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FORECASTING NON-PERFORMING FINANCING RATIO IN ISLAMIC BANKING POST-COVID-19 PANDEMIC

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ABOUT THE ISLAMIC FINANCIAL SERVICES BOARD (IFSB)

The IFSB is an international standard-setting organisation which was officially inaugurated on 3 November 2002 and started operations on 10 March 2003. The organisation promotes and enhances the soundness and stability of the Islamic financial services industry by issuing global prudential standards and guiding principles for the industry, broadly defined to include banking, capital markets, and insurance sectors. The standards prepared by the IFSB follow a lengthy due process as outlined in its Guidelines and Procedures for the Preparation of Standards/Guidelines, which involves, among others, the issuance of exposure drafts, holding of workshops, and, where necessary, public hearings. The IFSB also conducts research and coordinates initiatives on industry-related issues, as well as organises roundtables, seminars, and conferences for regulators and industry stakeholders. Towards this end, the IFSB works closely with relevant international, regional, and national organisations, research/educational institutions, and market players.

For more information about the IFSB, please visit **www.ifsb.org**.

ABBREVIATIONS

ADF	Augmented dickey fuller
AIC	Akaike information criterion
CAR	Capital adequacy ratio
CDS	Credit default spread
CESE	Central eastern south Europe
COVID-19	Coronavirus disease 2019
GFC	Global financial crisis
GDPG	Gross domestic product growth
IsDB	Islamic Development Bank
IFSB	Islamic Financial Services Board
IMF	International Monetary Fund
IIFS	Institutions offering Islamic financial services
LCR	Liquidity Coverage Ratio
MAE	Mean Absolute Error
NPF	Non-Performing Financing
NPL	Non-Performing Loans
NSFR	Net Stable Funding Ratio
PD	Probability of Default
ROA	Return on Assets
RMSE	Root Mean Square Error
RSA	Regulatory and Supervisory Authorities
SDGs	Sustainable Development Goals
SME	Small and Medium Enterprises
Theil	Theil Inequality Coefficient
VaR	Value-at-Risk
VARX	Vector Autoregressive Model with Exogenous Variable
VECMX	Vector Error Correction Model with Exogenous Variable
WHO	World Health Organization

Abstract

Regulatory and supervisory authorities (RSAs) across jurisdictions have suspended policy measures related to fiscal relief, moratorium policies, and financial support to SMEs and households as the economy continues to recover from the effect of the COVID-19 pandemic. Regulators and policymakers are nowadays more concerned about the impact of discontinuing the utilization of the aforementioned policies on Islamic banks` credit risk. In particular, ceasing the use of moratorium and repayment flexibility measures is most likely to engender a rapid surge of NPF. The increase in NPF may engender a deterioration of the capital adequacy ratio, harming the stability of the banking sector. Thus, forecasting the future trend of NPF is needed to assess the future trends of Islamic banks` credit risk during the recovery stage. This study aims at determining the expected trend of full-fledged Islamic banks` NPF rate during the recovery stage in selected jurisdictions offering Islamic financial services for the period ranging from 2021 Q4 to 2023 Q4. To do so, the vector autoregressive model with an exogenous variable and the vector error correction model with an exogenous variable is employed to perform the forecasting exercise. The paper selects nine jurisdictions that are prominent in Islamic banking development for this testing purpose, based on their quarterly data from 2013 Q4 to 2021 Q3. The forecasting exercise provides different shaped forms of NPF values across jurisdictions. Three groups of countries are identified. **Group 1** includes jurisdictions where Islamic banks` credit risk is most likely to increase during the recovery stage. **Group 2** represents the jurisdictions where full-fledged Islamic banks` NPF is relatively stabilized throughout the forecast period. Finally, **Group 3** contains the jurisdictions where the full-fledged Islamic banks` NPF is expected to follow a downward trend. Based on the aforementioned results, policy implications are derived to ensure the stability of Islamic banks across the examined jurisdictions during the post-pandemic era.

Keywords: *Forecasting, IIFS, Credit risk, Post-Pandemic, Regulations*

JEL Classifications: *G17, G 21, G 32*

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SECTION 1: INTRODUCTION

1.1 Background

The coronavirus disease 2019 (COVID-19)[1] has had a severe impact on ecosystems, and supply chains all over the world (Al-Awadhi *et al*., 2020). Governments have focused on containing the virus by adopting strict procedures such as social distancing, lockdowns, and quarantines, which have led to an economic downturn. Lockdowns of cities, border closures, and various health measures have been implemented all over the world to stop and slow the pandemic *(WHO Situation Report 67, 2020).* The adopted policies engendered economic recession around the world (Barro *et al*., 2020), and quickly spread to financial markets and the banking sector (Ramelli and Wagner, 2020; Zhang et al, 2020; *IMF Stability Report, 2020*; IFSB, *IFSI Stability Report, 2020*). This indicates that financial institutions are most likely to be vulnerable in times of economic downturn, due to the likelihood of non-performing financings (Goodwell, 2020).

Given the varied prudential and fiscal measures adopted globally to mitigate the negative impact of the pandemic on the financial systems, Islamic banks were highly exposed to the real economy in comparison to the conventional banking sector. Therefore, they were expected to record declined revenue, high pressure on earnings and lower growth in 2020 especially as the focus will be on preserving asset quality at the expense of business growth (IFSB, *IFSI Stability Report, 2020*).

In addition, increased pressure on liquidity position was also expected due to the mandatory postponement of repayment of existing financing extended to the small and medium enterprises (SMEs) and households in many jurisdictions where Islamic banking is practiced.

Fortunately, the Islamic banking sector entered the COVID-19 crisis from a resilient position, with adequate capital and liquidity buffers to weather any economic shocks, liquidity pressure, and other unfavorable conditions. Islamic banks demonstrated that the performance of the Islamic banking sector continues to be robust despite the economic impact of the pandemic (IFSB, *IFSI Stability Report, 2021)*.

During the Pandemic, the capital adequacy ratio (CAR) for Islamic banks was relatively stable and well capitalised. For some jurisdictions, an increase in the capital adequacy

[1] WHO situation report 1, 2019: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200121-sitrep-1-2019-ncov.pdf?sfvrsn=20a99c10_4

ratio both before and during the pandemic was observed, whereas minor adjustments have been faced by other jurisdictions, reflecting the impacts of the pandemic on their Islamic banking sector. The liquidity coverage ratio (LCR) of Islamic banks was observed to have provided resilience against potential liquidity pressures during the pandemic. Furthermore, RSAs provided a moratorium for non-performing financing (NFP), to mitigate the rapid surge of credit risk.

So far, the situation has been under control with decreasing cases and obligatory/voluntary vaccination to all people, which has encouraged several jurisdictions offering Islamic financial services to move on with the economic recovery plan. To achieve this purpose, RSAs have adopted: (i) specific exit policy measures for Islamic finance, (ii) fiscal and monetary policy measures for the benefit of both Islamic and conventional banks; and (iii) macro-financial policy measures to speed up the economic recovery process and ensure the resilience of the Islamic banking sector. Moratorium and regulatory reliefs provided during the pandemic were adopted for financing purposes, and addressed certain temporary distortions in the market with precautions and controls in place to prevent misuse/misapplication and are being monitored. More precisely, the purpose of the moratorium was not to mitigate the rapid surge of credit risk. Instead, it was designed to provide the financial system and businesses operating in the economy a temporary relief. The effectiveness of the measures was shown, while the Islamic banking sector is still found growing positively and progressively in the post-pandemic era for most jurisdictions.

Although the Islamic banking sector has shown strong resilience during the pandemic, governments will be ceasing to support several economic sectors as well as the banking sector, while most stimulus packages and measures have been considered for the short and medium terms only. More precisely, RSAs are most likely to cease some policy measures related to fiscal relief, moratorium policies, and financial support to SMEs and households as the economy is recovering. Intuitively, regulators and policymakers are nowadays more concerned about the impact of discontinuing the utilisation of the aforementioned policies on Islamic banks` credit risk.

In particular, ceasing the use of moratorium and repayment flexibility measures is most likely to engender a rapid surge of NPF, whereas it was under control during the pandemic. Considered an early warning signal for banks, the increase of NPF may engender a deterioration of the capital adequacy ratio, harming the stability of the banking sector. In this regard, forecasting the future trend of NPF is needed to assess the future trends of Islamic banks` credit risk during the recovery stage. The results, therefore, will be a fundamental key to identifying the appropriate policy recommendations in terms of exit policies relaxation or cessation.

Indeed, forecasting and stress testing analysis are essential elements within the risk management framework for gauging the strength of financial institutions. From the supervisory and regulatory perspective, forecasting needs to be conducted periodically using accurate and granular data to assess the resilience of the financial institution. This exercise enables supervisors to provide supervisory guidance to financial institutions to improve their risk management framework and enable them to anticipate any shortfalls due to external shocks[2].

This working paper is a part of the IFSB`s efforts in providing a dynamic assessment of the Islamic banking sector amid the COVID-19 pandemic. The dynamic assessment of the Islamic banking sector is under RSAs` discretion as each jurisdiction has specific models' scenarios and frameworks. Various methodologies and tools can be adopted such as stress testing, sensitivity analysis, and forecasting, subject to RSAs` guidelines. The assessment may cover several economic and financial sectors to consider necessary actions when identifying the most vulnerable ones.

In the same context, institutions offering Islamic financial services (IIFS), as part of their financial system have specificities of their risk management framework that differentiate them from their conventional counterparts. According to the Islamic Financial Services Board's IFSB-13: *Guiding Principles on Stress Testing for IIFS*, stress testing and forecasting for IIFS cover, among other matters, funding composition, including profit-sharing investment account holders, recognition of alpha in the treatment of the capital adequacy ratio (CAR), credit risk and market risk that takes into account *shari'ah*-compliant securitisation. A more detailed technical approach is offered by the IFSB's TN-2: *Technical Note on Stress Testing for IIFS*, which guides how to assess risks related to solvency, liquidity, and credit, as well as network contagion analysis. With the relevance of credit risk for IIFS during the post-pandemic era, this paper assesses and discusses the future trend of Islamic banks` credit risk during the economic recovery stage.

