724	30.53063	4.967400	15.64603	33.30993	14.14853	1.397476
16	0.009205	27.85552	6.228423	15.97414	34.06873	14.48703	1.386156
17	0.009673	25.50518	7.577374	16.12760	34.57950	14.84992	1.360425
18	0.010126	23.44208	8.987681	16.13707	34.88035	15.22859	1.324221
19	0.010567	21.63120	10.43332	16.03214	35.00693	15.61556	1.280842
20	0.010994	20.04053	11.89003	15.83933	34.99226	16.00482	1.233029
21	0.011409	18.64126	13.33649	15.58155	34.86610	16.39158	1.183011
22	0.011812	17.40780	14.75484	15.27824	34.65450	16.77211	1.132518
23	0.012203	16.31763	16.13069	14.94552	34.37974	17.14359	1.082818
24	0.012583	15.35113	17.45299	14.59640	34.06061	17.50408	1.034796

Variance Decomposition of IPSACA:

Period	S.E.	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
1	3.453224	2.263666	97.73633	0.000000	0.000000	0.000000	0.000000
2	4.776289	1.876028	90.41183	0.207412	0.554982	2.216695	4.733051
3	5.546662	1.476346	85.13551	0.408050	1.971886	3.567136	7.441068
4	6.126664	1.238046	82.59422	0.971896	2.891947	4.108266	8.195625
5	6.658372	1.121237	80.82024	1.757602	3.319113	4.568525	8.413281
6	7.157055	1.101706	79.14138	2.274908	3.647653	5.170032	8.664322
7	7.605884	1.116451	77.58184	2.526356	3.987038	5.772232	9.016088
8	8.002057	1.141342	76.25065	2.697286	4.285019	6.262249	9.363452
9	8.357784	1.188619	75.14101	2.853220	4.520008	6.665702	9.631437
10	8.684692	1.266666	74.17511	2.974092	4.718590	7.034515	9.831029
11	8.987241	1.368517	73.29538	3.047178	4.901680	7.384846	10.00240
12	9.266623	1.484274	72.48797	3.086496	5.067749	7.710105	10.16341
13	9.524789	1.610593	71.75654	3.106379	5.209401	8.006492	10.31060
14	9.764565	1.747102	71.09910	3.110444	5.326008	8.277270	10.44008
15	9.988323	1.891508	70.50802	3.098442	5.421457	8.525959	10.55462
16	10.19765	2.039930	69.97697	3.072352	5.498864	8.753404	10.65848
17	10.39381	2.189132	69.50251	3.035736	5.559683	8.959431	10.75351
18	10.57809	2.337014	69.08189	2.991526	5.605201	9.144347	10.84002
19	10.75171	2.481835	68.71179	2.941704	5.637203	9.308800	10.91867
20	10.91571	2.621829	68.38880	2.887926	5.657599	9.453287	10.99056
21	11.07097	2.755414	68.10984	2.831776	5.668066	9.578151	11.05675
22	11.21825	2.881416	67.87216	2.774645	5.670046	9.683811	11.11792
23	11.35827	2.999021	67.67303	2.717639	5.664856	9.770848	11.17461
24	11.49164	3.107664	67.50972	2.661624	5.653703	9.839954	11.22734

Variance Decomposition of CPISA:

Period	S.E.	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
1	1.759444	0.829862	0.131248	99.03889	0.000000	0.000000	0.000000
2	3.147912	1.865909	0.617589	88.33515	0.199621	7.010592	1.971136
3	4.151424	4.373928	0.840957	76.99243	0.991733	14.16725	2.633697
4	4.928997	5.316025	1.596919	70.91075	1.268886	18.77106	2.136366
5	5.648567	5.770508	2.395785	67.70105	1.064075	21.34013	1.728448
6	6.348885	6.438850	2.800602	64.95075	0.848585	23.43911	1.522100
7	7.014713	7.299368	2.963305	61.85986	0.699444	25.76559	1.412429
8	7.649682	8.102202	3.064657	58.78648	0.597458	28.14182	1.307386
9	8.273270	8.782044	3.125925	56.05751	0.519182	30.31150	1.203842
10	8.899121	9.395346	3.112965	53.66748	0.454206	32.25861	1.111393
11	9.529601	9.974213	3.025733	51.50555	0.401394	34.06669	1.026416
12	10.16341	10.50624	2.890198	49.52823	0.360303	35.77179	0.943244
13	10.80169	10.97733	2.726950	47.74102	0.329449	37.36348	0.861765
14	11.44765	11.39009	2.546423	46.13725	0.307269	38.83495	0.784017
15	12.10412	11.75329	2.356328	44.69019	0.293222	40.19588	0.711088
16	12.77281	12.07236	2.164545	43.37381	0.287451	41.45843	0.643399
17	13.45498	12.35011	1.977774	42.17194	0.289989	42.62875	0.581441
18	14.15195	12.58987	1.800709	41.07320	0.300584	43.70989	0.525748
19	14.86505	12.79597	1.636514	40.06590	0.318967	44.70597	0.476674
20	15.59546	12.97262	1.487337	39.13827	0.344956	45.62242	0.434395
21	16.34413	13.12336	1.354493	38.28029	0.378335	46.46455	0.398967
22	17.11191	13.25135	1.238571	37.48386	0.418746	47.23714	0.370331
23	17.89960	13.35956	1.139592	36.74209	0.465724	47.94472	0.348313
24	18.70790	13.45073	1.057170	36.04881	0.518759	48.59188	0.332652

Variance Decomposition of BSKUAOF:

Period	S.E.	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
1	0.916019	1.728633	6.138918	4.096700	88.03575	0.000000	0.000000
2	1.851025	0.459581	9.817151	7.554563	74.28293	7.343953	0.541824
3	2.653173	1.379757	12.34183	10.38905	62.93341	12.43793	0.518013
4	3.267189	2.522703	15.46992	12.61532	54.25355	14.51670	0.621821
5	3.716805	3.567325	18.24658	13.78080	48.23450	15.45720	0.713587
6	4.058478	4.549742	20.50274	13.86420	44.12983	16.21537	0.738110
7	4.340452	5.397027	22.48204	13.28072	41.12780	16.99370	0.718707
8	4.587768	6.071702	24.31114	12.47872	38.69594	17.76509	0.677401
9	4.808836	6.607995	25.96414	11.69316	36.59374	18.51195	0.629010
10	5.006180	7.045132	27.38492	10.98971	34.75409	19.24247	0.583682
11	5.181497	7.394171	28.56507	10.37337	33.16520	19.95673	0.545460
12	5.336728	7.654723	29.53262	9.841319	31.81231	20.64478	0.514246
13	5.474076	7.833519	30.31778	9.388707	30.66979	21.30143	0.488769
14	5.595871	7.944371	30.94242	9.006298	29.70884	21.93028	0.467786
15	5.704367	8.001210	31.42582	8.682907	28.90275	22.53708	0.450241
16	5.801581	8.015290	31.78813	8.408354	28.22820	23.12473	0.435304
17	5.889271	7.995918	32.04850	8.174519	27.66515	23.69347	0.422444
18	5.969011	7.951116	32.22296	7.975163	27.19653	24.24284	0.411394
19	6.042246	7.887517	32.32442	7.805502	26.80799	24.77251	0.402059
20	6.110287	7.810273	32.36370	7.661921	26.48750	25.28213	0.394465
21	6.174290	7.723286	32.35006	7.541786	26.22492	25.77125	0.388704
22	6.235250	7.629510	32.29135	7.443201	26.01162	26.23944	0.384884
23	6.294005	7.531163	32.19424	7.364707	25.84025	26.68656	0.383088
24	6.351245	7.429875	32.06445	7.305021	25.70456	27.11274	0.383358

Variance Decomposition of USDFXI:

Period	S.E.	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
1	0.117612	10.83153	0.581985	15.96116	4.332605	68.29272	0.000000
2	0.229217	18.04873	0.153316	7.014639	5.441913	69.29145	0.049946
3	0.295897	19.65952	0.294466	5.104363	5.217370	69.36463	0.359644
4	0.333655	20.59192	0.327822	5.420402	4.360029	68.57518	0.724646
5	0.362989	21.47464	0.311662	6.381735	3.694268	67.28086	0.856842
6	0.391072	22.21909	0.563129	6.782484	3.233885	66.29889	0.902522
7	0.418107	22.51670	0.880978	6.801982	3.034001	65.77530	0.991041
8	0.443698	22.45096	1.148125	6.931353	2.977130	65.37452	1.117921
9	0.468578	22.23559	1.422729	7.308816	2.927737	64.87584	1.229293
10	0.493390	21.97017	1.753326	7.784652	2.876701	64.29381	1.321341
11	0.518044	21.66329	2.126865	8.223152	2.850192	63.71861	1.417887
12	0.542321	21.31113	2.511043	8.624727	2.852168	63.17471	1.526228
13	0.566289	20.92880	2.892704	9.027058	2.872197	62.64333	1.635916
14	0.590162	20.53568	3.271128	9.435295	2.904392	62.11477	1.738728
15	0.614069	20.14297	3.642878	9.835060	2.948635	61.59502	1.835437
16	0.638035	19.75569	4.001114	10.21949	3.004131	61.09046	1.929108
17	0.662067	19.37792	4.341024	10.59087	3.067862	60.60212	2.020198
18	0.686189	19.01389	4.661021	10.95077	3.136978	60.12980	2.107535
19	0.710433	18.66668	4.960593	11.29718	3.210004	59.67506	2.190477
20	0.734818	18.33783	5.239061	11.62777	3.286079	59.24008	2.269177
21	0.759353	18.02798	5.495960	11.94184	3.364154	58.82621	2.343854
22	0.784048	17.73739	5.731517	12.23961	3.443045	58.43395	2.414499
23	0.808913	17.46605	5.946536	12.52111	3.521754	58.06347	2.481078
24	0.833956	17.21361	6.142073	12.78622	3.599551	57.71487	2.543685

Variance Decomposition of BISTRE:

Period	S.E.	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
1	6.030858	3.090678	0.003628	3.364926	2.258538	7.572115	83.71012
2	6.338081	4.734325	0.019919	4.038036	2.093950	9.648623	79.46515
3	6.445464	5.787444	0.099654	4.114043	2.051458	10.75006	77.19734
4	6.539219	5.643282	0.100255	4.239322	2.029827	12.88012	75.10720
5	6.564357	5.777169	0.265972	4.309154	2.023276	13.08677	74.53766
6	6.580233	6.061143	0.280465	4.288672	2.135845	13.04964	74.18423
7	6.592874	6.255866	0.329650	4.276891	2.182464	13.04516	73.90997
8	6.600413	6.382090	0.406171	4.267254	2.184674	13.01820	73.74161
9	6.608580	6.504068	0.426791	4.256795	2.263532	12.98606	73.56275
10	6.617135	6.614719	0.427035	4.269354	2.358569	12.95277	73.37755
11	6.625216	6.685275	0.425995	4.330616	2.435301	12.92159	73.20123
12	6.632272	6.722561	0.425290	4.401053	2.509147	12.89412	73.04783
13	6.638550	6.745030	0.427014	4.455365	2.589025	12.87026	72.91331
14	6.644469	6.760194	0.436092	4.499761	2.668280	12.84817	72.78751
15	6.650062	6.768278	0.455344	4.540864	2.739879	12.82775	72.66788
16	6.655276	6.769762	0.484619	4.576916	2.803395	12.80979	72.55551
17	6.660177	6.766873	0.524124	4.604819	2.860183	12.79444	72.44956
18	6.664876	6.761558	0.574478	4.624905	2.910114	12.78108	72.34787
19	6.669436	6.754847	0.635096	4.639033	2.952721	12.76913	72.24917
20	6.673875	6.747298	0.704202	4.648462	2.988532	12.75839	72.15312
21	6.678215	6.739298	0.779978	4.653914	3.018695	12.74875	72.05936
22	6.682480	6.731113	0.861018	4.656165	3.044221	12.74000	71.96748
23	6.686681	6.722897	0.946024	4.656073	3.065828	12.73191	71.87727
24	6.690815	6.714746	1.033627	4.654352	3.084132	12.72433	71.78881

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: NPLPERC IPSACA CPISA BSKUAOF USDFXI BISTRE

Appendix 6: The Descriptive Statistics and Residual Checks Results of Candidate Model One

The Descriptive Statistics of Variables, Level

	NPLPERC	TITISACA	RSCISA	BSKUAOF	USDFXI
Mean	0.0390	116.4402	103.3824	17.2149	3.0957
Median	0.0352	89.2452	105.8000	16.2130	2.1413
Maximum	0.0665	414.9344	117.0000	37.6825	8.6069
Minimum	0.0282	37.5195	59.8000	9.9950	1.1696
Srd. Dev.	0.0110	84.4879	10.0433	4.9002	2.0363
Skewness	1.0094	1.4971	-2.6126	1.4087	1.1957
Kurtosis	3.0825	4.8431	10.8302	5.8032	3.2458
Sum	6.881	20493.480	18195.300	3029.830	544.853
Sum Sq. Dev.	0.012	1249187.000	17651.980	4202.109	735.665
Observations	176	176	176	176	176

The Descriptive Statistics of Variables, First Difference

	NPLPERC1	TITISACA1	RSCI1	BSKUAOF1	USDFXI1
Mean	-0.0001	0.0144	0.0012	0.0017	0.0109
Median	-0.0006	0.0157	0.0028	-0.0072	0.0096
Maximum	0.1327	0.1874	0.2217	0.3076	0.2068
Minimum	-0.0892	-0.2774	-0.3681	-0.2137	-0.0829
Srd. Dev.	0.0329	0.0423	0.0532	0.0678	0.0386
Skewness	0.5387	-1.1928	-1.3127	1.0869	1.4111
Kurtosis	4.5192	17.2936	19.5887	7.0942	8.5952
Sum	-0.0313	2.5305	0.2240	0.3145	1.9220
Sum Sq. Dev.	0.1890	0.3111	0.4927	0.8003	0.2603
Observations	175	175	175	175	175

VECM Stability Condition Check

Roots of Characteristic Polynomial
Endogenous variables: NPLPERC TITISACA
RSCI BSKUAOF USDFXI
Exogenous variables:
Lag specification: 1 3
Date: 11/07/21 Time: 21:11

Root	Modulus
1.038986	1.038986
1.000000	1.000000
1.000000	1.000000
1.000000	1.000000
0.825618 - 0.161248i	0.841217
0.825618 + 0.161248i	0.841217
0.205390 + 0.677814i	0.708249
0.205390 - 0.677814i	0.708249
0.474883 - 0.484789i	0.678627
0.474883 + 0.484789i	0.678627
-0.661787	0.661787
0.516413 - 0.370306i	0.635459
0.516413 + 0.370306i	0.635459
-0.352182 - 0.462486i	0.581313
-0.352182 + 0.462486i	0.581313
-0.173000 - 0.533029i	0.560401
-0.173000 + 0.533029i	0.560401
-0.036671 - 0.355075i	0.356964
-0.036671 + 0.355075i	0.356964
-0.004654	0.004654

VEC specification imposes 3 unit root(s).

The Residual Covariance Matrix

	NPLPERC	TITISACA	RSCI	BSKUAOF	USDFXI
NPLPERC	8.0612	0.0002	0.0001	1.9859	-3.5724
TITISACA	0.0002	53.0119	15.8538	1.8074	0.1470
RSCI	0.0001	15.8538	20.0558	-0.2637	-0.2004
BSKUAOF	1.9859	1.8074	-0.2637	0.8330	0.0275
USDFXI	-3.5724	0.1470	-0.2004	0.0274	0.0174

The Residual Correlation Matrix

	NPLPERC	TITISACA	RSCI	BSKUAOF	USDFXI
NPLPERC	1	0.0327	0.0432	0.0242	-0.3019
TITISACA	0.0327	1	0.4862	0.2719	0.1532
RSCI	0.0432	0.4862	1	-0.0645	-0.3397
BSKUAOF	0.0242	0.2719	-0.0645	1	0.2286
USDFXI	-0.3019	0.1532	-0.3397	0.2286	1

VECM Residual Serial Correlation LM Tests

VEC Residual Serial Correlation LM Tests
Date: 11/07/21 Time: 21:12
Sample: 2007M01 2021M08
Included observations: 172

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	38.39203	25	0.0423	1.557226	(25, 540.2)	0.0424
2	42.71574	25	0.0150	1.739488	(25, 540.2)	0.0151
3	49.22256	25	0.0027	2.016483	(25, 540.2)	0.0027
4	39.40865	25	0.0335	1.599953	(25, 540.2)	0.0336

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	38.39203	25	0.0423	1.557226	(25, 540.2)	0.0424
2	70.29419	50	0.0307	1.429330	(50, 641.9)	0.0309
3	103.8976	75	0.0153	1.416067	(75, 650.8)	0.0156
4	130.1592	100	0.0230	1.330814	(100, 638.9)	0.0238

*Edgeworth expansion corrected likelihood ratio statistic.