[2] See BCBS (2009), Principles for Sound Stress Testing Practices and Supervision, for the theoretical understanding the elements and rules of forecasting and stress testing principles

1.2 Objectives of the Paper

This paper assesses the future trends of full-fledged Islamic banks` credit risk (NPF) in Islamic banking systemically important jurisdictions during the post-pandemic period. The study, therefore, aims at:

a. Determining and analyzing the expected trends of full-fledged Islamic banks` NPF during the post-pandemic period in selected jurisdictions;
b. Providing policy recommendations for RSAs in jurisdictions where full-fledged Islamic banks` NPF is expected to be increasing, stabilizing, and decreasing throughout the forecast period, respectively;

1.3 Scope of the Paper

This forecasting paper discusses cross-country analysis by examining the future trend of non-performing financing to explain financing risk during the post-pandemic period, based on econometric modeling. The paper does not discuss the sensitivity analysis as part of the stress testing framework or interconnectedness among countries, which might also affect the results of the analysis. For the cross-country analysis provided in this research paper, nine jurisdictions are selected (see paragraph 3.2).

1.4 Methodological Assumptions and Limitations

In performing the forecasting exercise with an appropriate methodology, various risks can be addressed to assess the financial strength of financial institutions, subject to data availability. Nevertheless, based on previous research papers,[3] financing risk (as measured by the non-performing financings (NPF ratio), profitability (as captured by the return on assets [ROA]), and capital strength (as defined by the [CAR]) are the main financial indicators employed, due to their direct impact on the resilience of the banking system at both the idiosyncratic and systemic levels. Different measurements have been adopted with the aim of identifying and assessing the risk components (Sorge, 2004).

Admitting that this study aims to forecast full-fledged Islamic banks` NPF during the post-pandemic period, two bank-specific variables are incorporated in the model namely, Islamic banks' profitability (ROA); and the capital adequacy ratio (CAR) to gauge capital strength. As for the methodology, the forecasting exercise is conducted

[3] See Louzis et al. (2012), Banerjee and Murali (2017), Laviola et al. (2009), Berge and Boye (2007), Ferrari et al. (2011), Gambera (2000) and Nkusu (2011) for examinations of the different approaches adopted in macro stress testing.

using the vector autoregressive model with exogenous variable (VARX)[4] to predict NPF`s trends depending on Islamic bank's specific variables (ROA and CAR), and the macroeconomic growth (GDPG).

The forecasting exercise relies on the PISIFIs data and does not consider components such as (i) the internal reserve rates (IRR) for risk prevention, (ii) the different NPF stages adopted by RSAs when assessing the credit risk, (iii) regulatory and prudential policies that RSAs might consider to assess the credit risk, and (iii) the various financing strategies adopted by Islamic banks in different jurisdictions offering Islamic financial services. The incorporation of the aforementioned elements and the adoption of more granular data might have more accurate results, whereas the data at hand can also provide a general outlook of the future trends of Islamic banks` NPF during the recovery stage.

1.5 Structure of the Paper

This paper comprises five sections. Section 2 provides a literature review. Section 3 describes the methodology and data characteristics. Section 4 discusses the results. Section 5 provides a review of the policy implications, as well as a conclusion.

SECTION 2: LITERATURE REVIEW

Research addressing credit risk[5] assessment has increased significantly during the past decade, due to the financial challenges emanating from the global economic environment. Credit risk is considered to be one of the most important risks in the banking sector, and several studies have examined its impact on banks` stability to mitigate any expected losses emanating from NPLs, and ensure that sufficient capital is available to handle distressing situations. Thus, several studies focused on examining credit risk for conventional[6] and Islamic banks[7]` respectively. The existing studies in the field stressed the importance of risk assessment within the banking sector, while, the selection of the appropriate framework depends on the specificity

[4] See Hoggarth et al. (2005) for the theoretical underpinning of using the value-at-risk model and impulse response functions in macro stress testing.
[5]See Onder et al. (2017), Alexander and Sheedy (2008), Wilson (1997a, 1997b), Boss (2002), Sorge and Virolainen (2006), Foglia (2009) and for the theoretical understanding of different macro stress testing approaches for credit risk assessment.
[6] See Dua and Kapur (2018), Pati (2017), Artesis and Jia (2018) , Küçükkocaoğlu and Altintas (2016), for the theoretical understanding of risk assessment for conventional banks
[7] See Kurniadi et al. (2018), Takinsoy (2018), Chatta and Archer (2016) for the theoretical understanding of risk assessment for Islamic banks

and the characteristics of the banking sector, banking regulations and policies, level of development, as well as the availability of data and information.

Although the COVID-19 pandemic has negatively affected the global economic and financial sector[8], banks` resilience has been questioned during the pandemic and even in the post-pandemic period. Thus, several studies have been conducted to assess the resilience of the conventional and Islamic banking sectors amid the COVID-19 pandemic, and to mitigate the adverse effect of the pandemic on the whole industry.

Dealing with conventional banks, the study by Kozak (2021) examined the impact of an increase of NPL on the equity level and profitability of 141 banks in 18 countries of Central Eastern South Europe (CESE). Three main results were found. First, it was revealed that banks in CESE were well-capitalized and could maintain capital requirements even when NPL reaches 12%. Second, smaller and non-public banks are most likely to show a greater ability to preserve the appropriate level of equity, although there is a risk that they may postpone the time of provisioning credit risk and additionally increase lending to lower the NPL ratio. Third, larger banks were more profitable in times of crisis.

Demirguc-Kunt, *et al* (2020) utilized bank stock prices around the world to assess the impact of the COVID-19 pandemic on the banking sector. Using a global database of policy responses during the crisis, the authors examined the role of financial sector policy announcements on the performance of bank stocks. The results suggested that the crisis and the countercyclical lending role that banks are expected to play have put banking systems under significant stress, with bank stocks underperforming their domestic markets and other non-bank financial firms. The authors also indicated that the effectiveness of policy interventions has been mixed. Measures of liquidity support, borrower assistance, and monetary easing have relatively moderated the adverse impact of the crisis.

Barua and Baura (2021), investigated the possible impacts of the pandemic on the banking sector in Bangladesh. The authors estimated the impacts of the COVID-19 pandemic on three particular dimensions namely, firm value, capital adequacy, and interest income, under different NPL shock scenarios. Findings suggested that all banks are likely to show a fall in risk-weighted asset values, capital adequacy ratios, and interest income at the individual and sectoral levels. Results also revealed that

[8] See Abu Bakar and Rosbi (2021), for the theoretical understanding of the impact of COVID-19 outbreak on the banking industry and financial markets in general.

larger banks are relatively more vulnerable. Intuitively, Barua and Baura (2021), concluded that the decline in all three dimensions will increase disproportionately if NPL shocks become larger. Findings further showed that a 10% NPL shock could force the capital adequacy of all banks to go below the minimum BASEL III requirement, while a shock of 13% or more could turn it to zero or negative at the sectoral level.

In the same context, the study by Beck and Keil (2021) showed a general increase in loan loss provisions and NPLs in the United States. More precisely, the authors indicated that banks` exposure to COVID-19 can explain banks` variation in loan loss provisions and NPLs over time. Beck and Keil (2021) revealed that in the second quarter of 2020, there was an average 69% increase in loan loss provisions across all American banks, whereas the growth rate of loan loss provisions increases by 5 percentage points when bank exposure to COVID-19 deaths doubles.

The study by Cakranegara (2020), attempted to look at the effects of the COVID-19 pandemic on the Indonesian banking sector and compare it with the 1998 monetary crisis. Results showed that the banking conditions in Indonesia were currently more resistant to the current crisis compared to the 1998 monetary crisis. Furthermore, the author revealed that the adoption of macroeconomic policies is still needed to maintain economic stability.

Aldasoro *et al*, (2020) revealed that Banks' performance on equity and debt markets since the COVID-19 outbreak has been on a par with that experienced after the collapse of Lehman Brothers in 2008. During the initial phase, the market sell-off swept over all banks, which underperformed significantly to other sectors. Still, markets showed some differentiation by bank nationality, and credit default swap (CDS) spreads rose the most for banks that had entered the crisis with the highest level of credit risk. Interestingly, the subsequent stabilisation, brought about by forceful policy measures since mid-March 2020, has favoured banks with higher profitability and healthier balance sheets. Furthermore, the authors indicated that less profitable banks saw their long-term rating outlooks revised to negative. And the CDS spreads of the riskiest banks continued increasing even through the stabilisation phase.

Dealing with the Islamic banking sector, the study by Pujiharto *et al*., (2021) assessed the credit risk and profitability of banks in Indonesia. The authors considered 71 Indonesian banks listed on the Indonesian Stock Exchange and Financial Services Authority, both conventional and Islamic. The results showed significant differences in non-performing financings (NPF) before and after the COVID-19 pandemic in conventional banking. However, there is no significant difference in Islamic banking.

This evidence indicates that Indonesia's banking restructuring policies to anticipate the impact of COVID-19 did not work optimally (Pujiharto *et al*, 2021).

Almonifi *et al* (2021) assessed the impact of the COVID-19 pandemic on the performance of the Islamic banking sector in the Kingdom of Saudi Arabia. More precisely, the study looked at Al Rajhi Bank's progress[9] before and during the COVID-19 pandemic. The authors showed that the COVID-19 crisis has had a minor impact on Saudi Arabia's Islamic banking system, especially the bank under investigation, indicating that Islamic banks are capable of escaping the financial and economic risks associated with the crisis (Almonifi *et al*., 2021).

The study by Sugiharto *et al* (2021) aimed at analysing the impact of the COVID-19 pandemic on Islamic commercial banks' performance in Indonesia. The results indicated that banks' performances were not negatively affected by the COVID-19 pandemic. Similarly, the authors indicated that the growth rate of total assets, the capital adequacy ratio (CAR), non-performing financing (NPF), and operating efficiency ratio were not negatively affected by this pandemic, however, returns on assets, financing to deposits ratio, and net operating margin were negatively affected by the pandemic.

The latest study by Mansour *et al*. (2021) forecasted the response of Islamic banks' dynamics (size, profitability, non-performing financing, and stability) to the COVID-19 pandemic over the period ranging from 2019 Q4 to 2021 Q4. Nine jurisdictions were considered based on their Islamic banks' systemic importance – namely, Bahrain, Brunei, Indonesia, Kuwait, Malaysia, Pakistan, Saudi Arabia, Turkey, and UAE. Using the bi-variate VARX model, the authors showed that the Islamic banks' response to the COVID-19 pandemic is not uniform across jurisdictions. While the Islamic banks' dynamics in Saudi Arabia, UAE, and Kuwait are less likely to be impaired, Bahrain, Brunei, Malaysia, Pakistan, and Turkey are expected to be relatively more affected, especially in terms of their size. Intuitively, Mansour *et al*. (2021) indicated that Saudi Arabia will continue to lead the growth momentum of the global Islamic banking sector. Furthermore, the authors proposed a prioritisation approach for the implementation of the policy measures by the jurisdictions based on their banks' specific responses to the COVID-19 pandemic.[10]

[9] Al Rajhi Bank is one of the largest banks in the Kingdom of Saudi Arabia and the world, with SAR 512 billion in deposits, a total asset of SAR 624 billion, and a large employee base (see AL Rajhi Bank Annual Report (2021), Available at https://www.alrajhibank.com.sa/ir/index.html

[10] See Mansour et al. (2021) for further details about the prioritisation approach for the implementation of the policy measures.

Overall, the existing studies in the field showed that the impact of the COVID-19 Pandemic was observed in the Islamic[11] and conventional banking sectors, respectively. The IFSB`s RSA members and data extracted from the IFSB Prudential and Structural Islamic Financial Indicators (PSIFIs) somewhat align with the IsDB (2020) on the COVID-19 Crisis and Islamic Finance. The IFSI is not immune to the consequences of the pandemic. The expected shortfall in performance of IFSI is not substantially different from the conventional industry as was the case during the Global Financial Crisis (GFC). The industry's sectors that were negatively impacted by the COVID-19 outbreak are mainly Islamic banking and Islamic capital market sectors.

Thus, there has been a suite of swift policy responses[12] by various regulatory authorities, governments, and international organizations to mitigate the effect of the pandemic on the financial industry. These include a combination of monetary, fiscal, and other policy measures aimed at promoting financial stability and supporting economic activities. The same policies, especially in countries having a dual banking system, have been applied to both conventional and Islamic financial sectors to maintain financial stability during and after the crisis.

As part of the IFSB`s initiatives to assess Islamic banks` stability during the post-pandemic, a lack of specific measures for Islamic finance is found, rather broad-based prudential policy measures have been imposed on both the conventional and Islamic finance institutions. Nevertheless, the uniqueness of Islamic finance is brought to the fore in terms of how Islamic social finance has been used to cushion the financial ailment in the economy.

Upon the application of the specialized Islamic financial sector policies, some countries improved their banks` resilience by maintaining sufficient capital buffer and liquidity with impaired loan/financing remaining at low levels. Furthermore, the availability of finance to the real sector on subsidized rates has helped the domestic economy to remain afloat albeit on a slow pace relative to the pre-pandemic period. The relief in terms of moratorium of principal payments also facilitates entrepreneurs to remain operational. Especially, measures taken for small and medium-term industries helped economic sentiments remain alive. Up to 2021 Q2, Islamic banks across IFSB`s

[11] See IsDB. (2020) to further understand the impact of the COVID Crisis on Islamic Finance, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3834859

[12] See FSB (2020), for the theoretical understanding of COVID 19 Pandemic implications on the banking sector and policy measures taken. Financial Stability Board. https://www.fsb.org/wp-content/uploads/P150420.pdf

jurisdictions showed a strong resilience against the adverse effect of the pandemic after adopting various extraordinary policy measures.

As part of the dynamic assessment process of the COVID-19 pandemic, the IFSB provided a comprehensive analysis in terms of assessing the effectiveness of post pandemic policy measures in ensuring the stability of the Islamic finance sector. Various exit policy measures were considered in relation to (i) Islamic social finance,[13] (ii) Digital finance,[14] (iii) fiscal and monetary policies,[15] and (iv) macroprudential policy measures,[16]

Admitting that the policy measures were meant to support the economic sector and help the most vulnerable population to mitigate the adverse effect of the pandemic, it was found that they were effective in achieving their main purpose. This implies that the majority of RSAs were able to protect vulnerable economic sectors and support the private sectors workers and SMEs during the post-pandemic period, leading to a faster economic recovery.

The development of digital social finance instruments strengthened the economies of scale and limited the cash flow of small businesses by covering legal and collateral expenditures during the recovery stage. Similarly, the adoption of Fintech in zakat focused more on redistributing wealth to assist the poor in maintaining their purchasing power. In the long run, all these instruments are expected to achieve Sustainable Development Goals (SDGs), such as reducing poverty, overcoming hunger, improving health and education, and reducing social inequality.

From a fiscal and monetary perspective, the majority of RSAs indicated that the adopted policies and measures were effective/very effective in achieving their main purpose which is boosting the real sector activity and maintaining the stability of the monetary system during the post-pandemic phase. Due to the economic uncertainty caused by COVID-19, RSAs developed the concept of complementary and mutually

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[13] The use of Pension funds, Waqaf and Zakat to support vulnerable sectors and households in the short run

[14] Encouraging contactless payments and financial transactions; the adoption of fintech for zakat distribution

[15] Flexibility in repayment; extending working capital; incentivizing business to avoid laying out workers; instigating the private sector; cutting the policy rate; waiving digital banking related charges; utilizing Rental relief; stimulating investment in new manufacturing plants and machinery, waiving the minimum deposit requirement.

[16] Conducting financial stress tests; adjusting the liquidity ratios limit of LCR and NSFR; reducing the legal reserve ratio; relaxing the regulatory criteria for restructuring loans and debt burden ratios for consumer loans; adjusting the capital conservation buffer; reducing the risk weight for the SMEs financing for the CAR calculation; relaxing loan to value ratios for new residential mortgages; increasing the regulatory limit in extension of credit to SMEs,

reinforcing relationships between monetary and macroprudential policy for economic growth and financial stability. As a result, RSAs policies – monetary, macroprudential, and payment systems – were all being used in an effective and integrated manner.

Monetary and Fiscal Policies were directed to achieve stability in asset pricing (financial and housing) to ensure that an asset price bubble (which commonly builds up during economic upswings) does not burst and result in financial crises and economic recession. Moreover, monetary policy also affected the circulation of money in the economy according to the monetary target. Accordingly, the various policies focused on managing liquidity in the money market to facilitate real economic transactions and maintain price stability.

From a macroprudential point of view, it was found that the adopted policy measures were effective/very effective towards the financial sector sustainability and resilience for the majority of RSAs. The macroprudential policies concern regulation and supervision of financial services and focus on systemic risks to maintain financial system stability. Their objective was to mitigate the pro-cyclicality of the financial system (time-dimension), resulting from systemic risks associated with interconnectivity among financial institutions, markets infrastructures, and payment systems (cross-section dimension). The macroprudential policy encouraged in the intermediation of the banking sector and promoted financial inclusion for financial stability.

Although the policy measures have been used in the short and medium terms, subject to the dynamic assessment of the economy, RSAs are most likely to cease the use of most of the policies during the recovery stage. The discontinuation may include moratoriums, fiscal relief, repayment flexibilities, stimulus packages for SMEs, as well as social financial support for households and damaged economic sectors. Consequently, a rapid surge of the credit risk might be triggered, leading to more complex issues related to Islamic banks` capital requirement, liquidity and profitability. In this regard, assessing the future trend of Islamic banks` NPF across jurisdictions is strongly needed to identify the appropriate policy recommendations to be considered during the recovery stage.

SECTION 3: RESEARCH METHODOLOGY AND DATA

3.1 Research Methodology

This paper adopts a quantitative methodology using the Vector Autoregressive model with Exogenous variable (VARX) to forecast full-fledged Islamic banks` NPF for the period ranging from 2021 Q4 to 2023 Q4. The forecasting exercise enables us to identify and trace the resilience of the Islamic banking sector in nine selected countries. To perform the forecasting exercise, ROA and CAR are employed to determine the expected future trends of full-fledged Islamic banks` NPF ratio[17] across jurisdictions during the economic recovery stage.

The vector autoregressive model with and variable is called the $VARX\ (p,s)$. The form of the $VARX\ (p,s)$ model can be written as:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i\, Y_{t-1} + \sum_{i=0}^{s} \theta_i\, X_{t-1} + \varepsilon_t \tag{1}$$

The component ε_t corresponds to the error term, and Y_t and Y_{t-1} represent the current and the lagged values of the bank-specific variables (endogenous variables). The component X_{t-1} reflects the lagged value of the exogenous variable, whereas the α represents the constant of the model. Finally, β_i and θ_i are the respective coefficient of the endogenous and exogenous variables for $i = (1,2,\dots,p)$ and $i = (1,2,\dots,s)$, respectively.