VECM Residual Normality Tests

VEC Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: Residuals are multivariate normal
Date: 11/07/21 Time: 21:13
Sample: 2007M01 2021M08
Included observations: 172

Component	Skewness	Chi-sq	df	Prob.*
1	-0.111726	0.357840	1	0.5497
2	-4.834820	670.0972	1	0.0000
3	-0.678700	13.20484	1	0.0003
4	0.051335	0.075546	1	0.7834
5	0.504907	7.308029	1	0.0069
Joint		691.0435	5	0.0000

Component	Kurtosis	Chi-sq	df	Prob.
1	3.542035	2.105577	1	0.1468
2	49.56324	15538.31	1	0.0000
3	5.850210	58.21982	1	0.0000
4	5.708978	52.59302	1	0.0000
5	7.811896	165.9395	1	0.0000
Joint		15817.16	5	0.0000

Component	Jarque-Bera	df	Prob.
1	2.463418	2	0.2918
2	16208.40	2	0.0000
3	71.42466	2	0.0000
4	52.66857	2	0.0000
5	173.2475	2	0.0000
Joint	16508.21	10	0.0000

*Approximate p-values do not account for coefficient estimation

VECM Residual Heteroskedasticity Tests (Levels and Squares) (White Heteroskedasticity)

VEC Residual Heteroskedasticity Tests (Levels and Squares)
Date: 11/07/21 Time: 21:13
Sample: 2007M01 2021M08
Included observations: 172

Joint test:

Chi-sq	df	Prob.
961.5214	510	0.0000

Individual components:

Dependent	R-squared	F(34,137)	Prob.	Chi-sq(34)	Prob.
res1*res1	0.359344	2.260099	0.0005	61.80719	0.0025
res2*res2	0.317310	1.872848	0.0062	54.57737	0.0141
res3*res3	0.311456	1.822666	0.0084	53.57047	0.0176
res4*res4	0.338332	2.060370	0.0019	58.19316	0.0060
res5*res5	0.431854	3.062800	0.0000	74.27889	0.0001
res2*res1	0.320589	1.901331	0.0052	55.14131	0.0124
res3*res1	0.278924	1.558640	0.0394	47.97487	0.0565
res3*res2	0.314224	1.846286	0.0073	54.04656	0.0158
res4*res1	0.311936	1.826751	0.0082	53.65308	0.0173
res4*res2	0.357127	2.238407	0.0006	61.42583	0.0027
res4*res3	0.257427	1.396873	0.0927	44.27746	0.1116
res5*res1	0.432695	3.073317	0.0000	74.42359	0.0001
res5*res2	0.391198	2.589181	0.0001	67.28607	0.0006
res5*res3	0.338532	2.062206	0.0019	58.22747	0.0060
res5*res4	0.328610	1.972180	0.0033	56.52084	0.0090

Appendix 7: Unit Root Test results of Candidate Model One

	Level		First Difference	
Variables	**ADF Unit Root Test**	**KPSS Unit Root Test**	**ADF Unit Root Test**	**KPSS Unit Root Test**
NPLPERC	-2.955046	0.232691***	-3.803987**	0.059507
TITISACA	2.211656	0.346669***	-12.50126***	0.062493
RSCI	-3.946864**	0.076608	-10.62086***	0.034581
BSKUAOF	-3.003187	0.201057**	-7.516706***	0.028483
USDFXI	-0.235765	0.403493***	-10.12361***	0.026952

Note: *** denotes significant at 1%; ** denotes significant at 5%; * denotes significant at 10%.

Appendix 8: Johansen Cointegration Test Results of Candidate Model One

Date: 11/07/21 Time: 21:09
Sample: 2007M01 2021M08
Included observations: 171
Series: NPLPERC TITISACA RSCI BSKUAOF USDFXI
Lags interval: 1 to 4

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	1	2	2	2	2
Max-Eig	1	2	2	2	2

*Critical values based on MacKinnon-Haug-Michelis (1999)

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or	No Intercept	Intercept	Intercept	Intercept	Intercept
No. of CEs	No Trend	No Trend	No Trend	Trend	Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	-159.9473	-159.9473	-152.0558	-152.0558	-138.0866
1	-122.0027	-121.3240	-120.3476	-117.6214	-114.1437
2	-112.4569	-100.8573	-100.0140	-96.22634	-92.93738
3	-109.1620	-95.10521	-94.37163	-86.82016	-84.94626
4	-107.2397	-92.15829	-91.43312	-82.03343	-80.22550
5	-106.8575	-91.24615	-91.24615	-79.28051	-79.28051
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	3.040320	3.040320	3.006500	3.006500	2.901597
1	2.713482	2.717240	2.752604	2.732414	2.738523
2	2.718795	2.606518*	2.631743	2.610834	2.607455
3	2.797216	2.667897	2.682709	2.629476	2.630950
4	2.891692	2.762085	2.765300	2.702145	2.692696
5	3.004182	2.880072	2.880072	2.798602	2.798602
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	4.877550	4.877550	4.935592	4.935592	4.922550
1	4.734435*	4.756565	4.865418	4.863601	4.943199
2	4.923471	4.847939	4.928280	4.944117	4.995854
3	5.185615	5.111413	5.162970	5.164853	5.203073
4	5.463815	5.407697	5.429283	5.439618	5.448541
5	5.760027	5.727779	5.727779	5.738171	5.738171

Appendix 9: Lag Length Selection of Candidate Model One

VAR Lag Order Selection Criteria
Endogenous variables: NPLPERC1 TITISACA1 RSCI1 BSKUAOF1 USDFXI1
Exogenous variables: C
Date: 11/07/21 Time: 21:03
Sample: 2007M02 2021M08
Included observations: 167

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1453.396	NA	2.02e-14	-17.34606	-17.25271	-17.30817
1	1578.169	240.5793	6.10e-15	-18.54094	-17.98083*	-18.31360*
2	1613.986	66.91617	5.36e-15	-18.67049	-17.64361	-18.25370
3	1646.044	57.97245	4.94e-15	-18.75502	-17.26137	-18.14878
4	1671.705	44.86841*	4.92e-15*	-18.76293*	-16.80252	-17.96724
5	1686.173	24.43179	5.61e-15	-18.63681	-16.20963	-17.65167
6	1705.474	31.43583	6.07e-15	-18.56855	-15.67460	-17.39396
7	1721.178	24.63684	6.87e-15	-18.45722	-15.09650	-17.09318
8	1738.302	25.84076	7.67e-15	-18.36290	-14.53542	-16.80941

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix 10: The Estimation Results of Candidate Model One

Vector Error Correction Estimates
Date: 11/07/21 Time: 21:11
Sample (adjusted): 2007M05 2021M08
Included observations: 172 after adjustments
Standard errors in ( ) & t-statistics in [ ]

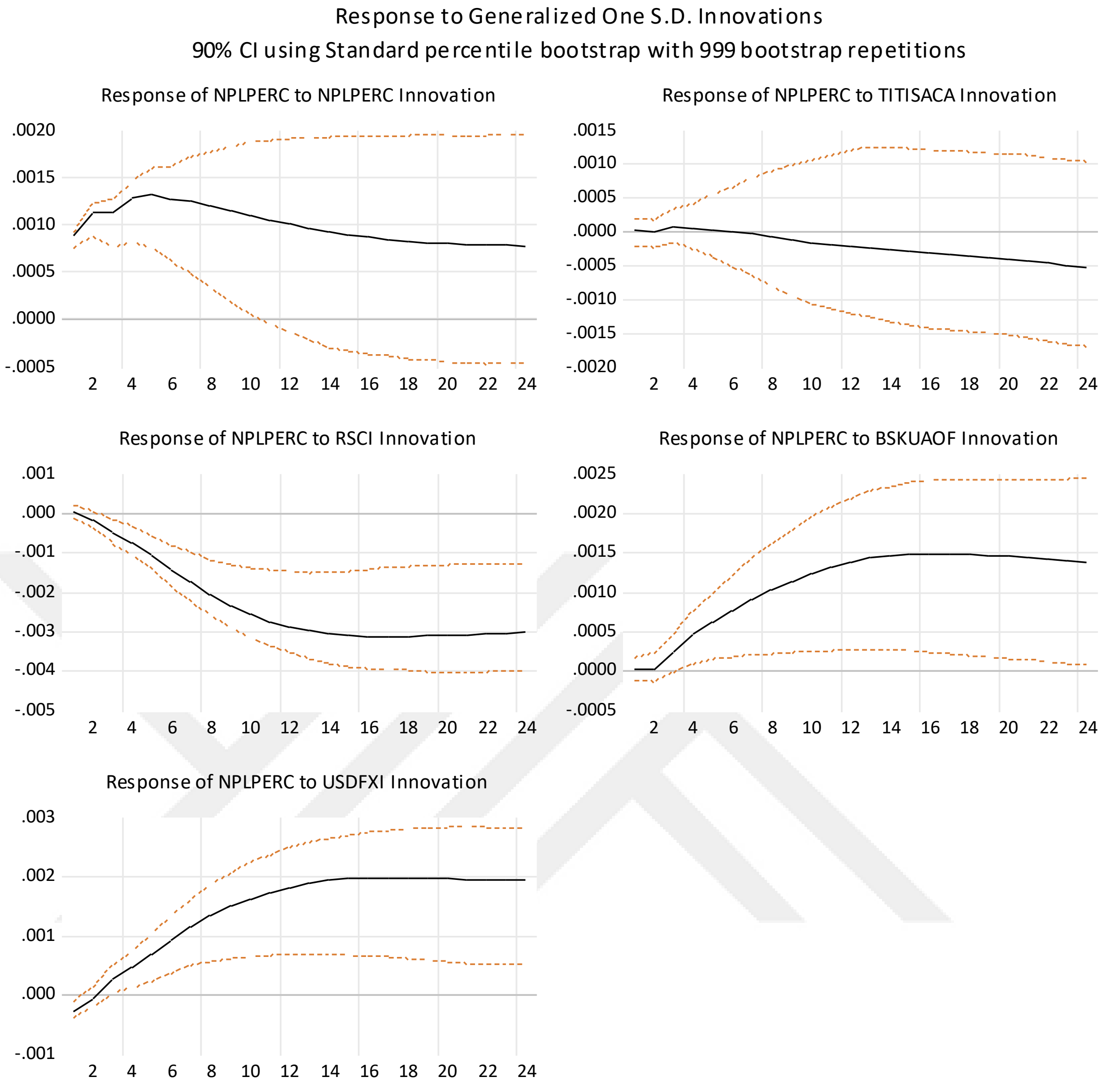
Cointegrating Eq:	CointEq1	CointEq2
NPLPERC(-1)	1.000000	0.000000
TITISACA(-1)	0.000000	1.000000
RSCI(-1)	0.001686	-2.500593
	(0.00025)	(0.78551)
	[6.77106]	[-3.18341]
BSKUAOF(-1)	-0.000675	0.204212
	(0.00054)	(1.70639)
	[-1.24787]	[0.11967]
USDFXI(-1)	-0.001614	-14.93578
	(0.00127)	(4.01300)
	[-1.26865]	[-3.72185]
C	-0.196333	184.5679

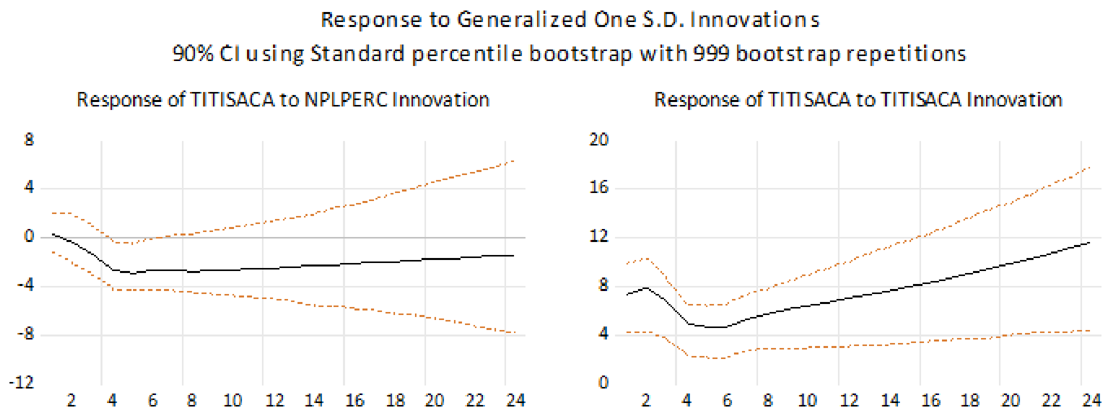
Error Correction:	D(NPLPERC)	D(TITISACA)	D(RSCI)	D(BSKUAOF)	D(USDFXI)
CointEq1	-0.029457	-72.21194	-90.94369	-20.15574	-0.742244
	(0.00676)	(54.8308)	(33.7255)	(6.87388)	(0.99237)
	[-4.35655]	[-1.31700]	[-2.69659]	[-2.93222]	[-0.74795]
CointEq2	-4.75E-06	0.066241	0.008409	-0.007360	0.000388
	(2.0E-06)	(0.01600)	(0.00984)	(0.00201)	(0.00029)
	[-2.40520]	[4.13976]	[0.85444]	[-3.66881]	[1.34031]
D(NPLPERC(-1))	0.404902	-657.6933	-67.66090	-154.0339	-42.00516
	(0.08015)	(649.935)	(399.764)	(81.4793)	(11.7630)
	[5.05204]	[-1.01194]	[-0.16925]	[-1.89047]	[-3.57096]
D(NPLPERC(-2))	0.013199	-689.1627	-128.9516	-153.7117	22.72724
	(0.08498)	(689.097)	(423.851)	(86.3888)	(12.4718)
	[0.15532]	[-1.00010]	[-0.30424]	[-1.77930]	[1.82229]
D(NPLPERC(-3))	0.259401	-1438.961	-456.4897	110.6142	-0.249147
	(0.07891)	(639.896)	(393.589)	(80.2207)	(11.5813)
	[3.28737]	[-2.24874]	[-1.15981]	[1.37887]	[-0.02151]
D(TITISACA(-1))	6.48E-06	-0.021413	0.085130	0.041008	0.000513
	(1.3E-05)	(0.10427)	(0.06414)	(0.01307)	(0.00189)
	[0.50392]	[-0.20535]	[1.32731]	[3.13704]	[0.27167]
D(TITISACA(-2))	3.07E-05	-0.150730	-0.199696	0.026486	0.001220
	(1.3E-05)	(0.10641)	(0.06545)	(0.01334)	(0.00193)
	[2.33943]	[-1.41647]	[-3.05102]	[1.98538]	[0.63358]

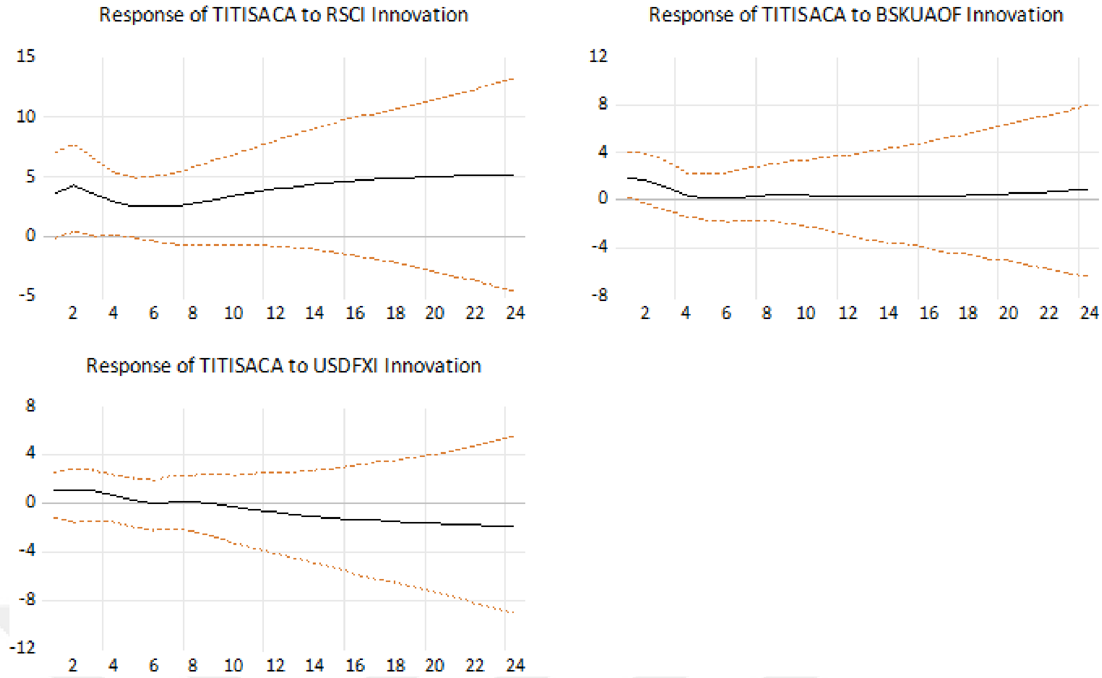
D(TITISACA(-3))	-1.36E-05	-0.214768	-0.056160	0.030744	0.003752
	(1.3E-05)	(0.10903)	(0.06706)	(0.01367)	(0.00197)
	[-1.01292]	[-1.96977]	[-0.83742]	[2.24919]	[1.90117]
D(RSCI(-1))	6.70E-06	0.434987	0.137464	0.013651	0.002839
	(2.1E-05)	(0.17415)	(0.10711)	(0.02183)	(0.00315)
	[0.31216]	[2.49784]	[1.28335]	[0.62530]	[0.90066]
D(RSCI(-2))	-2.63E-05	0.131550	0.270693	-0.021125	-0.002195
	(2.1E-05)	(0.17141)	(0.10543)	(0.02149)	(0.00310)
	[-1.24219]	[0.76748]	[2.56754]	[-0.98309]	[-0.70762]
D(RSCI(-3))	2.22E-05	0.216747	0.174579	0.016348	-0.003759
	(2.1E-05)	(0.17013)	(0.10464)	(0.02133)	(0.00308)
	[1.05879]	[1.27401]	[1.66831]	[0.76650]	[-1.22068]
D(BSKUAOF(-1))	-0.000101	-0.543892	-0.448110	0.466117	0.008954
	(8.0E-05)	(0.64832)	(0.39877)	(0.08128)	(0.01173)
	[-1.26917]	[-0.83893]	[-1.12373]	[5.73495]	[0.76310]
D(BSKUAOF(-2))	0.000141	-0.051353	0.272836	-0.201960	-0.016459
	(8.8E-05)	(0.71719)	(0.44113)	(0.08991)	(0.01298)
	[1.59498]	[-0.07160]	[0.61850]	[-2.24624]	[-1.26798]
D(BSKUAOF(-3))	5.07E-05	-0.281724	-0.567411	-0.038036	-0.009401
	(7.0E-05)	(0.56867)	(0.34978)	(0.07129)	(0.01029)
	[0.72230]	[-0.49541]	[-1.62221]	[-0.53353]	[-0.91346]
D(USDFXI(-1))	0.002032	1.706993	-8.200260	2.521125	0.436423
	(0.00067)	(5.46713)	(3.36274)	(0.68539)	(0.09895)
	[3.01431]	[0.31223]	[-2.43857]	[3.67839]	[4.41062]
D(USDFXI(-2))	-0.000522	2.001987	7.545953	-1.435667	-0.378058
	(0.00072)	(5.80502)	(3.57057)	(0.72775)	(0.10506)
	[-0.72861]	[0.34487]	[2.11338]	[-1.97275]	[-3.59838]
D(USDFXI(-3))	0.000431	-1.855342	1.564463	1.478869	-0.020657
	(0.00068)	(5.49622)	(3.38063)	(0.68903)	(0.09947)
	[0.63656]	[-0.33757]	[0.46277]	[2.14629]	[-0.20766]
C	-0.000141	2.823033	0.291604	-0.307383	0.028138
	(8.8E-05)	(0.71468)	(0.43959)	(0.08960)	(0.01293)
	[-1.60126]	[3.95007]	[0.66336]	[-3.43077]	[2.17538]
R-squared	0.626469	0.267063	0.220699	0.591634	0.411821
Adj. R-squared	0.585235	0.186154	0.134672	0.546555	0.346892
Sum sq. resids	0.000124	8163.845	3088.597	128.3066	2.674178
S.E. equation	0.000898	7.280933	4.478373	0.912776	0.131776
F-statistic	15.19302	3.300791	2.565468	13.12429	6.342649
Log likelihood	972.1178	-576.0154	-492.4235	-218.8532	114.0339
Akaike AIC	-11.09439	6.907155	5.935157	2.754107	-1.116673
Schwarz SC	-10.76500	7.236544	6.264546	3.083496	-0.787284
Mean dependent	-2.87E-05	2.186092	-0.021512	0.002602	0.041369
S.D. dependent	0.001394	8.070787	4.814264	1.355507	0.163058

Determinant resid covariance (dof adj.)	5.44E-06
Determinant resid covariance	3.13E-06
Log likelihood	-130.2378
Akaike information criterion	2.677184
Schwarz criterion	4.507122
Number of coefficients	100

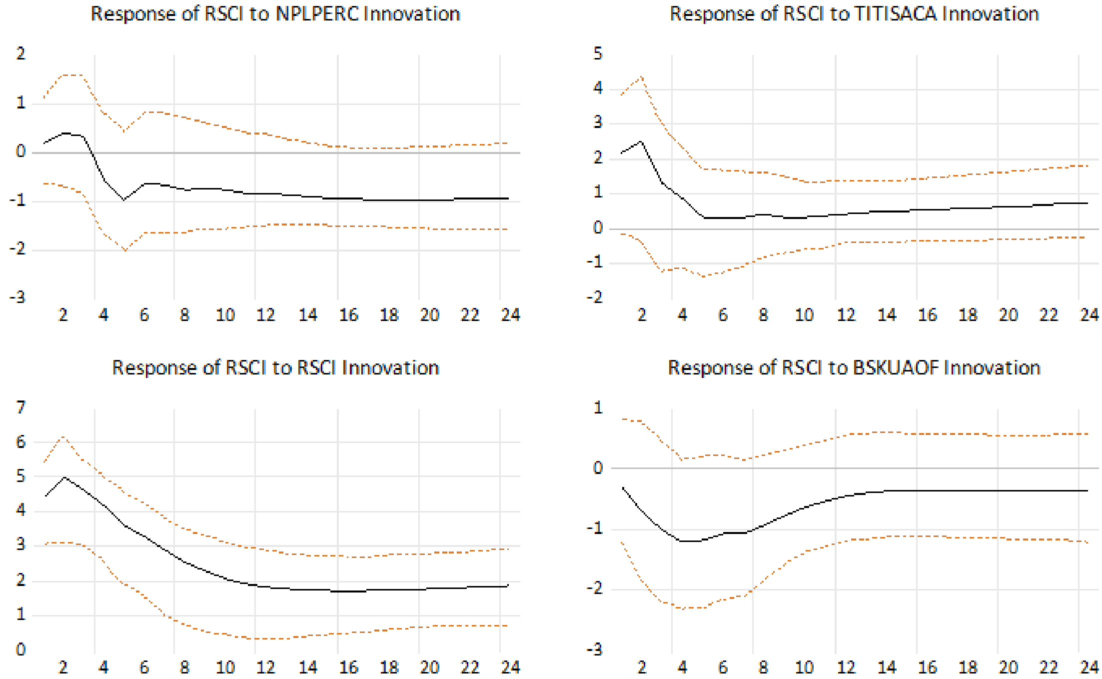
Appendix 11: Impulse Response Functions of Candidate Model One

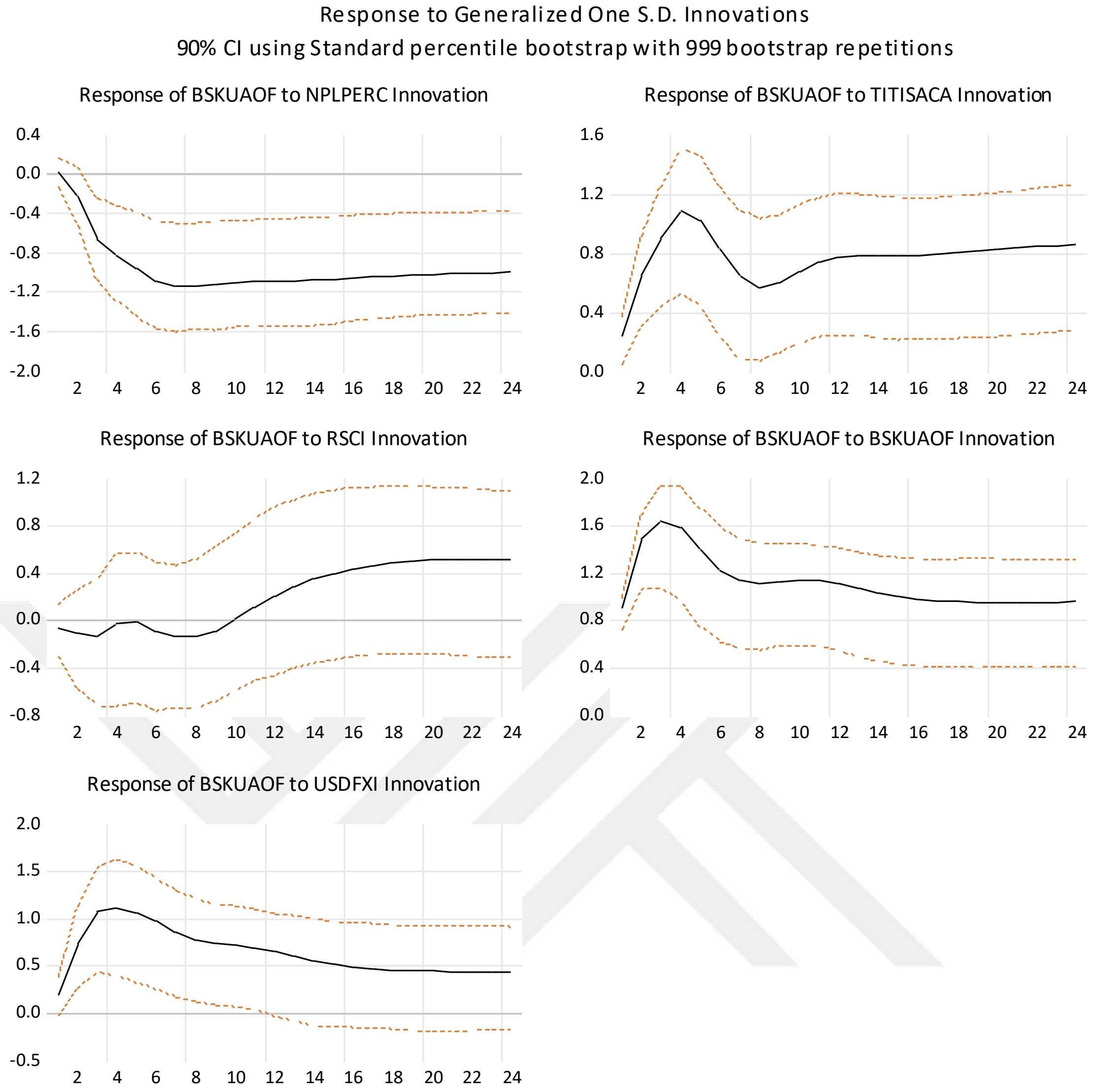


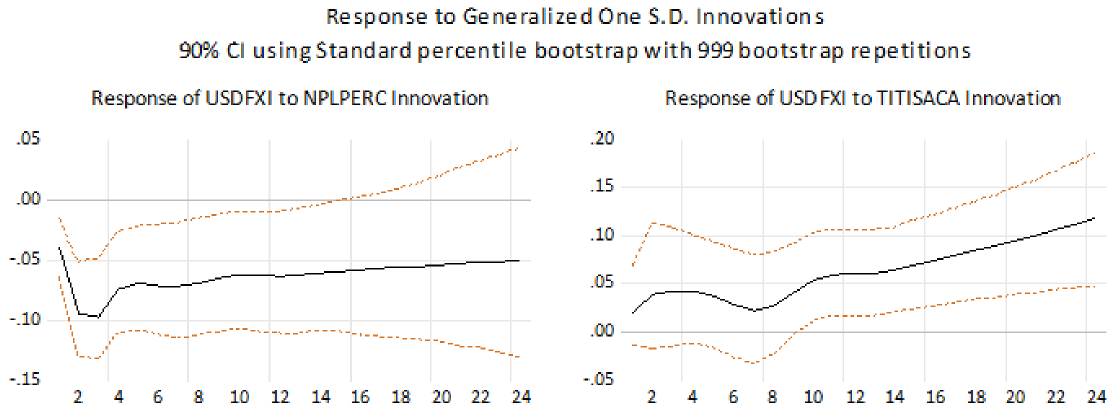


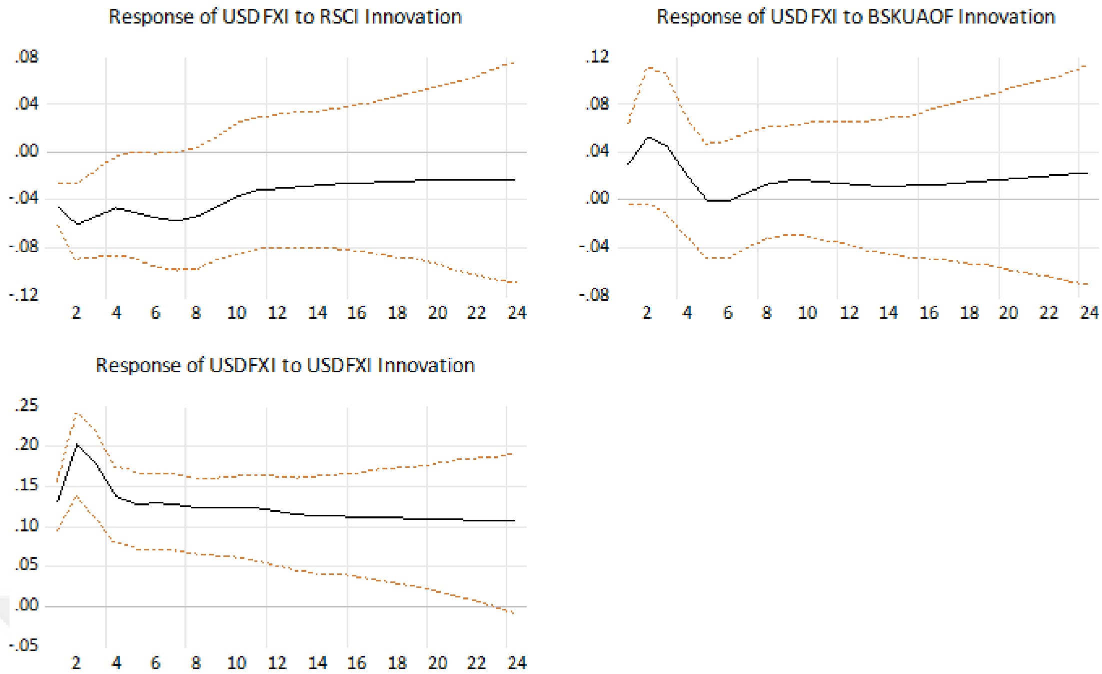


Response to Generalized One S.D. Innovations
90% CI using Standard percentile bootstrap with 999 bootstrap repetitions




Response to Generalized One S.D. Innovations
90% CI using Standard percentile bootstrap with 999 bootstrap repetitions
Response of BSKUAOF to NPLPERC Innovation
Response of BSKUAOF to TITISACA Innovation
Response of BSKUAOF to RSCI Innovation
Response of BSKUAOF to BSKUAOF Innovation
Response of BSKUAOF to USDFXI Innovation


Response to Generalized One S.D. Innovations
90% CI using Standard percentile bootstrap with 999 bootstrap repetitions
Response of USDFXI to NPLPERC Innovation
Response of USDFXI to TITISACA Innovation


Response of USD FXI to RSCI Innovation
Response of USD FXI to BSKUAOF Innovation
Response of USDFXI to USDFXI Innovation

Appendix 12: The Descriptive Statistics and Residual Checks Results of Candidate Model Two

The Descriptive Statistics of Variables, Level

	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI
Mean	0.0412	78.7062	190.4993	16.6881	1.8074
Median	0.0369	76.5990	181.5951	16.2037	1.5873
Maximum	0.0713	106.4598	291.9037	26.3850	3.4864
Minimum	0.0282	57.0014	114.0440	9.9995	1.1696
Srd. Dev.	0.0123	14.9453	51.0043	3.8669	0.5528
Skewness	0.8215	0.3070	0.2816	0.4697	1.1333
Kurtosis	2.3999	1.7478	1.9196	2.4127	3.2635
Sum	5.9400	11333.7000	27341.8900	2403.0950	260.271
Sum Sq. Dev.	0.0219	31940.8000	373007.0000	2138.2730	43.710
Observations	144	144	144	144	144

The Descriptive Statistics of Variables, First Difference

	NPLPERC1	IPSACA1	CPISA1	BSKUAOF1	USDFXI1
Mean	-0.0046	0.0041	0.0066	-0.0026	0.0072
Median	-0.0012	0.0039	0.0060	-0.0132	0.0022
Maximum	0.0926	0.0743	0.0255	0.2853	0.0198
Minimum	-0.0892	-0.0677	-0.0047	-0.1557	-0.0588
Srd. Dev.	0.0303	0.0223	0.0052	0.0551	0.0336
Skewness	0.1541	-0.2328	0.4073	1.9109	1.6420
Kurtosis	3.9394	4.3111	3.3967	10.1298	9.8554
Sum	-0.6692	0.5931	0.9448	-0.3790	1.0229
Sum Sq. Dev.	0.1308	0.0708	0.0038	0.4319	0.1605
Observations	143	143	143	143	143

VECM Stability Condition Check

Roots of Characteristic Polynomial
Endogenous variables: NPLPERC IPSACA
CPISA BSKUAOF USDFXI
Exogenous variables: DUMMY M2 M3 M4 M5
M6 M7 M8 M9 M10 M11 M12
Lag specification: 1 2
Date: 11/14/21 Time: 23:11

Root	Modulus
1.000000	1.000000
1.000000	1.000000
1.000000	1.000000
1.000000	1.000000
0.817863 - 0.132371i	0.828506
0.817863 + 0.132371i	0.828506
0.267141 - 0.442998i	0.517312
0.267141 + 0.442998i	0.517312
-0.437833 - 0.064603i	0.442573
-0.437833 + 0.064603i	0.442573
-6.37e-05 - 0.411831i	0.411831
-6.37e-05 + 0.411831i	0.411831
0.027286 - 0.349641i	0.350704
0.027286 + 0.349641i	0.350704
0.305586	0.305586

VEC specification imposes 4 unit root(s).