The specific form of the VARX model has been widely used. This model includes endogenous and exogenous variables when conducting a forecasting exercise[18]. More precisely, it aims to forecast the trend of full-fledged Islamic banks' NPF ratio, subject to Islamic banks profitability (ROA) and capital adequacy ratio (CAR) in addition to the IMF forecasted gross domestic product growth (GDPG) by country for the period ranging from 2021Q4 to 2023 Q4. Following the studies by Carusoa *et al*. (2019), Russel *et al*. (2019), Mansour *et al*. (2021), and Alderiny *et al*. (2020), the NPF ratio is forecasted based on its own lagged value, the lagged values of the endogenous variables ROA and CAR, and the lagged value of the GDPG. The VARX equation of the NPF forecasting, therefore, is illustrated as follows:

$$NPF_t = \alpha + \beta_1\, NPF_{t-1} + \beta_2\, ROA_{t-1} + \beta_3\, CAR_{t-1} + \theta\, GDPG_{t-1} + \varepsilon_t \tag{2}$$

The component ε_t corresponds to the error term, and GDPG_{t-1} represents the macroeconomic growth, which is an exogenous variable. The basic form of the VARX

[17]See Blaschke et al. (2001) for the theoretical understanding of the NPF rate as a proxy of default.
[18] See Carpio, (2019); Zuo et al., (2019); Djigbenou-Kre and Park, (2016); Nicholson et al., (2017); Lütkepohl and Markus, (2004); Lütkepohl et al., 2006; and Primus, (2018) for the theoretical understanding of the adoption of VARX model in forecasting and macro stress testing

model is only employed when the series are not cointegrated. If a cointegration relationship exists, the vector error correction model with an exogenous variable (VECMX) is used to perform the forecasting. The error correction model with exogenous variables can be written as follows:

$$\Delta Y_t = \alpha\beta^{`} Y_{t-1} + \sum_{i=1}^{p} \beta_i^* \, \Delta Y_{t-1} + \sum_{i=0}^{s} \theta_i^* \, X_{t-1} + \varepsilon_t \qquad (3)$$

where:

Δ: Operator differencing, with $\Delta Y_t = \; Y_t - Y_{t-1}$

Y_{t-1}: Vector variable endogenous with the 1-st lag.

ε_t: Vector residual.

β_i^* and θ_i^* : respective coefficients of the endogenous and exogenous variables of the i-th variable.

α: Vector adjustment, matrix with order (k × r) β

$\beta^{`}$: Vector cointegration (long-run parameter)

By incorporating the variables of interest in equation (3), the following VECM model is considered to forecast Islamic banks` credit risk:

$$\Delta NPF_t = \alpha\beta^{`} NPF_{t-1} + \beta_1^* \Delta NPF_{t-1} + \beta_2^* \Delta ROA_{t-1} + \beta_3^* \Delta CAR_{t-1} + \theta_1^* X_{t-1} + \varepsilon_t \qquad (4)$$

Admitting that the IMF provides annual macroeconomic indicators, the variable GDPG needs to be converted every quarter to perform our forecasting exercise. Two types of frequency conversion approaches are commonly used namely, high-frequency to low-frequency conversion and low-frequency to high-frequency conversion (Rodriguez *et al*., 2003; Lisman and Sandee, 1964; Harvey, 1981). Following the study by Mansour *et al.* (2021), this research paper considers the second approach[19] for converting the GDPG annual observation (low frequency) into quarterly observations (high frequency). More precisely, a quadratic-match sum method to generate quarterly data (Mansour *et al*., 2021; Mack and Martinez-Garcia, 2011). This approach is meant to fit a local parabola of three points for each low-frequency observation, instead of fitting a straight line to two points as with linear interpolation. Quadratic interpolation is simple to implement and provides significantly better results than linear interpolation.

3.2 Data

This research paper attempts to forecast the expected trend of full-fledged Islamic banks` NPF in nine jurisdictions. The selection of jurisdictions depends on three main criteria namely, (i) their systemic importance (i), (ii) their geographical location, and (iii)

[19] See Boot et al. (1976), Chan (1993), Denton (1971), and Mack and Martinez-Garcia (2011) for the theoretical understanding of low-frequency to high-frequency conversion.

data availability and usefulness (Mansour et al, 2021). A quarterly dataset from the fourth quarter of 2013 to the third quarter of 2021[20] is built to forecast Islamic banks' NPF depending on CAR and ROA for the period ranging from 2021 Q4 to 2023 Q4. Furthermore, a quarterly dataset of IMF-forecasted GDPG, ranging from the fourth quarter of 2013 to the fourth quarter of 2023, is considered to forecast full-fledged Islamic banks' NPF ratio for the period ranging from 2021 Q4 to 2023 Q4.

Following the studies by Artesis and Jia (2018), Küçükkocaoğlu and Altintas (2016), Pati (2017), Kurniadi et al. (2018), Dua and Kapur (2018), and Mansour et al. (2021), the most important variables adopted for assessing banks' credit risk are considered. Table 1 explains the main variables, NPF, CAR, ROA, and GDPG. The NPF and CAR can be used as proxies for default and capital strength, respectively, whereas ROA captures Islamic banks' profitability. According to the Prudential and Structural Islamic Financial Indicators (PSIFIs Database), the credit risk proxy (NPF) represents the gross non-performing financing ratio (Kanas and Molyneux, 2018; Dua and Kapur, 2018; Başarır, 2016; and Mansour et al., 2021).

The GDPG is employed as an exogenous macroeconomic proxy because it captures economic growth over time. Although the study examines Islamic banks' credit risk in nine different jurisdictions, the GDPG[21] is employed as a macroeconomic proxy, reflecting various economic conditions across jurisdictions. In the case of an economic downturn, the GDPG is most likely to experience a decrease. This decrease will significantly affect households and SMEs, engendering an increase in the non-performing financings ratio (NPF) (Mansour et al, 2021). The increase in (NPF) will also lead to a decrease in the banks' profitability and the deterioration of the capital adequacy ratio. In this situation, ensuring banks' resilience becomes critical (Chatta and ALhabshi 2018).

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[20] For Islamic banks in (Country G), the bank-specific data ranges from 2013Q4 to 2021 Q2, whereas for the remaining jurisdictions, it varies from 2013 Q3 to 2021. Thus, the forecasting period for full-fledged Islamic banks` NPF ratio in (Country G) starts from 2021 Q3 to 2023 Q4; whereas for the remaining jurisdictions it is performed from 2021 Q4 to 2023 Q4.

[21] See Kanas and Molyneux (2018), Dua and Kapur (2018), and Başarır (2016), for the theoretical understanding of the forecasting exercise in assessing banks` resilience

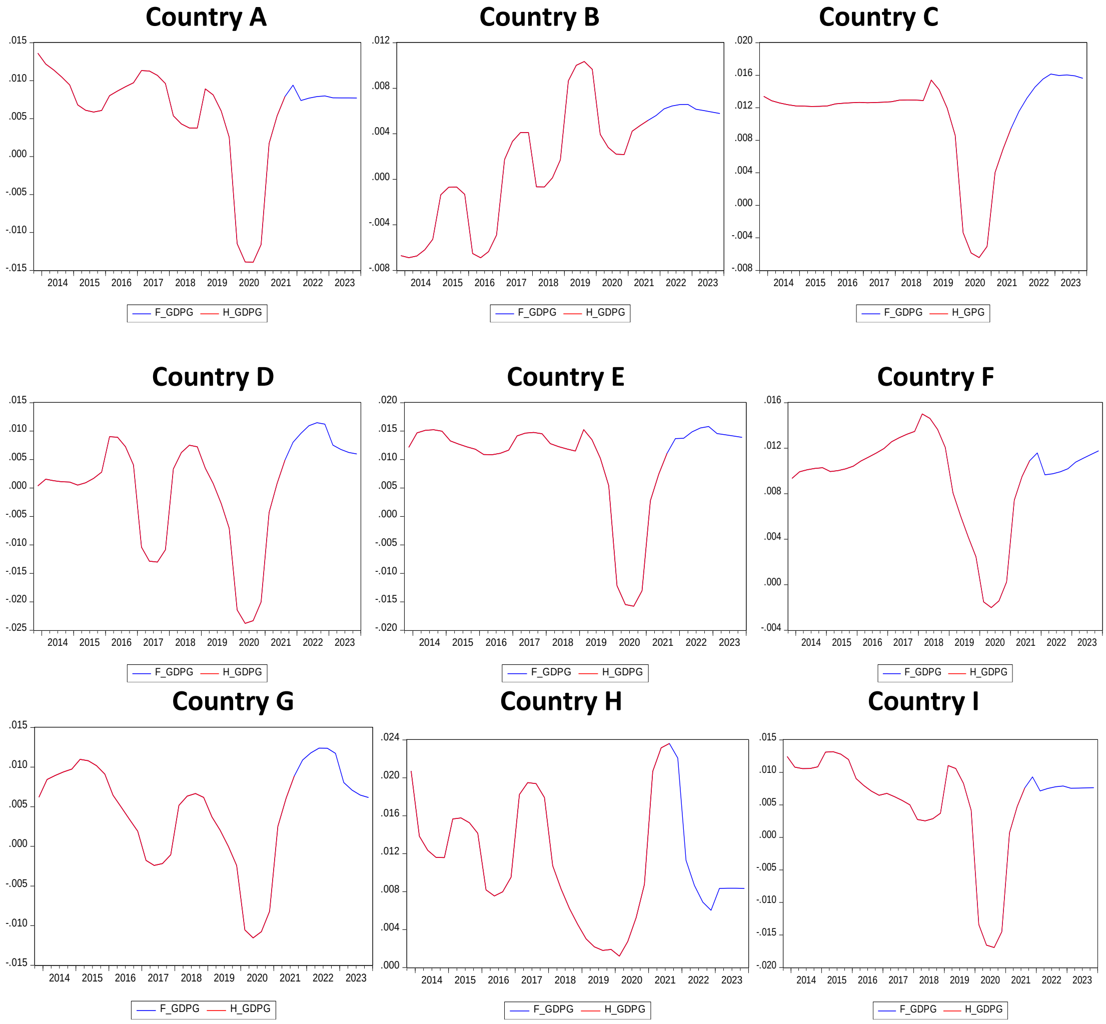
Table 1 List of Variables

Variables*	Specificities	Rationale
GDPG	Macroeconomic factor	To reflect the real sector shock to the banking and financial systems
Gross NPF (non-performing financings)	Country-specific variable	To explain the performance and resilience of banks' financing activities
CAR (capital adequacy ratio)	Country-specific variable	To assess the capital strength of the banking sector
ROA (return on assets)	Country-specific variables	To identify the bank's financing performance

* Sources: Based on IMF and IFSB data.