The Residual Covariance Matrix

	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI
NPLPERC	5.9191	1.7166	-2.0208	6.4016	-6.5392
IPSACA	1.7166	2.7872	0.0654	-0.0618	0.0038
CPISA	-2.0208	0.0654	1.1674	0.0884	0.0190
BSKUAOF	6.4016	-0.0618	0.0884	0.5338	0.0048
USDFXI	-6.5392	0.0038	0.0190	0.0048	0.0028

The Residual Correlation Matrix

	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI
NPLPERC	1	0.0133	-0.0243	0.1138	-0.1596
IPSACA	0.0134	1	0.0362	-0.0506	0.0430
CPISA	-0.0243	0.0362	1	0.1120	0.3305
BSKUAOF	0.1138	-0.0506	0.1120	1	0.1249
USDFXI	-0.1596	0.0430	0.3305	0.1249	1

VECM Residual Serial Correlation LM Tests

VEC Residual Serial Correlation LM Tests
Date: 11/14/21 Time: 23:12
Sample: 2005M01 2016M12
Included observations: 141

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	19.91832	25	0.7511	0.793539	(25, 402.7)	0.7514
2	25.46046	25	0.4368	1.021207	(25, 402.7)	0.4372
3	17.09340	25	0.8784	0.678660	(25, 402.7)	0.8785

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	19.91832	25	0.7511	0.793539	(25, 402.7)	0.7514
2	62.89532	50	0.1042	1.276208	(50, 473.1)	0.1051
3	86.72529	75	0.1672	1.170260	(75, 473.6)	0.1703

*Edgeworth expansion corrected likelihood ratio statistic.

VECM Residual Normality Tests

VEC Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: Residuals are multivariate normal
Date: 11/14/21 Time: 23:13
Sample: 2005M01 2016M12
Included observations: 141

Component	Skewness	Chi-sq	df	Prob.*
1	-0.587889	8.121904	1	0.0044
2	-0.124847	0.366290	1	0.5450
3	0.342984	2.764499	1	0.0964
4	0.940165	20.77188	1	0.0000
5	0.469683	5.184160	1	0.0228
Joint		37.20873	5	0.0000

Component	Kurtosis	Chi-sq	df	Prob.
1	4.073737	6.773359	1	0.0093
2	4.143798	7.686104	1	0.0056
3	3.807632	3.832085	1	0.0503
4	5.262297	30.06818	1	0.0000
5	3.609945	2.185690	1	0.1393
Joint		50.54542	5	0.0000

Component	Jarque-Bera	df	Prob.
1	14.89526	2	0.0006
2	8.052394	2	0.0178
3	6.596585	2	0.0369
4	50.84006	2	0.0000
5	7.369850	2	0.0251
Joint	87.75415	10	0.0000

*Approximate p-values do not account for coefficient estimation

VECM Residual Heteroskedasticity Tests (Levels and Squares) (White Heteroskedasticity)

VEC Residual Heteroskedasticity Tests (Levels and Squares)
Date: 11/14/21 Time: 23:13
Sample: 2005M01 2016M12
Included observations: 141

Joint test:

Chi-sq	df	Prob.
633.6669	510	0.0001

Individual components:

Dependent	R-squared	F(34,106)	Prob.	Chi-sq(34)	Prob.
res1*res1	0.162584	0.605289	0.9522	22.92431	0.9253
res2*res2	0.386271	1.962196	0.0049	54.46420	0.0144
res3*res3	0.279705	1.210647	0.2291	39.43846	0.2397
res4*res4	0.553212	3.860262	0.0000	78.00287	0.0000
res5*res5	0.328995	1.528590	0.0530	46.38833	0.0764
res2*res1	0.269919	1.152628	0.2872	38.05857	0.2898
res3*res1	0.229368	0.927927	0.5861	32.34094	0.5491
res3*res2	0.242089	0.995829	0.4868	34.13461	0.4613
res4*res1	0.279222	1.207742	0.2318	39.37025	0.2420
res4*res2	0.435150	2.401777	0.0004	61.35614	0.0028
res4*res3	0.342605	1.624776	0.0322	48.30725	0.0530
res5*res1	0.165244	0.617155	0.9455	23.29945	0.9166
res5*res2	0.279179	1.207485	0.2320	39.36421	0.2422
res5*res3	0.277824	1.199373	0.2397	39.17323	0.2489
res5*res4	0.267719	1.139800	0.3013	37.74841	0.3018

Appendix 13: Unit Root Test Results of Candidate Model Two

	Level		First Difference	
Variables	**ADF Unit Root Test**	**KPSS Unit Root Test**	**ADF Unit Root Test**	**KPSS Unit Root Test**
NPLPERC	-4.334676***	0.085961	-3.402389*	0.070371
IPSACA	-1.599081	0.232970***	-14.88055***	0.061056
CPISA	-0.374009	0.374991***	-10.28829***	0.094133
BSKUAOF	-2.955146	0.177414**	-7.712785***	0.035802
USDFXI	0.038724	0.331660***	-8.790286***	0.027119

Note: *** denotes significant at 1%; ** denotes significant at 5%; * denotes significant at 10%.

Appendix 14: Johansen Cointegration Test Results of Candidate Model Two

Date: 11/14/21 Time: 23:08
Sample: 2005M01 2016M12
Included observations: 141
Series: NPLPERC IPSACA CPISA BSKUAOF USDFXI
Exogenous series: DUMMY M2 M3 M4 M5 M6 M7 M8 M9 M10 M11 M12
Warning: Rank Test critical values derived assuming no exogenous series
Lags interval: 1 to 2

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	1	2	1	3	3
Max-Eig	1	2	2	1	3

*Critical values based on MacKinnon-Haug-Michelis (1999)

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	430.6498	430.6498	446.3232	446.3232	450.7285
1	455.1251	455.5569	464.2693	465.7462	470.1512
2	466.7359	471.0499	479.1899	481.2071	485.6102
3	471.6936	482.0400	485.6437	495.7324	500.0905
4	472.4254	486.9359	486.9867	502.0071	502.7921
5	472.5774	487.3682	487.3682	503.1354	503.1354
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	-5.399288	-5.399288	-5.550684	-5.550684	-5.542249
1	-5.604611	-5.596552	-5.663395	-5.670159	-5.675904
2	-5.627459	-5.660282	-5.733190	-5.733434	-5.753336
3	-5.555938	-5.660141	-5.682889	-5.783439	-5.816886*
4	-5.424474	-5.573559	-5.560095	-5.716413	-5.713364
5	-5.284786	-5.423663	-5.423663	-5.576389	-5.576389
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	-4.353628	-4.353628	-4.400459*	-4.400459*	-4.287457
1	-4.349820	-4.320847	-4.304037	-4.289888	-4.211980
2	-4.163536	-4.154532	-4.164701	-4.123119	-4.080280
3	-3.882882	-3.924347	-3.905268	-3.943078	-3.934699
4	-3.542287	-3.607719	-3.573342	-3.646007	-3.622045
5	-3.193467	-3.227778	-3.227778	-3.275938	-3.275938

Appendix 15: Lag Length Selection of Candidate Model Two

VAR Lag Order Selection Criteria
Endogenous variables: NPLPERC1 IPSACA1 CPISA1 BSKUAOF1 USDFXI1
Exogenous variables: DUMMY M2 M3 M4 M5 M6 M7 M8 M9 M10 M11 M12 C
Date: 11/14/21 Time: 22:52
Sample: 2005M02 2016M12
Included observations: 135

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1626.611	NA	6.19e-17	-23.13498	-21.73614	-22.56653
1	1744.933	205.0907	1.56e-17	-24.51752	-22.58067*	-23.73044*
2	1772.558	45.83752	1.51e-17*	-24.55641*	-22.08155	-23.55070
3	1785.110	19.89763	1.85e-17	-24.37200	-21.35912	-23.14765
4	1808.324	35.07946	1.93e-17	-24.34555	-20.79466	-22.90256
5	1821.520	18.96263	2.37e-17	-24.17067	-20.08176	-22.50905
6	1840.202	25.46309	2.70e-17	-24.07707	-19.45015	-22.19682
7	1869.810	38.16127*	2.64e-17	-24.14534	-18.98040	-22.04645
8	1892.907	28.05893	2.89e-17	-24.11715	-18.41420	-21.79963

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix 16: The Estimation Results of Candidate Model Two

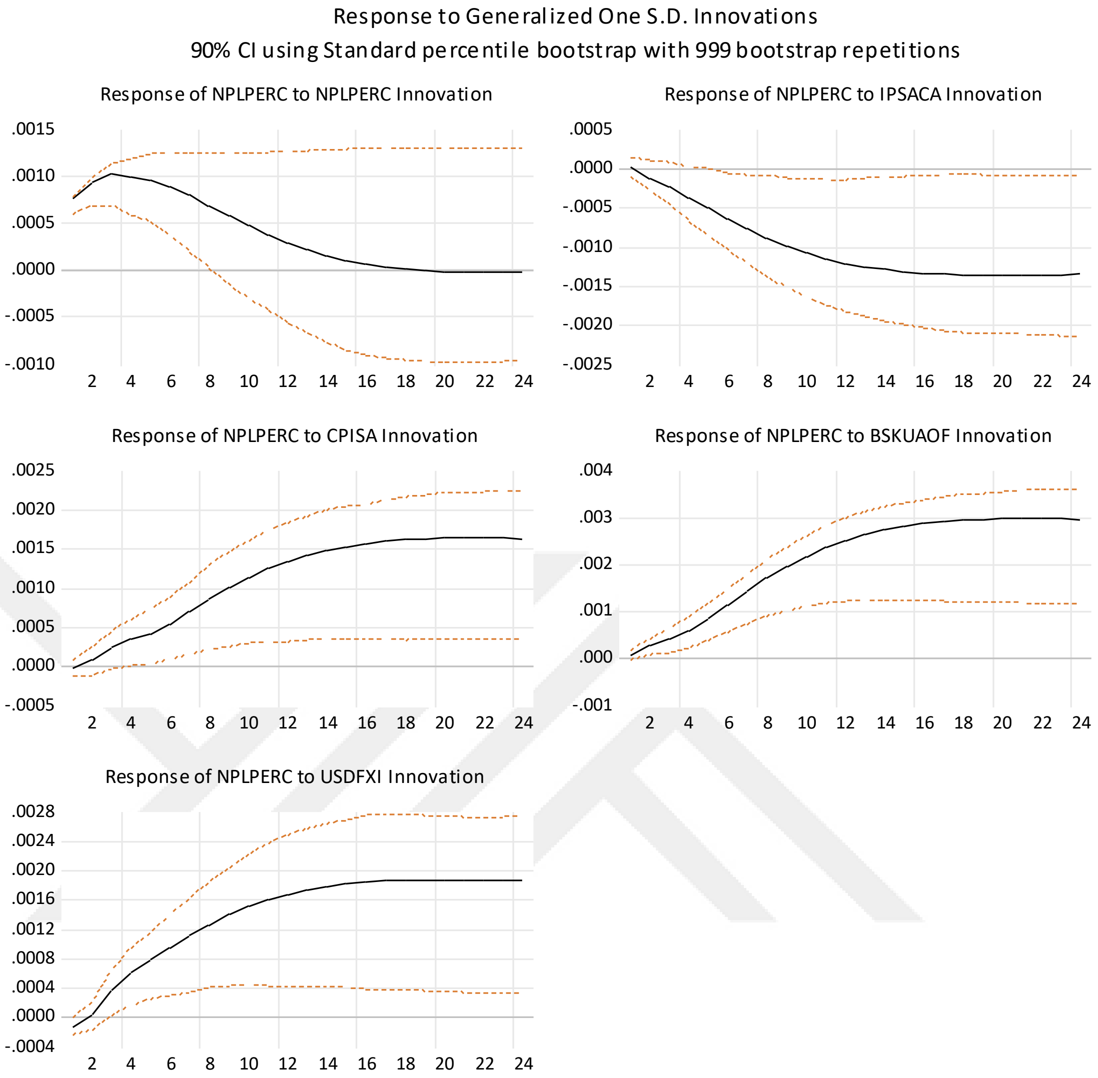
Vector Autoregression Estimates
Date: 11/14/21 Time: 22:48
Sample (adjusted): 2005M04 2016M12
Included observations: 141 after adjustments
Standard errors in ( ) & t-statistics in [ ]

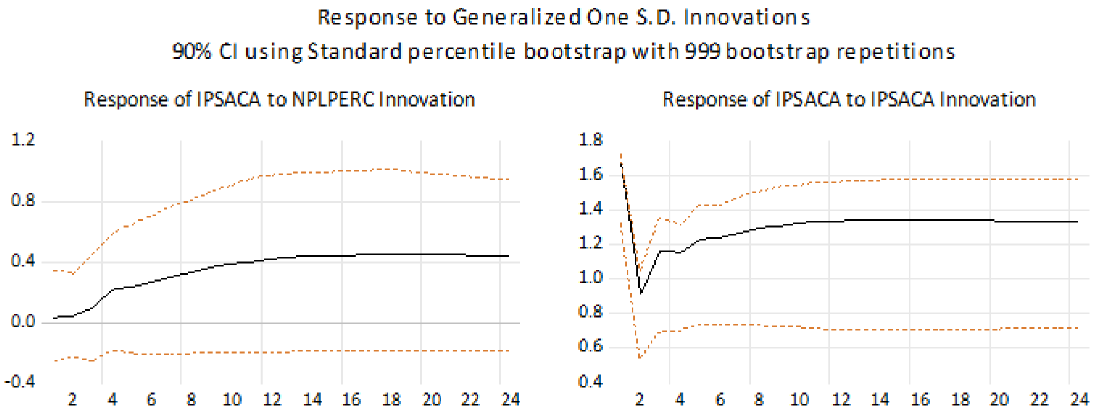
	NPLPERC1	IPSACA1	CPISA1	BSKUAOF1	USDFXI1
NPLPERC1(-1)	0.430907	-0.150815	-0.040190	-0.307204	-0.341227
	(0.08735)	(0.09183)	(0.02375)	(0.17693)	(0.13324)
	[4.93307]	[-1.64224]	[-1.69231]	[-1.73628]	[-2.56100]
NPLPERC1(-2)	0.306286	-0.057459	0.000509	-0.080370	0.144380
	(0.08765)	(0.09215)	(0.02383)	(0.17754)	(0.13370)
	[3.49432]	[-0.62353]	[0.02137]	[-0.45268]	[1.07988]
IPSACA1(-1)	-0.160175	-0.334131	0.017706	0.262581	-0.156265
	(0.08316)	(0.08742)	(0.02261)	(0.16844)	(0.12684)
	[-1.92620]	[-3.82194]	[0.78318]	[1.55894]	[-1.23197]
IPSACA1(-2)	-0.122371	-0.032883	-0.015679	-0.311627	-0.129579
	(0.08533)	(0.08971)	(0.02320)	(0.17284)	(0.13016)
	[-1.43410]	[-0.36655]	[-0.67585]	[-1.80300]	[-0.99556]
CPISA1(-1)	0.143641	-0.177521	0.095155	1.042614	-1.127025
	(0.35923)	(0.37767)	(0.09767)	(0.72764)	(0.54795)
	[0.39985]	[-0.47004]	[0.97427]	[1.43287]	[-2.05679]
CPISA1(-2)	0.484373	-0.630536	-0.063334	1.714755	-0.322109
	(0.36464)	(0.38336)	(0.09914)	(0.73859)	(0.55620)
	[1.32836]	[-1.64477]	[-0.63884]	[2.32165]	[-0.57912]
BSKUAOF1(-1)	0.016094	0.040274	0.002702	0.300810	-0.043007
	(0.04523)	(0.04755)	(0.01230)	(0.09161)	(0.06899)
	[0.35584]	[0.84701]	[0.21970]	[3.28361]	[-0.62341]
BSKUAOF1(-2)	-0.033714	-0.079394	-0.005552	-0.037760	0.042603
	(0.03821)	(0.04017)	(0.01039)	(0.07740)	(0.05829)
	[-0.88226]	[-1.97622]	[-0.53443]	[-0.48784]	[0.73091]
USDFXI1(-1)	0.215206	-0.155267	-0.004816	0.692421	0.424303
	(0.06093)	(0.06406)	(0.01657)	(0.12342)	(0.09295)
	[3.53177]	[-2.42368]	[-0.29069]	[5.61006]	[4.56506]
USDFXI1(-2)	0.091829	-0.106104	0.005654	-0.106730	-0.193963
	(0.06878)	(0.07231)	(0.01870)	(0.13931)	(0.10491)
	[1.33515]	[-1.46736]	[0.30238]	[-0.76611]	[-1.84884]
DUMMY	-0.000439	-0.002990	-0.000526	-0.009893	-0.009583
	(0.00351)	(0.00369)	(0.00095)	(0.00710)	(0.00535)
	[-0.12518]	[-0.81109]	[-0.55152]	[-1.39315]	[-1.79187]
M2	-0.026789	0.002934	0.000827	-0.020030	0.010434
	(0.00936)	(0.00984)	(0.00255)	(0.01896)	(0.01428)
	[-2.86152]	[0.29811]	[0.32476]	[-1.05628]	[0.73066]

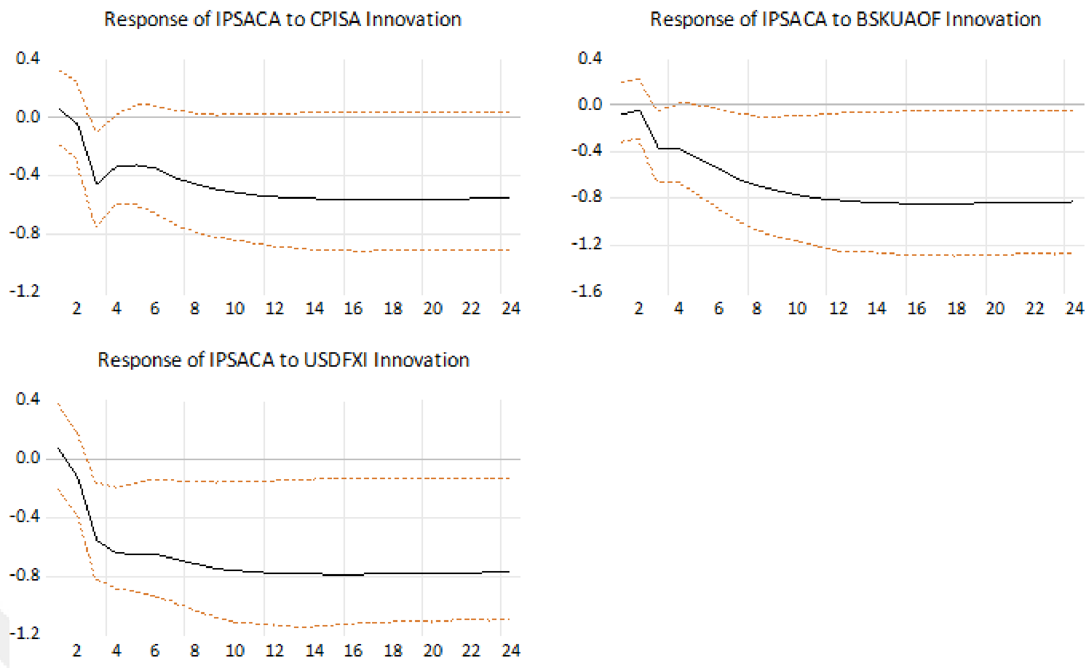
M3	-0.042698	0.011509	0.000476	-0.021068	0.011193
	(0.00868)	(0.00913)	(0.00236)	(0.01758)	(0.01324)
	[-4.91926]	[1.26124]	[0.20165]	[-1.19833]	[0.84544]
M4	-0.016300	0.002827	8.99E-05	-0.048048	-0.020362
	(0.00842)	(0.00886)	(0.00229)	(0.01706)	(0.01285)
	[-1.93493]	[0.31920]	[0.03927]	[-2.81597]	[-1.58470]
M5	-0.030359	0.007406	0.001016	-0.006385	0.016416
	(0.00879)	(0.00924)	(0.00239)	(0.01779)	(0.01340)
	[-3.45569]	[0.80188]	[0.42552]	[-0.35878]	[1.22499]
M6	-0.042405	0.004987	-0.000964	-0.019594	0.008780
	(0.00861)	(0.00905)	(0.00234)	(0.01744)	(0.01314)
	[-4.92410]	[0.55082]	[-0.41154]	[-1.12329]	[0.66839]
M7	-0.002988	-0.001332	6.32E-05	0.002693	-0.016983
	(0.00849)	(0.00893)	(0.00231)	(0.01720)	(0.01296)
	[-0.35176]	[-0.14915]	[0.02739]	[0.15654]	[-1.31086]
M8	-0.006875	0.002953	-0.002073	-0.022175	0.015995
	(0.00933)	(0.00981)	(0.00254)	(0.01891)	(0.01424)
	[-0.73649]	[0.30089]	[-0.81700]	[-1.17281]	[1.12336]
M9	-0.025823	0.010621	-0.000400	-0.025194	0.007890
	(0.00870)	(0.00915)	(0.00237)	(0.01763)	(0.01328)
	[-2.96680]	[1.16068]	[-0.16888]	[-1.42904]	[0.59431]
M10	-0.015823	0.005212	0.000192	-0.021616	0.003388
	(0.00842)	(0.00886)	(0.00229)	(0.01706)	(0.01285)
	[-1.87840]	[0.58851]	[0.08390]	[-1.26690]	[0.26365]
M11	-0.028885	0.005649	-0.000547	-0.012833	0.008806
	(0.00860)	(0.00904)	(0.00234)	(0.01741)	(0.01311)
	[-3.36029]	[0.62507]	[-0.23387]	[-0.73707]	[0.67162]
M12	-0.038056	0.001705	-0.000347	-0.043693	0.009360
	(0.00848)	(0.00891)	(0.00231)	(0.01717)	(0.01293)
	[-4.48836]	[0.19128]	[-0.15057]	[-2.54406]	[0.72373]
C	0.017228	0.009121	0.006640	-0.000160	0.015710
	(0.00724)	(0.00761)	(0.00197)	(0.01466)	(0.01104)
	[2.38040]	[1.19877]	[3.37427]	[-0.01092]	[1.42310]
R-squared	0.641168	0.246027	0.102303	0.545186	0.315692
Adj. R-squared	0.574267	0.105455	-0.065064	0.460391	0.188109
Sum sq. resids	0.046768	0.051693	0.003457	0.191880	0.108814
S.E. equation	0.019908	0.020930	0.005413	0.040325	0.030367
F-statistic	9.583841	1.750192	0.611251	6.429407	2.474403
Log likelihood	364.7274	357.6690	548.3654	265.2045	305.1945
Akaike AIC	-4.847197	-4.747078	-7.451992	-3.435525	-4.002758
Schwarz SC	-4.366194	-4.266075	-6.970988	-2.954522	-3.521755
Mean dependent	-0.004466	0.004581	0.006651	-0.001656	0.007541
S.D. dependent	0.030512	0.022130	0.005245	0.054895	0.033702

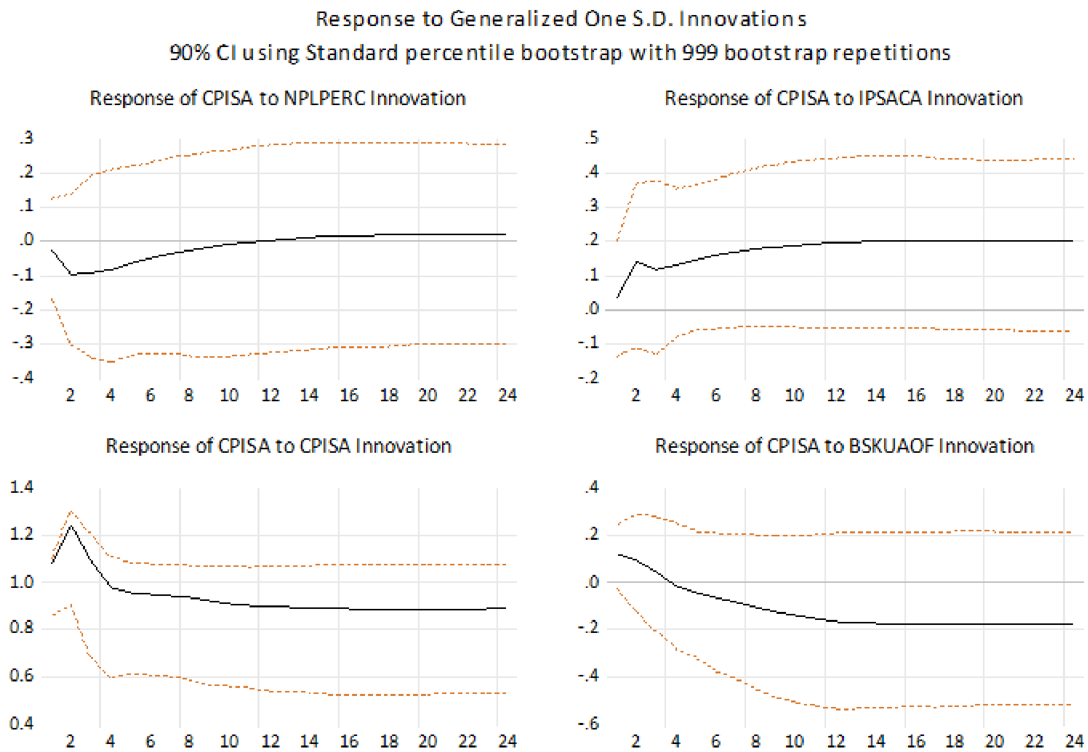
Determinant resid covariance (dof adj.)	6.54E-18
Determinant resid covariance	2.68E-18
Log likelihood	1852.036
Akaike information criterion	-24.63881
Schwarz criterion	-22.23379
Number of coefficients	115

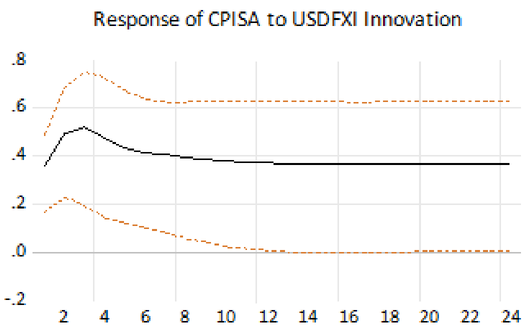
Appendix 17: Impulse Response Functions of Candidate Model Two



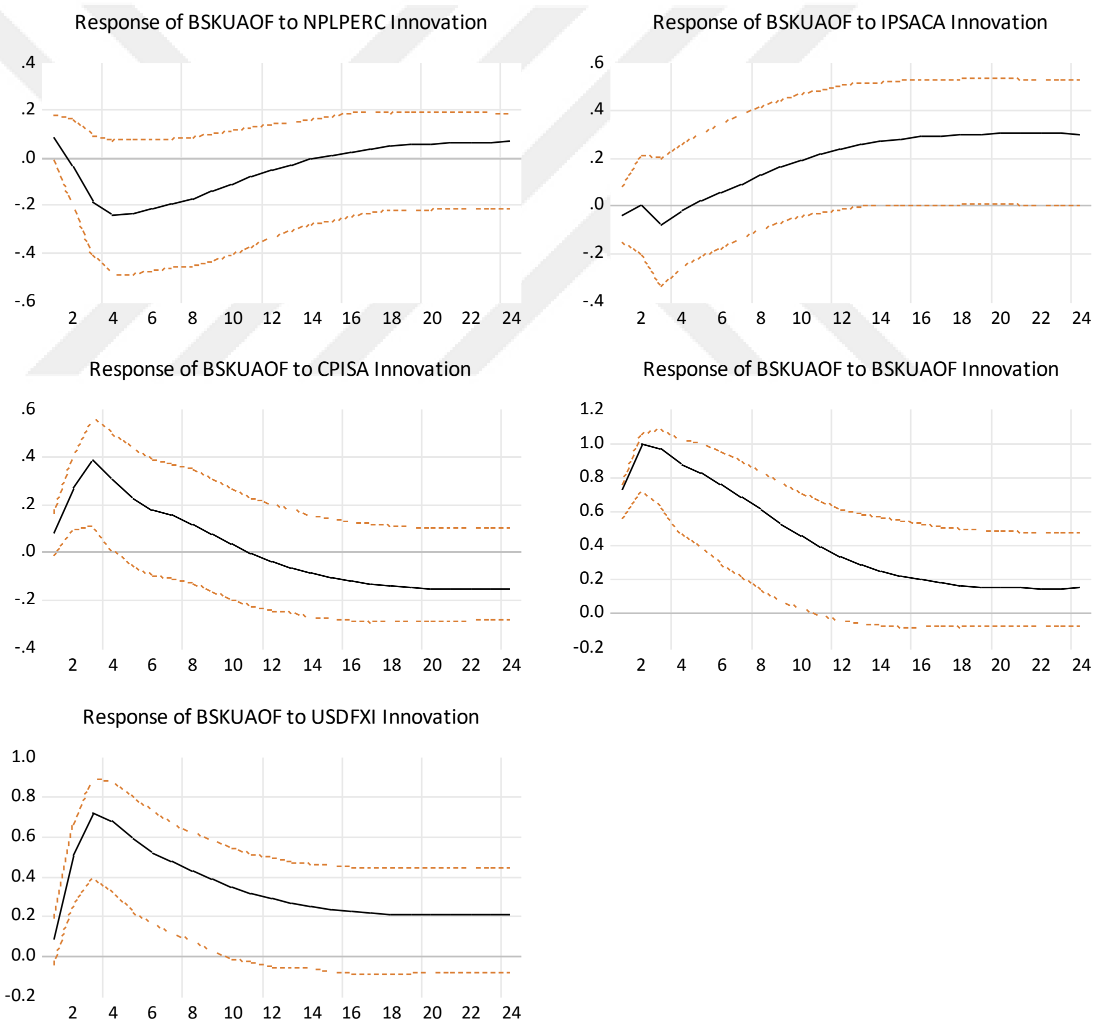


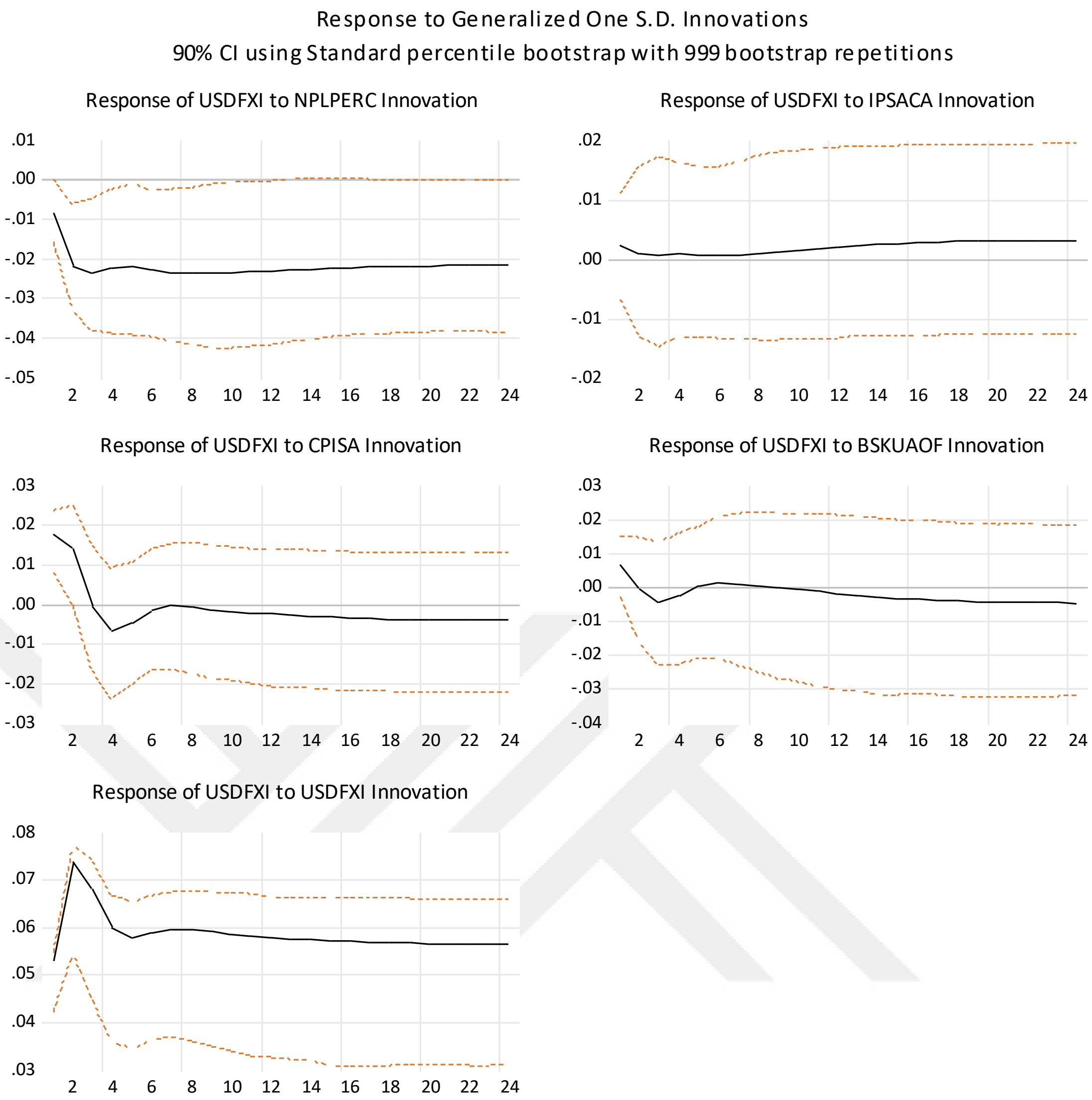

Response of IPSACA to CPISA Innovation
Response of IPSACA to BSKUAOF Innovation
Response of IPSACA to USDFXI Innovation
0.4
0.0
-0.4
-0.8
-1.2
-1.6
2 4 6 8 10 12 14 16 18 20 22 24