Figure 1 illustrates the GDPG across countries for the period ranging from 2013 Q4 to 2023 Q4. The red line represents the actual GDPG (from 2013 Q4 to 2021 Q3), whereas the blue line captures the IMF forecasted GDPG for each country (from 2021 Q4 to 2023 Q4).

Figure 1: Quarterly Gross Domestic Product Trend, 2013 Q4 to 2023 Q4



Source: IMF, *World Economic Outlook* database, April 2021

Figure 1 shows that the GDPG has experienced a downward trend during the year 2020 for most countries except for countries (B and H). Table 2 below indicates that the lowest quarterly GDPG of countries (A, C, D, E, F, G, H and I) reached -1.31% (2020 Q3), -0.64% (2020 Q3), -2.37% (2020 Q2), -1.57% (2020 Q3), -0.20% (2020 Q2), -1.15% (2020 Q2) and -1.69% (2020 Q3), respectively. The lowest quarterly GDPG of countries (B, and H) during the same period was around 0.21% (2020 Q4) and 0.11% (2020 Q1), respectively.

Up to 2021, the GPDG experienced an up-ward trend in all jurisdictions, which represents the beginning of the economic recovery. This improvement in terms of economic growth continued for most jurisdictions during 2021 except for country (H), which is mostly attributed to the remarkable increase of inflation. Interestingly, the blue line, representing the IMF forecasted GDPG shows that economic growth is expected to be stabilized and positive for all jurisdictions including country (H), indicating a healthy economic condition in 2022 and 2023, respectively.

Table 2 also shows that Islamic banks in countries (A, E, and I), are characterised by higher NPF ratios, whereas Islamic banks in countries (D and G) have the lowest mean NPF values. Intuitively, a higher NPF ratio may reflect a higher probability of default because, in most jurisdictions, almost 50% of total Islamic financing is devoted to household financing (IFSB, *IFSI Stability Report 2021*). This higher concentration may cause a higher risk of default when economic situations become more severe due to the lack of diversification.

The descriptive statistics indicate that countries (B and G) have the highest CAR ratios as measured by the mean, whereas countries (F and H) have the lowest mean values. This implies that the jurisdictions having a higher CAR are most likely to ensure their banking resilience. More precisely, the total regulatory capital is largely higher than the risk-weighted assets, allowing Islamic banks to operate safely (Mansour *et al*., 2021).

In terms of mean value, the highest ROA ratios correspond to country (G and B), indicating that these jurisdictions are most likely to generate higher income when deploying their total Islamic banks’ assets. In contrast, countries (A and E) have the lowest mean values.

Table 2: Descriptive Statistics

	Country A				Country B				Country C			
	NPF	**CAR**	**ROA**	**GDPG**	**NPF**	**CAR**	**ROA**	**GDPG**	**NPF**	**CAR**	**ROA**	**GDPG**
Mean	0.111	0.186	0.0099	0.005	0.050	0.2029	0.0167	0.0005	0.041	0.1821	0.012	0.0098
Median	0.115	0.183	0.0088	0.007	0.046	0.1984	0.0166	0.0009	0.040	0.1744	0.013	0.0125
Maximum	0.148	0.220	0.0391	0.013	0.084	0.2313	0.0327	0.0103	0.056	0.249	0.022	0.0153
Minimum	0.066	0.172	-0.0083	-0.013	0.031	0.1726	0.0105	-0.0068	0.027	0.1409	0.005	-0.0064
Std.Dev	0.020	0.012	0.0085	0.007	0.013	0.0193	0.0047	0.0053	0.008	0.0321	0.005	0.0061
	Country D				**Country E**				**Country F**			
	NPF	**CAR**	**ROA**	**GDPG**	**NPF**	**CAR**	**ROA**	**GDPG**	**NPF**	**CAR**	**ROA**	**GDPG**
Mean	0.0248	0.177	0.0120	-0.0023	0.084	0.1653	0.0103	0.0088	0.051	0.1493	0.014	0.0089
Median	0.0227	0.178	0.0118	0.0009	0.085	0.16535	0.0105	0.0119	0.046	0.1465	0.011	0.0102
Maximum	0.0442	0.19	0.0183	0.00902	0.105	0.1822	0.0127	0.0152	0.075	0.1952	0.026	0.0150
Minimum	0.0155	0.163	0.0016	-0.0237	0.066	0.1386	0.0055	-0.0157	0.033	0.1290	0.007	-0.0020
Std.Dev	0.0078	0.007	0.0029	0.0096	0.010	0.0119	0.0015	0.0092	0.012	0.0168	0.005	0.0047
	Country G				**Country H**				**Country I**			
	NPF	**CAR**	**ROA**	**GDPG**	**NPF**	**CAR**	**ROA**	**GDPG**	**NPF**	**CAR**	**ROA**	**GDPG**
Mean	0.0119	0.201	0.0222	0.0028	0.040	0.1633	0.0118	0.0113	0.062	0.1710	0.014	0.0049
Median	0.0120	0.2016	0.0218	0.0049	0.038	0.16514	0.0123	0.0111	0.063	0.1706	0.0149	0.0069
Maximum	0.0146	0.218	0.0280	0.0109	0.065	0.1910	0.0172	0.0236	0.092	0.2005	0.018	0.0131
Minimum	0.0084	0.166	0.0177	-0.0115	0.030	0.1397	0.0039	0.0011	0.047	0.1540	0.008	-0.0169
Std.Dev	0.0016	0.010	0.0026	0.00654	0.009	0.0150	0.0032	0.0067	0.010	0.0106	0.002	0.0085

3.4 Model Specifications

3.4.1 Unit Root Test

The unit root test determines whether all variables are integrated of the same order, which is a necessary precondition for the application of vector autoregressive modelling. The Augmented Dickey-Fuller (ADF) and Phillips-Peron tests are used to determine if the data possess a unit root. In the same context, a set of information criteria can be utilised to reject the existence of a unit root. In this study, therefore, the ADF test and the Akaike Information Criterion (AIC)[22] are employed to perform the unit root[23] test for our dataset.

Table 3: Variables Specifications

Variables	Country A		Country B		Country C	
	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
NPF	-1.262718	-6.4723***	-2.0586	-5.1559***	-1.6768	-3.927***
CAR	-3.06605**	-5.6116***	-1.8769	-5.8577***	0.023906	-5.771***
ROA	-2.771523*	-5.4795***	-3.5433**	-6.0051***	-0.1813	-5.768***
GDPG	-0.000718	-9.0947***	-0.7303	-10.137***	-2.0431	-4.178***
Variables	Country D		Country E		Country F	
	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
NPF	-1.808974	-6.3629***	-2.4996	-4.7178***	-1.557537	-4.0999***
CAR	-3.12415**	-7.2904***	-1.2971	-6.5346***	-0.29686	-5.6101***
ROA	-2.5895	-4.6023***	-2.4832	-5.5666***	-0.78771	-4.4765***
GDPG	-1.862692	-6.3814***	-0.528	-7.0715***	-2.75618*	-5.2317***
Variables	Country G		Country H		Country I	
	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
NPF	-2.0022	-4.8177***	-2.14840	-4.7285***	-2.6575*	-8.162***
CAR	0.4668	-4.1858***	-1.87820	-6.6487***	-1.6233	-4.2106***
ROA	-3.0822**	-7.9341***	-2.34938	-5.6442***	-2.6614*	-6.9106***
GDPG	-1.3207	-8.8269***	-2.11564	-4.2040***	0.841039	-10.093***

Note: 'ADF' denotes the Augmented Dickey-Fuller test. ***, ** and * denote the statistical significance at the 1%, 5% and 10% levels, respectively.

Although the level of significance is an important input to hypothesis testing, modern statistical textbooks allocate surprisingly little space on the discussion as to how it should be chosen for sound statistical inference (Jae, 2015). While the conventional levels may still serve as useful benchmarks, mindless and mechanical choice of these levels should be avoided (Jae, 2015). It is required to understand that the level of significance should be chosen with relevant contexts in mind, in careful consideration of the key factors such as sample size and expected losses.

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[22] See Engle and Granger (1987) for the theoretical underpinning of the ADF test and the AIC.
[23] The null hypothesis cannot be rejected when time series data possess a unit root in the ADF result. The null hypothesis is rejected when the p_value is less than 5%, or when the ADF test statistic is more negative than the ADF critical value.

The level at 0.05 (0.01 or 0.10) is only a convention, based on Fisher's argument that one in twenty chance represents an unusual sampling occurrence (Moore and McCabe, 1993). However, there is no scientific basis for this choice (Lehmann and Romano, 2005), while it depends on how important the variable(s) are in the model to explain and reach the purpose of the research. Traditionally, researchers have used either the 0.05 level (5% level) or the 0.01 level (1% level), whereas the choice is largely subjective. The lower the significance level, the more conservative the statistical analysis and the more the data must diverge from the null hypothesis to be significant (Leamer, 1978; Skipper et al, 1971). To this extent, this study considers the 1% level as a benchmark when testing the stationarity of our series.

When the ADF test statistic is higher than the ADF critical value in terms of absolute value, the null hypothesis of the presence of the unit root test can be rejected (Greene, 2002; Said and Dickey, 1984). Table 3 shows that bank-specific variables and the macroeconomic variable (GDPG) are stationary after the first difference at the 1% level for all jurisdictions.

3.4.2 Johansen Cointegration Test

The Johansen cointegration[24] test is used to investigate the long-run relationships between the variables in a certain jurisdiction. The Johansen test is a test for the cointegration of several I (1) time-series data. The advantage of the Johansen test comes from its ability to handle several time-series variables. It is possible to choose either the (i) trace test or (ii) the maximum eigenvalue test to interpret the outcome of the Johansen cointegration test (Johansen, 1991).

The study by Lütkepohl *et al*. (2001) indicated that the maximum eigenvalue test and the trace test perform quite similarly in a small sample size. However, an excessive size distortion is more pronounced for the trace test than for the maximum eigenvalue test (Lütkepohl *et al*., 2001). This implies that the maximum eigenvalue test is more appropriate when examining a small sample size.

Table 3.4.2 shows that all series are cointegrated except for countries (A, F and I). Based on the maximum eigenvalue at the 5% level of significance, the results indicate the existence of long-run relationships among variables for countries (B, C, D, E, G and H), whereas a short-run relationship is found for countries (A, F and I). To examine the short-run relationship across variables, the VARX model needs to be estimated,

[24] See Seiler (2004) for the theoretical understanding of the cointegration relationship between variables.

whereas the long-run relationship assessment for the remaining jurisdictions requires the use of the VECMX model.

Table 4: Johansen Cointegration Test

Countries	Null	Max Eigen		Countries	Null	Max Eigen	
		***T*-Stat**	**CV**			***T*-Stat**	**CV**
A	None	19.93693	27.58434	**B**	None	24.06888	27.58434
	At most one	11.29563	21.13162		At most one	18.01269	21.13162
	At most two	7.698505	14.26460		At most two	11.20419	14.26460
	At most three	2.853164	3.841466		At most three	2.104982	3.841466
C	None	34.57361	27.58434	**D**	None	28.99597	27.58434
	At most one	18.20304	21.13162		At most one	19.30696	21.13162
	At most two	8.233492	14.26460		At most two	11.87274	14.26460
	At most three	0.002783	3.841466		At most three	6.436208	3.841466
E	None	28.26434	27.58434	**F**	None	21.06019	27.58434
	At most one	12.89259	21.13162		At most one	12.21020	21.13162
	At most two	7.490964	14.26460		At most two	7.214438	14.26460
	At most three	4.248446	3.841466		At most three	0.277232	3.841466
G	None	23.07870	27.58434	**H**	None	31.97257	27.58434
	At most one	16.88127	21.13162		At most one	13.36400	21.13162
	At most two	8.410780	14.26460		At most two	6.149612	14.26460
	At most three	0.043551	3.841466		At most three	3.504296	3.841466
I	None	26.06423	27.58434				
	At most one	15.34607	21.13162				
	At most two	6.142085	14.26460				
	At most three	5.764146	3.841466				

After estimating both models, the forecasting tool is adopted to determine the expected trend of Islamic banks' NPF, depending on Islamic banks' profitability, capital strength, and macroeconomic conditions. For the period ranging from 2021 Q4 to 2023 Q4. Following the studies by Mansour *et al*. (2021), three main steps need to be considered:

- The data need to be extended from 2021 Q4 to 2023 Q4, which is the forecast period[25]. Although the variable GDPG is forecasted until 2023 Q4 (IMF, *World Economic Outlook*, 2021), Islamic banks' NPF needs to be forecasted, subject to its own lagged values, the lagged values of CAR and ROA, and the lagged value of the GDPG.
- The forecasted series are plotted to illustrate the trend NPF, where the red line represents the actual values and the blue line reflects forecasted values.

[25] The available Islamic banks` data in (Country G) when performing the analysis ranges from 2013 Q4 to 2021 Q2. Thus, it is extended from 2021 Q3 to 2023 Q4, which is the forecast period.

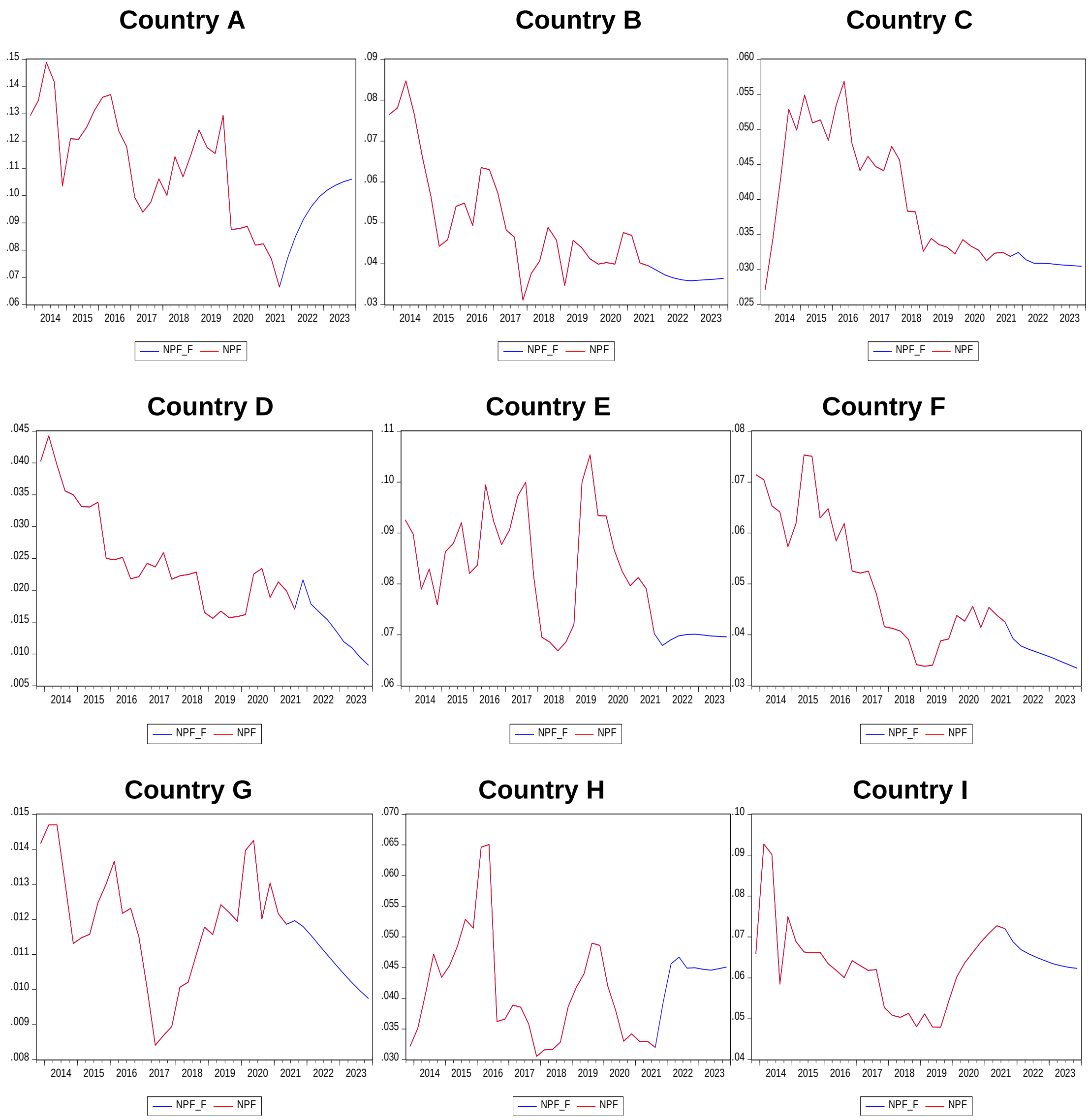
SECTION 4: FORECAST RESULTS

4.1 Forecasting Non-performing Financing (NPF) for Islamic Banks

Figure 2 below provides a forecast of Islamic banks' non-performing financing (NPF), for the period ranging from 2021 Q4 to 2023 Q4. Six shapes were found after performing the forecasting exercise on Islamic banks' NPF, as in the following.

- **Increased shaped form:** This form is followed by country A. The forecasted NPF values exhibit an upward trend during the first few quarters of 2022 until reaching a maximum value of 10.6% in 2023 Q4.
- **Decreasing shaped form:** This form is represented by country (G, F, and I). The forecasted NPF values experience an immediate decline for countries G, F, and I, reaching 0.974%, 6.23%, and 3.34%, respectively, in 2023 Q4. This reveals that Islamic banks` NPF values in these countries are less likely to increase during the recovery stage, indicating a low credit risk level compared to other jurisdictions offering Islamic financial services.
- **Inverted-V shaped form:** This form is only followed by country D. The forecasted NPF is expected to increase from 1.70% in 2020 Q3 to 2.16% in 2021 Q4, followed by a remarkable decrease after the fourth quarter of 2021 until reaching 0.82% in 2023 Q4. This indicates that Islamic banks` NPF in this jurisdiction is characterized by a low level of credit risk in the long run.
- **Quasi-L shaped form:** Only country E is following this form. Results show that NPF decreases from 7.02% in 2021 Q3 to 6.7% in 2021 Q4. Then it is expected to remain relatively stable until reaching 6.9% in 2023 Q4. Islamic banks in country E are, therefore, less likely to experience a rapid surge of NPF during the recovery stage, which indicates the resilience of the Islamic banking sector in this particular jurisdiction.

Figure 2: Islamic Banks' NPF



- **Inverted quasi-L-shaped form:** This form is only represented by country H. The results reveal that the NPF is expected to increase from 3.2% in 2021 Q3 to 4.67% in 2022 Q2, followed by a slight decrease in 2022 Q3 after reaching 4.44%. From 2022 Q4 onward, the NPF of Islamic banks is expected to remain relatively stable until reaching 4.45% in 2023 Q4.