Response to Generalized One S.D. Innovations
90% CI using Standard percentile bootstrap with 999 bootstrap repetitions
Response of CPISA to NPLPERC Innovation
Response of CPISA to IPSACA Innovation
Response of CPISA to CPISA Innovation
Response of CPISA to BSKUAOF Innovation
.5
.4
.3
.2
.1
.0
-.1
-.2
-.3
-.4
1.4
1.2
1.0
0.8
0.6
0.4
-.4
-.6
2 4 6 8 10 12 14 16 18 20 22 24



Response to Generalized One S.D. Innovations
90% CI using Standard percentile bootstrap with 999 bootstrap repetitions




Response to Generalized One S.D. Innovations
90% CI using Standard percentile bootstrap with 999 bootstrap repetitions
Response of USDFXI to NPLPERC Innovation
Response of USDFXI to IPSACA Innovation
Response of USDFXI to CPISA Innovation
Response of USDFXI to BSKUAOF Innovation
Response of USDFXI to USDFXI Innovation

Appendix 18: The Descriptive Statistics and Residual Checks Results of Candidate Model Three

The Descriptive Statistics of Variables, Level

	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
Mean	0.0412	78.7062	190.4993	16.6881	1.8074	0.3586
Median	0.0369	76.5990	181.5951	16.2037	1.5873	0.4900
Maximum	0.0713	106.4598	291.9037	26.3850	3.4864	19.0600
Minimum	0.0282	57.0014	114.0440	9.9995	1.1696	-25.9300
Srd. Dev.	0.0123	14.9453	51.0043	3.8669	0.5528	6.7922
Skewness	0.8215	0.3070	0.2816	0.4697	1.1333	-25.9300
Kurtosis	2.3999	1.7478	1.9196	2.4127	3.2635	4.2688
Sum	5.9400	11333.7000	27341.8900	2403.0950	260.271	51.280
Sum Sq. Dev.	0.0219	31940.8000	373007.0000	2138.2730	43.710	6551.079
Observations	144	144	144	144	144	143

The Descriptive Statistics of Variables, First Difference

	NPLPERC1	IPSACA1	CPISA1	BSKUAOF1	USDFXI1	BISTRE1
Mean	-0.0046	0.0041	0.0066	-0.0026	0.0072	-1.4567
Median	-0.0012	0.0039	0.0060	-0.0132	0.0022	-0.7040
Maximum	0.0926	0.0743	0.0255	0.2853	0.0198	30.4318
Minimum	-0.0892	-0.0677	-0.0047	-0.1557	-0.0588	-143.5000
Srd. Dev.	0.0303	0.0223	0.0052	0.0551	0.0336	12.8829
Skewness	0.1541	-0.2328	0.4073	1.9109	1.6420	-7.6798
Kurtosis	3.9394	4.3111	3.3967	10.1298	9.8554	72.4511
Sum	-0.6692	0.5931	0.9448	-0.3790	1.0229	-205.4032
Sum Sq. Dev.	0.1308	0.0708	0.0038	0.4319	0.1605	2936073.0000
Observations	143	143	143	143	143	141

VECM Stability Condition Check

Roots of Characteristic Polynomial
Endogenous variables: NPLPERC IPSACA
CPISA BSKUAOF USDFXI BISTRE
Exogenous variables: DUMMY M2 M3 M4 M5
M6 M7 M8 M9 M10 M11 M12
Lag specification: 1 2
Date: 11/14/21 Time: 23:56

Root	Modulus
1.000000	1.000000
1.000000 - 2.35e-15i	1.000000
1.000000 + 2.35e-15i	1.000000
1.000000	1.000000
0.854957 - 0.153723i	0.868667
0.854957 + 0.153723i	0.868667
0.348289 + 0.497458i	0.607264
0.348289 - 0.497458i	0.607264
-0.083092 - 0.559971i	0.566103
-0.083092 + 0.559971i	0.566103
-0.484648 - 0.170575i	0.513790
-0.484648 + 0.170575i	0.513790
0.272798 + 0.324175i	0.423685
0.272798 - 0.324175i	0.423685
-0.421593	0.421593
-0.005078 - 0.383419i	0.383452
-0.005078 + 0.383419i	0.383452
0.298500	0.298500

VEC specification imposes 4 unit root(s).

The Residual Covariance Matrix

	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
NPLPERC	5.5829	-3.6246	-6.6424	7.8672	-7.5621	0.0006
IPSACA	-3.6246	2.8052	0.0280	0.0353	0.0045	-0.9025
CPISA	-6.6424	0.0280	1.1973	0.1194	0.0119	-2.1384
BSKUAOF	7.8672	0.0353	0.1194	0.4873	0.0004	-0.7015
USDFXI	-7.5621	0.0045	0.0198	0.0046	0.0029	-0.2281
BISTRE	0.0006	-0.9025	-2.1384	-0.7015	-0.2281	39.4925

The Residual Correlation Matrix

	NPLPERC	IPSACA	CPISA	BSKUAOF	USDFXI	BISTRE
NPLPERC	1	-0.0289	-0.0812	0.1508	-0.1861	0.1337
IPSACA	-0.0289	1	0.0153	0.0302	0.0500	-0.0857
CPISA	-0.0812	0.0153	1	0.1563	0.3332	-0.3109
BSKUAOF	0.1508	0.0302	0.1563	1	0.1221	-0.1599
USDFXI	-0.1861	0.0500	0.3332	0.1221	1	-0.6675
BISTRE	0.1337	-0.0857	-0.3109	-0.1599	-0.6675	1

VECM Residual Serial Correlation LM Tests

VEC Residual Serial Correlation LM Tests
Date: 11/14/21 Time: 23:58
Sample: 2005M01 2016M12
Included observations: 137

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	34.00050	36	0.5640	0.944001	(36, 437.5)	0.5648
2	26.23614	36	0.8839	0.722166	(36, 437.5)	0.8842
3	27.31171	36	0.8508	0.752670	(36, 437.5)	0.8512

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	34.00050	36	0.5640	0.944001	(36, 437.5)	0.5648
2	66.60797	72	0.6573	0.920843	(72, 511.8)	0.6603
3	100.0867	108	0.6938	0.918646	(108, 505.8)	0.7012

*Edgeworth expansion corrected likelihood ratio statistic.

VECM Residual Normality Tests

VEC Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: Residuals are multivariate normal
Sample: 2005M01 2016M12
Included observations: 137

Component	Skewness	Chi-sq	df	Prob.*
1	-0.506284	5.852726	1	0.0156
2	-0.130937	0.391467	1	0.5315
3	0.256577	1.503157	1	0.2202
4	1.011023	23.33949	1	0.0000
5	0.391219	3.494702	1	0.0616
6	0.248392	1.408782	1	0.2353
Joint		35.99032	6	0.0000

Component	Kurtosis	Chi-sq	df	Prob.
1	3.239352	0.327028	1	0.5674
2	4.380710	10.88213	1	0.0010
3	3.704298	2.831540	1	0.0924
4	5.404636	33.00716	1	0.0000
5	3.401063	0.918195	1	0.3379
6	3.068495	0.026781	1	0.8700
Joint		47.99283	6	0.0000

Component	Jarque-Bera	df	Prob.
1	6.179754	2	0.0455
2	11.27360	2	0.0036
3	4.334697	2	0.1145
4	56.34665	2	0.0000
5	4.412896	2	0.1101
6	1.435562	2	0.4878
Joint	83.98315	12	0.0000

*Approximate p-values do not account for coefficient estimation

VECM Residual Heteroskedasticity Tests (Levels and Squares)

(White Heteroskedasticity)

VEC Residual Heteroskedasticity Tests (Levels and Squares)
Date: 11/14/21 Time: 23:59
Sample: 2005M01 2016M12
Included observations: 137

Joint test:

Chi-sq	df	Prob.
1022.135	840	0.0000

Individual components:

Dependent	R-squared	F(40,96)	Prob.	Chi-sq(40)	Prob.
res1*res1	0.148318	0.417952	0.9987	20.31951	0.9959
res2*res2	0.422709	1.757348	0.0133	57.91112	0.0332
res3*res3	0.363267	1.369238	0.1082	49.76752	0.1385
res4*res4	0.626845	4.031648	0.0000	85.87780	0.0000
res5*res5	0.417998	1.723696	0.0161	57.26570	0.0376
res6*res6	0.344351	1.260495	0.1798	47.17609	0.2026
res2*res1	0.308760	1.072019	0.3828	42.30006	0.3720
res3*res1	0.311464	1.085656	0.3647	42.67055	0.3570
res3*res2	0.300675	1.031883	0.4387	41.19254	0.4182
res4*res1	0.353792	1.313974	0.1408	48.46948	0.1684
res4*res2	0.548354	2.913900	0.0000	75.12454	0.0006
res4*res3	0.415160	1.703683	0.0181	56.87686	0.0405
res5*res1	0.292287	0.991203	0.4986	40.04326	0.4683
res5*res2	0.321500	1.137217	0.3009	44.04556	0.3044
res5*res3	0.367337	1.393491	0.0960	50.32522	0.1270
res5*res4	0.294634	1.002490	0.4817	40.36490	0.4541
res6*res1	0.251592	0.806808	0.7747	34.46814	0.7170
res6*res2	0.350456	1.294899	0.1539	48.01245	0.1799
res6*res3	0.247536	0.789523	0.7975	33.91250	0.7399
res6*res4	0.333660	1.201763	0.2318	45.71138	0.2469
res6*res5	0.393675	1.558272	0.0407	53.93344	0.0695

Appendix 19: Unit Root Test Results of Candidate Model Three

	Level		First Difference	
Variables	**ADF Unit Root Test**	**KPSS Unit Root Test**	**ADF Unit Root Test**	**KPSS Unit Root Test**
NPLPERC	-4.334676***	0.085961	-3.402389*	0.070371
IPSACA	-1.599081	0.232970***	-14.88055***	0.061056
CPISA	-0.374009	0.374991***	-10.28829***	0.094133
BSKUAOF	-2.955146	0.177414**	-7.712785***	0.035802
USDFXI	0.038724	0.331660***	-8.790286***	0.027119
BISTRE	-9.247004***	0.444133	-11.88195***	0.053483

Note: *** denotes significant at 1%; ** denotes significant at 5%; * denotes significant at 10%.

Appendix 20: Johansen Cointegration Test Results of Candidate Model Three

Date: 11/14/21 Time: 23:48
Sample: 2005M01 2016M12
Included observations: 135
Series: NPLPERC IPSACA CPISA BSKUAOF USDFXI BISTRE
Exogenous series: DUMMY M2 M3 M4 M5 M6 M7 M8 M9 M10 M11 M12
Warning: Rank Test critical values derived assuming no exogenous series
Lags interval: 1 to 3

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	2	4	3	3	4
Max-Eig	3	4	1	3	3

*Critical values based on MacKinnon-Haug-Michelis (1999)

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	34.81000	34.81000	53.42651	53.42651	58.62925
1	67.07156	67.36397	85.63167	89.11259	93.05560
2	91.34105	91.63375	101.8548	109.3294	112.3806
3	103.6474	107.7893	115.8614	125.5453	128.1239
4	109.0397	119.2125	123.3452	137.8592	139.9853
5	110.5052	124.6038	125.0510	145.1730	145.5497
6	110.9566	126.0619	126.0619	146.1950	146.1950
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	1.084296	1.084296	0.897385	0.897385	0.909196
1	0.784125	0.794608	0.598049	0.561295	0.576954
2	0.602355	0.627648	0.535484	0.454380	0.468436
3	0.597816	0.580900	0.505757	0.406737*	0.412979
4	0.695709	0.604259	0.572663	0.416901	0.415032
5	0.851775	0.716981	0.725170	0.501141	0.510375
6	1.022866	0.887972	0.887972	0.678592	0.678592
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	3.408516	3.408516	3.350728	3.350728	3.491663
1	3.366591	3.398595	3.309639	3.294405*	3.417667
2	3.443068	3.511402	3.505320	3.467257	3.567396
3	3.696776	3.744421	3.733840	3.699381	3.770186
4	4.052915	4.047548	4.058993	3.989313	4.030485
5	4.467228	4.440036	4.469746	4.353320	4.384075
6	4.896566	4.890795	4.890795	4.810539	4.810539

Appendix 21: Lag Length Selection of Candidate Model Three

VAR Lag Order Selection Criteria
Endogenous variables: NPLPERC1 IPSACA1 CPISA1 BSKUAOF1 USDFXI1 BISTRE1
Exogenous variables: DUMMYM2 M3 M4 M5 M6 M7 M8 M9 M10 M11 M12C
Date: 11/14/21 Time: 23:34
Sample: 2005M02 2016M12
Included observations: 121

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1023.723	NA	6.58e-15	-15.63178	-13.82954	-14.89982
1	1151.768	215.8778	1.45e-15	-17.15319	-14.51914*	-16.08340*
2	1189.663	60.13061*	1.44e-15*	-17.18451	-13.71865	-15.77689
3	1218.854	43.42489	1.66e-15	-17.07197	-12.77431	-15.32652
4	1246.556	38.46267	2.01e-15	-16.93482	-11.80535	-14.85154
5	1285.283	49.92866	2.07e-15	-16.97989	-11.01861	-14.55879
6	1327.709	50.49028	2.06e-15	-17.08610	-10.29302	-14.32717
7	1362.490	37.94318	2.40e-15	-17.06595	-9.441070	-13.96920
8	1409.069	46.19389	2.41e-15	-17.24081	-8.784121	-13.80623
9	1438.354	26.13891	3.39e-15	-17.12982	-7.841329	-13.35741
10	1482.274	34.84531	4.02e-15	-17.26073*	-7.140426	-13.15049

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix 22: The Estimation Results of Candidate Model Three

Vector Error Correction Estimates
Date: 11/14/21 Time: 23:53
Sample (adjusted): 2005M04 2016M12
Included observations: 137 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	CointEq2
NPLPERC(-1)	1.000000	0.000000
IPSACA(-1)	0.000000	1.000000
CPISA(-1)	-0.001831 (0.00073) [-2.50012]	0.307219 (0.30285) [1.01444]
BSKUAOF(-1)	-0.010421 (0.00406) [-2.56866]	1.886167 (1.67800) [1.12406]
USDFXI(-1)	0.123055 (0.05148) [2.39037]	-39.07689 (21.2918) [-1.83530]
BISTRE(-1)	-0.018932 (0.00248) [-7.62163]	7.334868 (1.02739) [7.13931]
C	0.263573	-99.86555

Error Correction:	D(NPLPERC)	D(IPSACA)	D(CPISA)	D(BSKUAOF)	D(USDFXI)	D(BISTRE)
CointEq1	-0.033483 (0.00619) [-5.40618]	19.03413 (13.8831) [1.37102]	4.105143 (9.07021) [0.45260]	6.815090 (5.78630) [1.17780]	-0.215364 (0.45075) [-0.47779]	-3.192731 (52.0907) [-0.06129]
CointEq2	-8.01E-05 (1.6E-05) [-5.02965]	0.062964 (0.03569) [1.76417]	0.017158 (0.02332) [0.73584]	0.006897 (0.01488) [0.46365]	-0.000445 (0.00116) [-0.38373]	-0.126919 (0.13391) [-0.94777]
D(NPLPERC(-1))	0.244239 (0.08619) [2.83372]	-124.5413 (193.202) [-0.64462]	-84.49036 (126.224) [-0.66937]	-53.09237 (80.5239) [-0.65934]	-11.04954 (6.27276) [-1.76151]	405.7498 (724.909) [0.55973]
D(NPLPERC(-2))	0.205982 (0.08193) [2.51419]	-23.50492 (183.647) [-0.12799]	55.01328 (119.981) [0.45852]	-39.18167 (76.5416) [-0.51190]	3.390338 (5.96254) [0.56861]	791.3506 (689.059) [1.14845]
D(IPSACA(-1))	-2.28E-05 (4.6E-05) [-0.49505]	-0.518467 (0.10305) [-5.03142]	0.020652 (0.06732) [0.30676]	0.026176 (0.04295) [0.60947]	-0.002042 (0.00335) [-0.61024]	0.548532 (0.38664) [1.41873]
D(IPSACA(-2))	-2.32E-05 (4.4E-05) [-0.52264]	-0.123903 (0.09936) [-1.24706]	-0.019840 (0.06491) [-0.30564]	-0.032063 (0.04141) [-0.77427]	-0.000271 (0.00323) [-0.08414]	0.729824 (0.37279) [1.95771]
D(CPISA(-1))	-1.58E-05 (7.2E-05) [-0.21913]	0.029935 (0.16201) [0.18478]	0.115111 (0.10584) [1.08756]	0.032128 (0.06752) [0.47581]	-0.011164 (0.00526) [-2.12253]	0.540532 (0.60787) [0.88923]

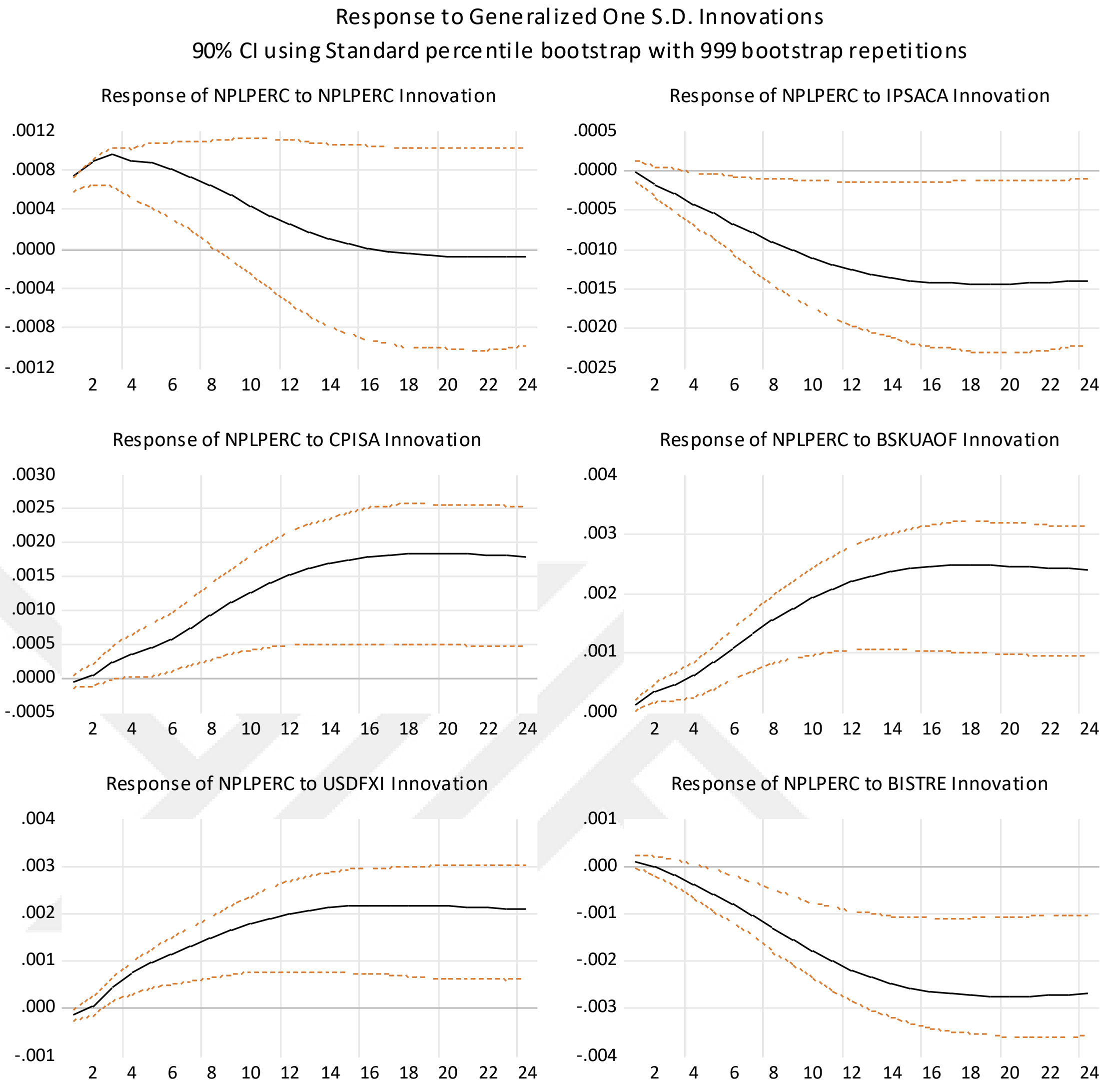
D(CPISA(-2))	5.52E-05	-0.283214	-0.127466	0.131190	-0.006188	0.464064
	(7.2E-05)	(0.16230)	(0.10603)	(0.06764)	(0.00527)	(0.60896)
	[0.76189]	[-1.74502]	[-1.20213]	[1.93944]	[-1.17441]	[0.76207]

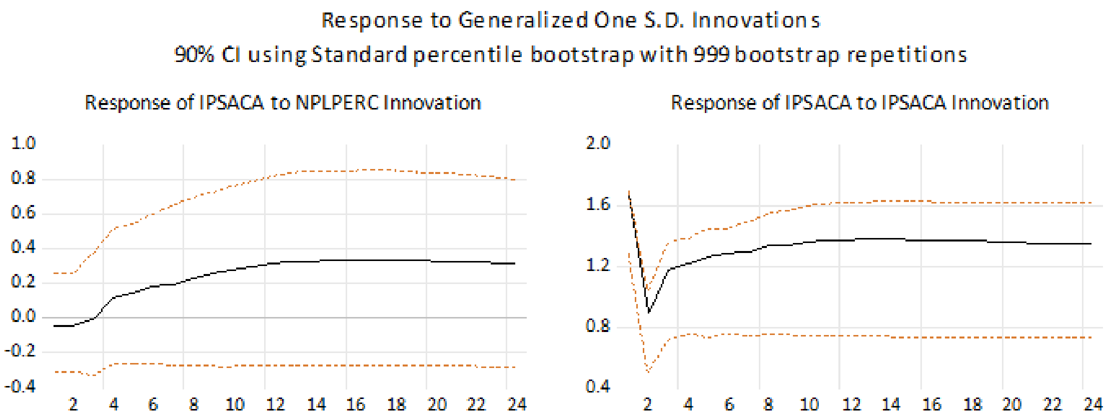
D(BSKUAOF(-2))	-0.000204	-0.236905	0.005457	-0.110657	0.006559	-0.287464
	(9.2E-05)	(0.20635)	(0.13482)	(0.08600)	(0.00670)	(0.77425)
	[-2.21667]	[-1.14806]	[0.04048]	[-1.28663]	[0.97902]	[-0.37128]
D(USDFXI(-1))	0.005285	1.379999	3.426181	3.624008	0.397707	-19.63364
	(0.00176)	(3.95608)	(2.58461)	(1.64884)	(0.12844)	(14.8435)
	[2.99439]	[0.34883]	[1.32561]	[2.19791]	[3.09635]	[-1.32271]
D(USDFXI(-2))	0.007000	-3.903014	4.035927	-3.154702	-0.007005	15.12051
	(0.00196)	(4.40321)	(2.87673)	(1.83520)	(0.14296)	(16.5212)
	[3.56341]	[-0.88640]	[1.40296]	[-1.71900]	[-0.04900]	[0.91522]
D(BISTRE(-1))	-3.96E-05	-0.031537	-0.033188	0.034502	-0.001635	0.062095
	(2.0E-05)	(0.04469)	(0.02919)	(0.01862)	(0.00145)	(0.16767)
	[-1.98584]	[-0.70573]	[-1.13677]	[1.85247]	[-1.12705]	[0.37034]
D(BISTRE(-2))	9.23E-06	-0.008191	0.001415	0.029368	-0.000400	0.017343
	(1.3E-05)	(0.02957)	(0.01932)	(0.01232)	(0.00096)	(0.11094)
	[0.69998]	[-0.27703]	[0.07323]	[2.38308]	[-0.41668]	[0.15633]
C	0.000769	0.839584	1.574247	0.037989	0.040916	0.363336
	(0.00029)	(0.64755)	(0.42306)	(0.26989)	(0.02102)	(2.42967)
	[2.66299]	[1.29655]	[3.72108]	[0.14076]	[1.94613]	[0.14954]
DUMMY	2.53E-06	-0.326816	-0.495958	-0.170985	-0.029721	1.003225
	(0.00015)	(0.33741)	(0.22044)	(0.14063)	(0.01095)	(1.26601)
	[0.01680]	[-0.96859]	[-2.24984]	[-1.21586]	[-2.71298]	[0.79243]
M2	-0.001315	-0.127830	-0.119145	-0.391728	0.006846	-3.040760
	(0.00037)	(0.82346)	(0.53799)	(0.34321)	(0.02674)	(3.08968)
	[-3.58085]	[-0.15524]	[-0.22146]	[-1.14138]	[0.25607]	[-0.98417]
M3	-0.001773	0.673535	-0.174116	-0.194467	0.009814	-3.910210
	(0.00034)	(0.76689)	(0.50103)	(0.31963)	(0.02490)	(2.87742)
	[-5.18151]	[0.87827]	[-0.34752]	[-0.60842]	[0.39415]	[-1.35893]
M4	-0.000743	0.110855	-0.024395	-0.745057	-0.042259	2.635473
	(0.00033)	(0.73318)	(0.47901)	(0.30558)	(0.02380)	(2.75096)
	[-2.27171]	[0.15120]	[-0.05093]	[-2.43817]	[-1.77524]	[0.95802]
M5	-0.001374	0.299751	0.138026	0.076783	0.024439	-4.446126
	(0.00035)	(0.77547)	(0.50663)	(0.32320)	(0.02518)	(2.90962)
	[-3.97232]	[0.38654]	[0.27244]	[0.23757]	[0.97067]	[-1.52808]
M6	-0.001906	0.261297	-0.322974	-0.290456	0.010080	-4.442155
	(0.00034)	(0.76773)	(0.50158)	(0.31998)	(0.02493)	(2.88058)
	[-5.56419]	[0.34035]	[-0.64392]	[-0.90774]	[0.40441]	[-1.54210]
M7	-0.000321	-0.125711	0.059673	0.217867	-0.029861	1.733273
	(0.00034)	(0.75461)	(0.49300)	(0.31451)	(0.02450)	(2.83135)
	[-0.95452]	[-0.16659]	[0.12104]	[0.69272]	[-1.21881]	[0.61217]
M8	-0.000633	0.062730	-0.547862	-0.184940	0.028133	-1.862836
	(0.00036)	(0.80359)	(0.52500)	(0.33492)	(0.02609)	(3.01513)
	[-1.76484]	[0.07806]	[-1.04354]	[-0.55219]	[1.07829]	[-0.61783]
M9	-0.001224	0.518384	-0.343007	-0.402311	0.009281	-0.610341
	(0.00034)	(0.75901)	(0.49588)	(0.31634)	(0.02464)	(2.84786)
	[-3.61533]	[0.68298]	[-0.69171]	[-1.27175]	[0.37662]	[-0.21432]
M10	-0.000946	0.142899	-0.335373	-0.078659	-0.006893	-3.225169
	(0.00034)	(0.75179)	(0.49116)	(0.31334)	(0.02441)	(2.82077)
	[-2.82017]	[0.19008]	[-0.68282]	[-0.25104]	[-0.28241]	[-1.14336]
M11	-0.001442	0.239660	-0.454989	0.003585	0.006912	-3.933286
	(0.00035)	(0.77946)	(0.50924)	(0.32487)	(0.02531)	(2.92460)
	[-4.14789]	[0.30747]	[-0.89347]	[0.01104]	[0.27312]	[-1.34490]
M12	-0.001706	-0.096452	-0.139471	-0.650010	0.023173	-1.820362
	(0.00034)	(0.75738)	(0.49482)	(0.31567)	(0.02459)	(2.84176)
	[-5.04973]	[-0.12735]	[-0.28186]	[-2.05917]	[0.94238]	[-0.64058]

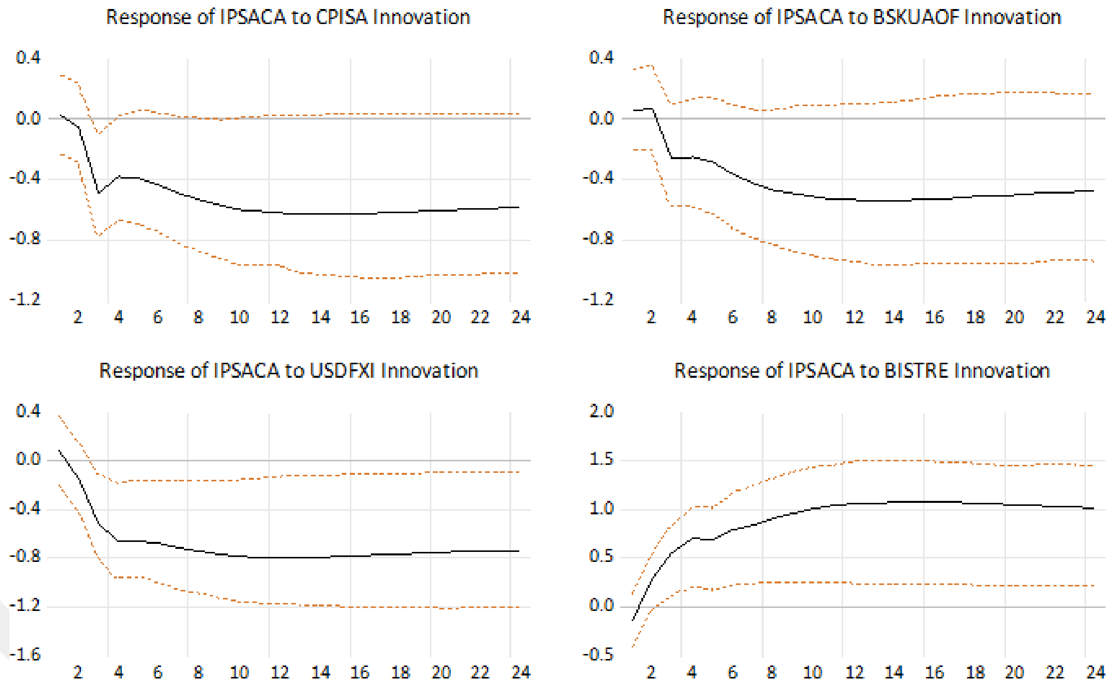
R-squared	0.764487	0.328256	0.206972	0.557196	0.337652	0.535556
Adj. R-squared	0.708821	0.169480	0.019529	0.452534	0.181097	0.425778
Sum sq. resids	6.14E-05	308.5773	131.7111	53.60316	0.325281	4344.185
S.E. equation	0.000747	1.674887	1.094246	0.698070	0.054379	6.284313
F-statistic	13.73330	2.067416	1.104189	5.323733	2.156760	4.878542
Log likelihood	806.9298	-250.0160	-191.6978	-130.1160	219.5541	-431.1725
Akaike AIC	-11.38584	4.044029	3.192668	2.293665	-2.811009	6.688650
Schwarz SC	-10.81037	4.619500	3.768139	2.869135	-2.235538	7.264121
Mean dependent	-0.000243	0.345769	1.255932	-0.043339	0.016593	0.178686
S.D. dependent	0.001385	1.837852	1.105090	0.943453	0.060092	8.293118