- **Fluctuating form:** This form is followed by countries B and C. The forecast results show that NPF is expected to be fluctuating with a decreasing trend for Islamic banks on both countries. More precisely, results indicate that the NPF of Islamic banks in countries B and C will be fluctuating between (3.83%; 3.64%) and (3.24%; 3.04), respectively, for the forecast period ranging from 2021 Q4 and 2023 Q4. The decreasing trend of the forecasted NPF is indicative of the resilience of the Islamic banking sector in both jurisdictions in the long run.

Based on the different shaped forms explained above, three groups of countries can be considered. **Group 1** represents countries when Islamic banks' credit risk is impaired (expected to increase in the long run) such as country A. The country under **Group 1**, is expected to be the most impaired because the corresponding NPF values is expected to reach the maximum forecasted value of 10.6% in 2023 Q4. The increased shaped form indicates that Islamic banks in country A are most likely to remain vulnerable to adverse credit risk movements, due to the adverse effect of the pandemic on various sectors such as accommodation, restaurants, entertainment, and recreation. This indicates that the overall share of stage 2[26] financings is expected to increase. Although stage 2 financings as a share of financings are still under moratoria, NPF is most likely to increase as the benefits of measures such as payment moratoria and loan guarantees will be ceasing gradually during the recovery stage. It is therefore recommended to focus on limiting the build-up of distressed exposures on Islamic banks` balance sheets.

Group 2 includes the countries where Islamic banks` NPF is relatively stable throughout the forecast period such as countries E, B, C and H. Countries in **Group 2** are less likely to experience a rapid surge of NPF ratio in the long run. The situation of Islamic banks for **Group 2** is under control as the credit risk is stabilized, whereas further policy measures are needed to maintain a low level of credit risk during the recovery stage.

Islamic banks under this group have maintained a high degree of vigilance over large exposures, with heightened monitoring of, and engagements with, customers observed among banks to proactively manage credit risks. This means that the level of provisions held by banks against such exposures has been prudent, which mostly reduces the need for banks to further increase provisions in this borrower segment by a significant amount, assuming gradually improving economic conditions. In contrast, Banks are preparing for higher defaults and have continued to build up provisions against the materialisation of potential credit losses when support measures are eventually unwound. Accordingly, the sector's strong capital structure indicates that the credit risk is expected to remain at manageable levels in the long run, which is in line with the forecast results.

[26] In the context of IFRS 9, stage 1 Financings are financial instruments that have not deteriorated significantly in credit quality since initial recognition or have low credit risk. Stage 2 Financings are financial instruments that have deteriorated significantly in credit quality but show no objective evidence of credit loss event. Stage 3 financings include financial assets that have objective evidence of impairment at the reporting date. For these assets, lifetime ECL are recognised and interest revenue is calculated on the next carrying amount.

Finally, **Group 3** contains the countries where the full-fledged Islamic banks` NPF ratio is decreasing in the long run such as countries G, I, and F. Full-fledged Islamic banks in countries under **Group 3** are characterized by a decreasing NPF trend over the forecast period, indicating a strong resilience in terms of credit risk.

Full-fledged Islamic banks under this group have continued to build provisions for post-COVID-19 deferral loan performance, which could also limit the downside risk once the Deferral Payment Program ends (*IFSI Financial Stability Report, 2021).* In addition, the resilience of the Islamic banking sector in these jurisdictions in terms of credit risk was strongly related to the sufficient liquidity that has been allocated during the recession and the recovery stage (*IFSI Financial Stability Report, 2021).* Interestingly, the liquidity indicators[27] liquid asset ratio (LAR) and liquid asset to short-term liabilities (LASTL) were remarkably high during the pandemic and the recovery stage (*IFSI Financial Stability Report, 2021*). This indicates that Islamic banks were able to honour their short and long-term obligations, despite the severity of macroeconomic conditions.

In a nutshell, Islamic banks in these jurisdictions are expected to remain sound in terms of credit risk based on the forecasted NPF values. In contrast, RSAs are advised to consider a dynamic risk assessment to utilize appropriate policies subject to microeconomic and macroeconomic conditions. This procedure will enable RSAs to mitigate asset quality deterioration, while the true impact is most likely masked in the short term by financing deferral programmes and regulatory flexibility for banks in recognising impairments.

Overall, the various post-pandemic policy measures enabled RSAs in most jurisdictions offering Islamic financial services to maintain the stability of the banking sector during the economic recovery stage. The effectiveness of the adopted exit policy measures during the post-pandemic stage was reflected in the forecast results, while Islamic banks' NPF is expected to be decreasing gradually for some jurisdictions, stabilized in the long run for others, except for country A. To this extent, some policy recommendations from a regulatory perspective are provided in the following section to ensure the soundness of the Islamic banking sector.

[27] Liquid asset ratio (LAR) is total liquid asset to total liabilities, Liquid asset to short term liabilities (LASTL) represents the total liquid asset to short term liabilities.

4.2 VAR Diagnostic Tests

The diagnostic tests are performed to ensure the accuracy of the results and the stability of our models. Table 5 displays the results of the autocorrelation test conducted for all jurisdictions. Various tests can be used to investigate the presence of the autocorrelation effect in vector autoregressive models namely, the Ljung–Box Portmanteau test, Breusch-Godfrey LM test, and Rao F-test, among others. The study by Hatemi (2004), therefore, showed that all three tests perform relatively well in stable vector autoregressive models as shown in Table 5). In contrast, the portmanteau test is most likely to show size distortions in unstable models (Hatemi, 2004).

Table 5: Autocorrelation Test

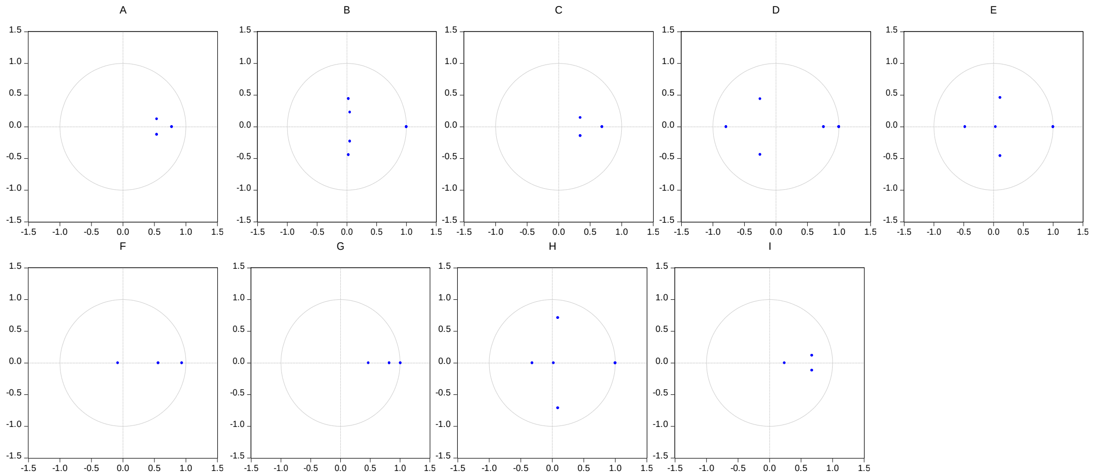
Country	Rao F-stat	P-value
A	0.958794	0.4843
B	0.912036	0.5222
C	1.579525	0.1496
D	0.786984	0.6294
E	0.761233	0.6519
F	1.091158	0.3856
G	0.554767	0.8268
H	0.436987	0.9079
I	0.487155	0.8765

Note. The Rao F-test investigates the existence of autocorrelation in our models. Null hypothesis: there is no autocorrelation. According to Rao (1973), the null hypothesis is rejected when the *p*-value of the Rao F-stat is higher than 5%. Our results prove that our models do not suffer from autocorrelation issues because the Rao F-stat's *P*-value is higher than 5% for all jurisdictions.

Following Edgerton and Shukur (1999) and Rao (1973), Rao's F-test is employed to test the autocorrelation effect. The null hypothesis assumes that there is no autocorrelation for all series. Our models do not exhibit autocorrelation issues since the null hypothesis cannot be rejected at a 5% level of statistical significance. More precisely, it is revealed that the Rao F-stat has a *P*-value higher than 5% for all models, indicating that our results do not suffer from autocorrelation effects.

Similarly, Figure 3 shows the stability diagnostic test for our models. This test assumes that the VARX and VECMX models satisfy the stability conditions if no root lies outside the unit circle. Across all jurisdictions, the results indicate that there is no root outside the circle, justifying the stability of our models.

Figure 3: Model Stability Test



Note: AR roots. This table reports the inverse roots of the characteristic AR polynomial; see Lütkepohl (1991). The estimated model is stable (stationary) if all roots have a modulus less than one and lie inside the unit circle.

4.3 Forecasting Evaluation Test

The forecasting Evaluation test is meant to assess the robustness of our results. To do so, it is necessary to perform an in-sample forecast evaluation test to ensure consistency. The in-sample forecast evaluation test enables us to assess whether the adopted model can predict actual data for a given period. Following the study by Antonio et al., (2018), Juselius and Tarashev (2020), and Mendez Marcano, (2021), three indicators are considered namely, RMSE, MAE, and Theil (U). The evaluation test imposes that the forecast is good when the respective coefficients of RMSE, MAE, and Theil (U) are close to Zero (Juselius and Tarashev, 2020; Mendez Marcano, 2021). The Root Mean Square Error (RMSE) is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are; RMSE is a measure of how spread out these residuals are. More precisely, it indicates how concentrated the data is around the line of best fit.

The Mean Absolute Error (MAE), refers to the magnitude of the difference between the prediction of an observation and the true value of that observation. MAE takes the average of absolute errors for a group of predictions and observations as a measurement of the magnitude of errors for the entire group. Theil Inequality Coefficient (U) provides a measure of how well a time series of forecasted values compares to a corresponding time series of observed values.

Figure 4: In Sample Forecasting

With regards to the in-sample forecast Figure 4 represents a plot of actual and in-sample forecasted data for a period ranging from 2019Q1 to 2021Q3 for all jurisdictions except country G. For country G, the data is forecasted from 2019Q1 to 2021Q2 due to the lack of 2021Q3 observation. This figure shows that the more fit the forecast line against the actual data line, the better the forecasting is. Overall, Figure 4 illustrates that the lagged values of the endogenous variables and the exogenous macroeconomic indicator (GDPD) are to some extent, appropriate to predict the future trend of NPF. Further explanation is provided in Table 6.

Table 6 represents a summary of the forecasting evaluation matrix for the in-sample and out-sample forecasts. Interestingly, the model is considered appropriate to predict the future trends of NPF rates if RMSE, MAE, MAPE, and Theil coefficients are close to zero, which is the case in this study. This indicates that our results are robust.

Table 6: Dynamic Forecasting Evaluation

Countries	RMSE	MAE	Theil
A	0.010818	0.008755	0.056008
B	0.006373	0.005496	0.079926
C	0.001970	0.001422	0.030217
D	0.002084	0.001800	0.055661
E	0.023626	0.022352	0.156905
F	0.002045	0.001518	0.024917
G	0.000961	0.000824	0.038226
H	0.005294	0.004788	0.069600
I	0.006089	0.005372	0.050811

Note: RMSE is the Root Mean Square Error, MAE represents the Mean Absolute Error, whereas Theil (U) indicates the Theil Inequality Coefficient.

SECTION 5: POLICY IMPLICATIONS AND CONCLUSION

5.1 Policy Implications

The results showed different shaped forms of the forecasted NPF values across jurisdictions. Following the above classification (see Paragraph 4.1), relevant policy recommendations are provided from an Islamic social finance perspective, fiscal and monetary point of view and macroprudential perspective, respectively.

First, RSAs under Groups 1-3 are strongly encouraged to keep implementing digital finance and continue its development as the economy is recovering over time. Measures related to Islamic social finance and digital finance have already shown their effectiveness in protecting vulnerable economic sectors and boosting the Islamic finance landscape during the pandemic and during the recovery stage. Hence, they are advised to continue the utilization of Islamic social finance instruments such as zakat and Cash Awqaf in the short and medium term (3 to 6 months). Intuitively, their continuation represents a fundamental key to achieving sustainable development goals (SDGs) (*IFSI Financial Stability Report, 2021*).

Second, the RSA in jurisdictions where NPF is most likely to be increasing throughout the forecast period (**Group 1**) needs to continue adopting the post-pandemic fiscal and monetary policy measures in the short and medium term, subject to a dynamic assessment of the ongoing economic and financial situations. More precisely, RSAs can adjust the policy rate depending on macroeconomic conditions, besides the utilization of flexibility in repayments. Working capital may also be extended to finance corporates and SMEs, as they are considered the cornerstone of the economy.

RSAs can also grant financing to critical sectors of the economy most affected by the pandemic like manufacturing, agriculture, mining, etc through IIFS at consensus rates and longer repayment periods (moratorium). Furthermore, stimulating investment in the industrial sector among other major sectors can also be adapted to create new jobs, leading to a gradual economic development and a decrease in the unemployment rate during the recovery stage. As a complementary measure, fiscal incentives can be allocated for businesses in sensitive sectors such as retail and services to avoid laying off their workers. These measures will help in supporting households and SMEs in particular to recover, which will lead to mitigating the rapid surge of NPF.

The proposed fiscal and monetary policy measures are also applicable based on a prioritization strategy for jurisdictions under (**Group 2**), where Islamic banks' NPF is most likely to be stabilized throughout the forecast period. More precisely, RSAs under (**Group 2**) need to identify the sectors that are still struggling during the recovery stage to ensure an appropriate calibration of the fiscal and monetary policy measures. Once identified, these sectors will benefit from governments` support in terms of stimulus packages, flexibility in repayment in addition to specific incentive packages to boost the economy compared to other sectors that have already recovered. Again, a dynamic assessment, preferably quarterly, is needed to adjust or cease the utilization of fiscal and monetary policies in the short and medium term. For jurisdictions where Islamic banks` NPF is expected to follow a downward trend throughout the forecast period (**Group 3**), fiscal and monetary policies can be ceased gradually as the economic situation is improving over time, whereas a dynamic assessment is needed to monitor the recovery process.

Third, the post pandemic stability assessment analysis showed that RSAs adopted various macroprudential policy measures to ensure the stability of the Islamic banking system during the recovery stage. More precisely, 40.43% of the RSAs adjusted the liquidity ratios limit of LCR and NSFR, whereas the legal reserve ratio has been reduced by 40% of the RSAs. The regulatory criteria for restructuring loans have been relaxed by 35% of the RSAs, whereas 30.43% of the RSAs have reduced the debt burden ratios for consumer loans. Furthermore, around 27% of the RSAs adjusted the capital conservation buffer. The risk weight for the SMEs financing for the CAR calculation and the loan-to-value ratios have been relaxed by 26.09% and 26% of the RSAs, respectively. Finally, 21.74% of RSAs increased the regulatory limit in extension of credit to SMEs. Overall, the above macroprudential policy measures showed their effectiveness in ensuring the resilience of the Islamic banking sector, leading to a smooth economic recovery in most jurisdictions offering Islamic financial services.

Based on our forecasting results, therefore, different macroprudential policy approaches might be considered for **Groups 1-3**. For jurisdictions where NPF is most likely to be increasing or relatively stable throughout the forecast period (**Groups 1 and 2**), RSAs are strongly encouraged to continue the adoption of the aforementioned policy measures and focus more on reinforcing the capital conservation buffer as well as their financing loss provisions to mitigate the expected rise of NPF. Maintaining a significant level of LCR and NSFR (above the 100% threshold) is also needed to avoid any unexpected liquidity shortage. In the same context, RSAs should conduct a dynamic assessment of the ongoing situation for optimal calibration of the macroprudential measures.

For jurisdictions where NPF is expected to experience a downward trend throughout the forecast period (**Group 3**), banks might signal no intention of drawing down their buffers to provide financing for corporates and households during the recovery stage. Banks are expected to maintain even wider buffers during the post-COVID-19 recovery (Abad and García Pascual, 2022; Berrospide et al. 2021; ECB, 2021) because economic uncertainty is still high in most jurisdictions. In this regard, RSAs under (**Group 3**) is not recommended to adjust their capital conservation buffers as well as their provisions, in the near future. In contrast, some macroprudential policy measures can be adjusted over time as long as the economy is improving.

More precisely, RSAs may communicate specific directives to Islamic banks to increase the legal reserve ratio, as well as the debt burden for consumer loans, with a gradual tightening of the regulatory criteria for restructuring loans until trending back to equilibrium (Pre-Pandemic situation). Furthermore, RSAs under (**Group 3**) are advised to adopt a careful and gradual adjustment of the risk weight for the SMEs financing for the CAR calculation, the loan-to-value ratios, and the regulatory limit in extension of credit to SMEs during the recovery stage until reaching the normal levels recorded during the pre-pandemic era.

5.2 Conclusion

The forecasting exercise of full-fledged Islamic banks` NPF ratio during the post-pandemic provides different results across jurisdictions offering Islamic financial services. More precisely, findings show that the Forecasted Islamic banks` NPF is expected to be increasing for **Group 1**, stabilized in the long run for **Group 2**, and decreasing for **Group 3**. Although the Post pandemic exit policy measures showed their effectiveness in boosting the economy and maintaining the stability of the Islamic banking sector, three scenarios are provided in the form of policy recommendations.

For jurisdictions where the NPF ratio is most likely to be increasing, RSAs are advised to continue implementing the exit policy measures, with the necessity to conduct a dynamic assessment to mitigate excessive risks. For jurisdictions where the NPF is stabilized in the long run, RSAs can keep adopting Islamic social finance measures and digital finance tools. In contrast, fiscal and monetary policy measures can be employed based on a prioritization strategy. This means that only the sectors that are still struggling during the recovery can benefit from these measures in short and medium term, subject to a dynamic assessment of the ongoing economic conditions. In the same context, a careful use of the macroprudential exit policy measures is advised to ensure the resilience of the Islamic banking sector during the recovery stage. In revanche, the calibration of these tools should be based on a comprehensive assessment.

For jurisdictions, where the NPF ratio is expected to decrease throughout the forecast period, RSAs are encouraged to cease the adoption of the exit fiscal and monetary policies gradually, whereas a dynamic assessment is needed to monitor the recovery process. From a macroprudential point of view, some exit policies can be adjusted gradually until reaching the pre-pandemic levels.

In the same context, RSAs are invited to look at a common issue related to the lack of diversification in terms of financing strategy. More precisely, Islamic banks' risk exposure might be triggered due to the lack of diversification by sector and by financing mode. To solve the concentration issue, a diversification strategy is needed to mitigate the higher exposure of Islamic banks, subject to the concentration risk limits by sector across jurisdictions (*IFSI Financial Stability Report*, 2021). For instance, RSAs can increase financing to other sectors that are embedded within the real economy, such as manufacturing and other productive industries, so that the risk of NPF can be reduced because the relative propensity for failure is less in these sectors compared to the real estate sector (Alandejani and Asutay, 2017).

One of the most salient limitations of this study is the sample size and the lack of granular data as well as regulatory and macroprudential inputs that may provide more accurate results. In contrast, this paper can be extended by considering the impact of exit policy measures on Islamic banks` credit risk during the recovery stage for selected jurisdictions, subject to data availability.

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