Determinant resid covariance (dof adj.)	4.60E-08
Determinant resid covariance	1.23E-08
Log likelihood	81.09504
Akaike information criterion	1.356277
Schwarz criterion	5.064866
Number of coefficients	174

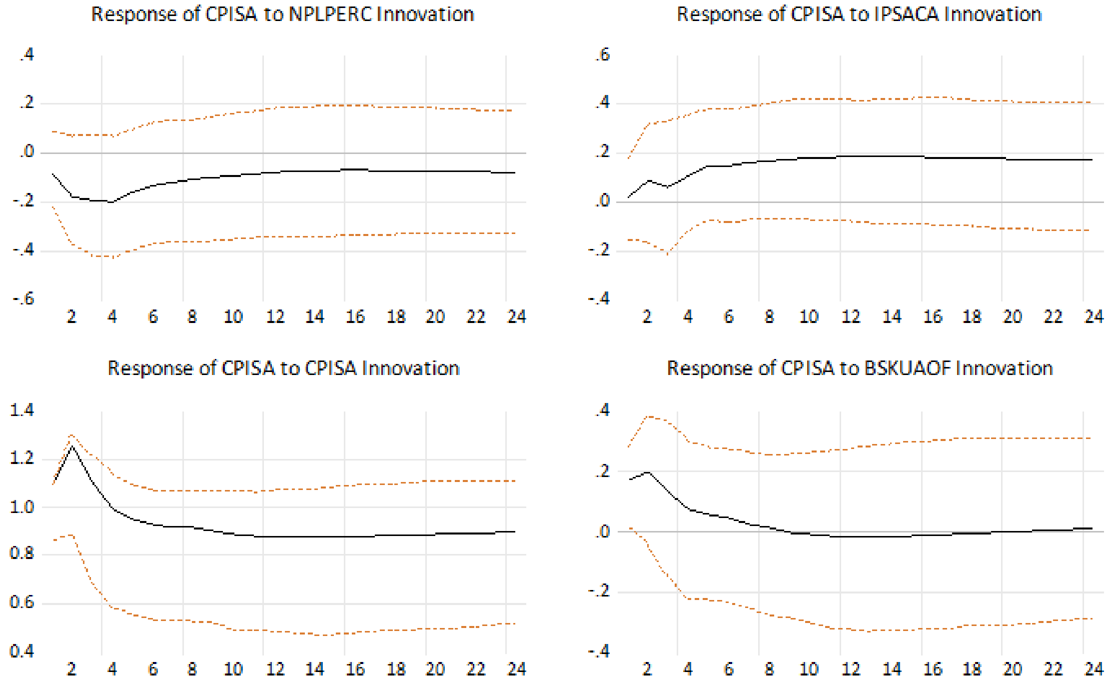
Appendix 23: Impulse Response Functions of Candidate Model Three

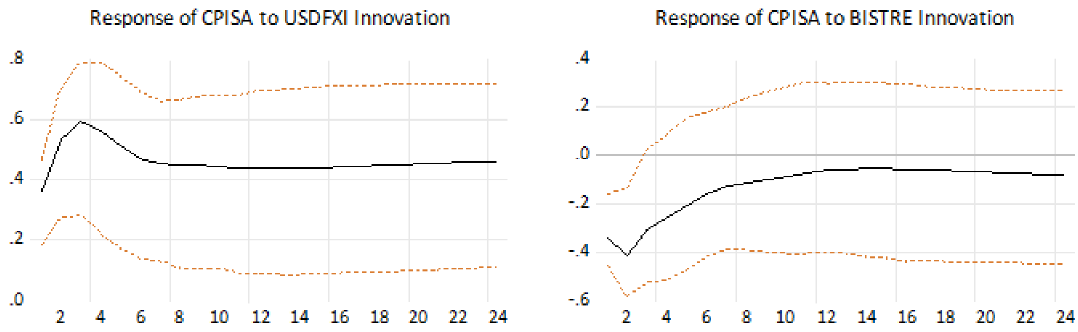




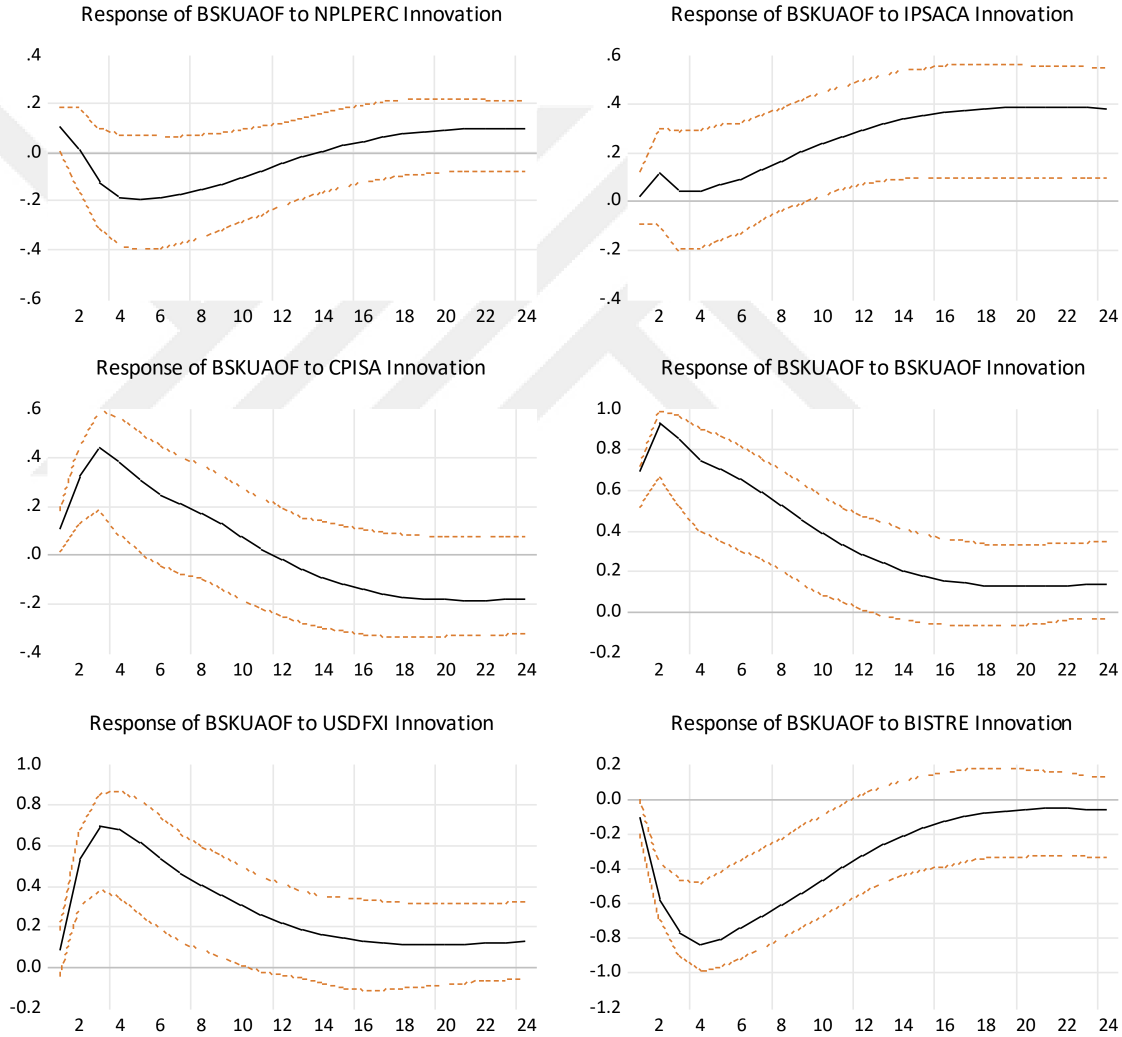


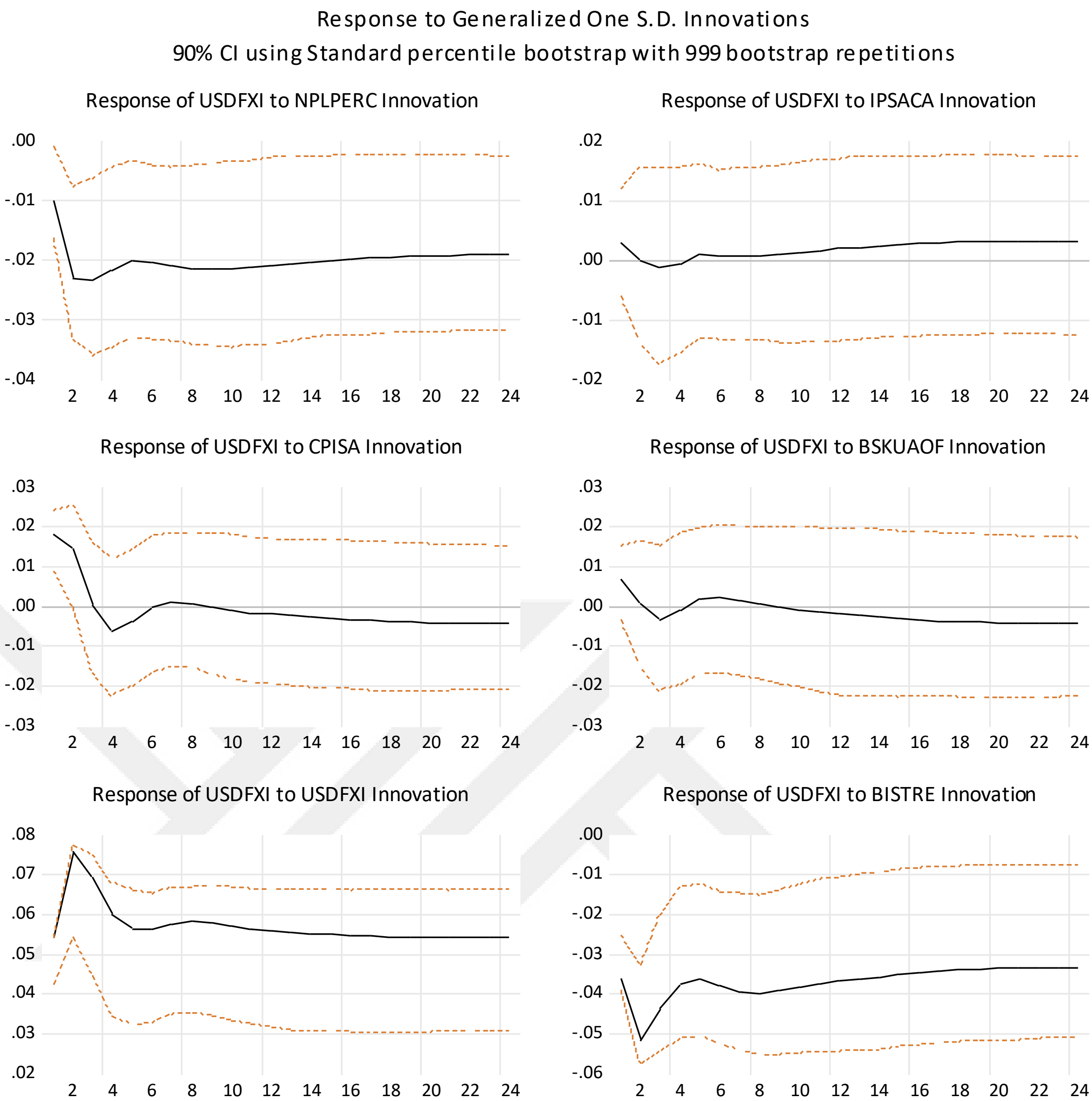
Response to Generalized One S.D. Innovations
90% CI using Standard percentile bootstrap with 999 bootstrap repetitions

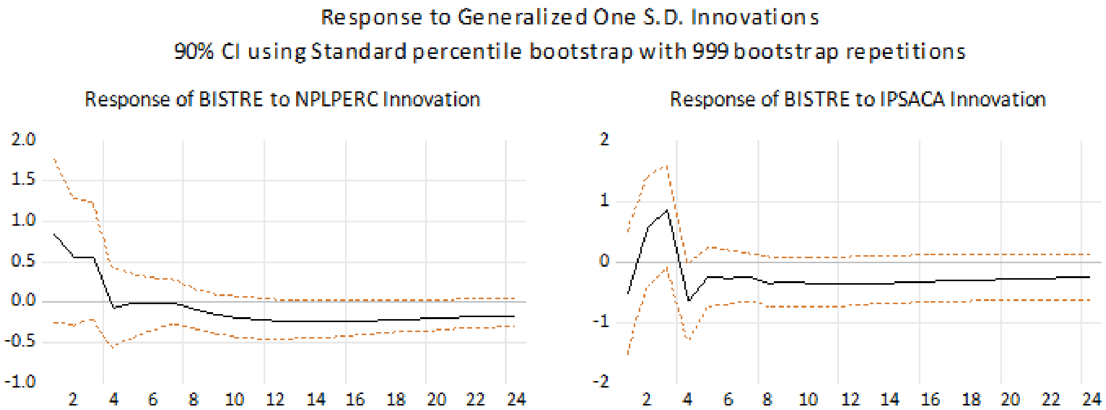


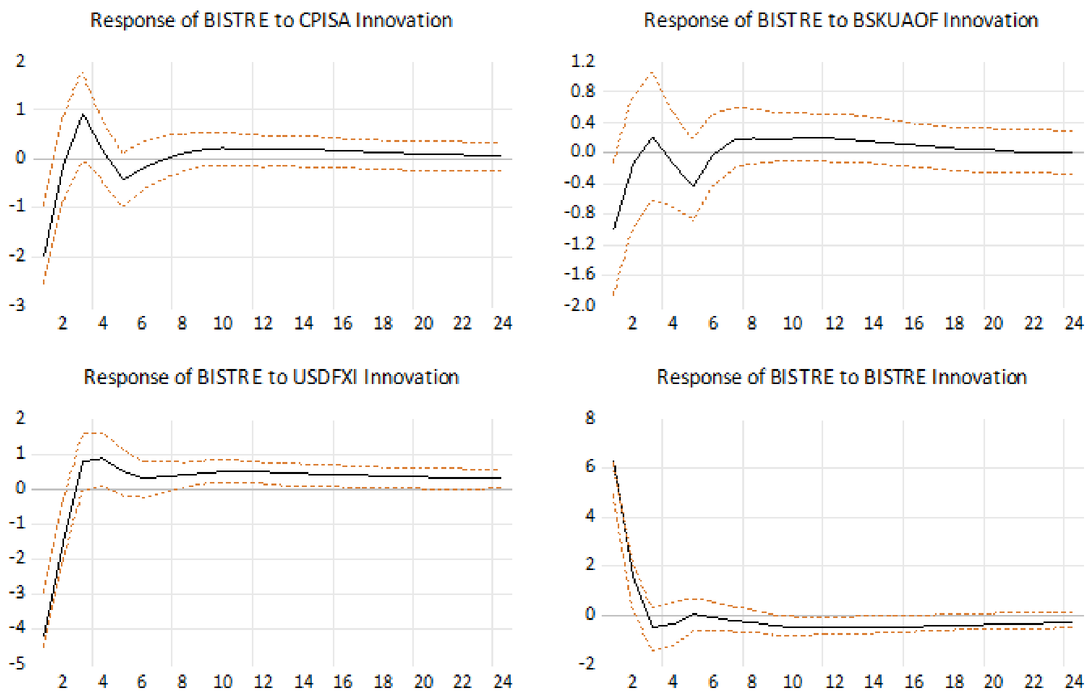


Response to Generalized One S.D. Innovations
90% CI using Standard percentile bootstrap with 999 bootstrap repetitions




Response to Generalized One S.D. Innovations
90% CI using Standard percentile bootstrap with 999 bootstrap repetitions
Response of USDFXI to NPLPERC Innovation
Response of USDFXI to IPSACA Innovation
Response of USDFXI to CPISA Innovation
Response of USDFXI to BSKUAOF Innovation
Response of USDFXI to USDFXI Innovation
Response of USDFXI to BISTRE Innovation


Response to Generalized One S.D. Innovations
90% CI using Standard percentile bootstrap with 999 bootstrap repetitions
Response of BISTRE to NPLPERC Innovation
Response of BISTRE to IPSACA Innovation


Response of BISTRE to CPISA Innovation
Response of BISTRE to BSKUAOF Innovation
Response of BISTRE to USDFXI Innovation
Response of BISTRE to BISTRE Innovation