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TECHNICAL NOTE ON STRESS TESTS, CREDIT CONCENTRATION, AND INTEREST RATE RISKS

This technical note on Bank Stress Test for Climate Change Risks was prepared by a staff team of the International Monetary Fund and World Bank in the context of a joint IMF-World Bank Financial Sector Assessment Program (FSAP). It is based on the information available at the time it was completed in July 2022.

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TECHNICAL NOTE

STRESS TESTS: CREDIT, CONCENTRATION, AND INTEREST RATE RISKS

Prepared by
Monetary and Capital Markets Department

This technical note was prepared by IMF staff in the context of a Financial Sector Assessment Program (FSAP) mission to the West African Economic and Monetary Union. The note contains technical analysis and detailed information underpinning the FSAP assessment's findings and recommendations. Further information on the FSAP can be found at http://www.imf.org/external/np/fsap/fssa.aspx.

CONTENTS

Glossary

BCEAO	Central Bank of West African States (In French: *Banque Centrale des États de l'Afrique de l'Ouest*)
CBU	Banking Commission of the West African Monetary Union (In French: C*ommission Bancaire de l'UMOA*)
FSAP	Financial Stability Assessment Program
GaR	Growth at Risk
GDP	Gross Domestic Product
IaR	Inflation at Risk
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PDs	Probabilities of Default
PLS	Partial Least Squares
RAM	Risk Assessment Matrix
RWA	Risk-weighted Assets
WAEMU	West African Economic and Monetary Union (Benin, Burkina Faso, Côte d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal, and Togo)

EXECUTIVE SUMMARY

This technical note presents the stress tests on credit, interest rate, and concentration risk conducted by the WAEMU FSAP.[1] Stress tests on contagion and liquidity risks are addressed separately.[2] Stress tests are an important tool for detecting financial sector vulnerabilities, setting up targeted banking sector monitoring, imposing preventive measures, and informing public decision-makers of macrofinancial risks and costs.

The solvency and interest rate stress tests analyze the impact of macroeconomic crisis scenarios on bank capitalizations via an impairment of their credit portfolios and profitability. These stress tests are based on a new methodology that captures the macroeconomic, financial, and idiosyncratic sources of risk. The approach includes four steps: (i) construction of base and adverse macroeconomic scenarios; (ii) clustering of banks in homogenous groups using statistical methods; (iii) estimation of the sensitivities of the probabilities of default and return on assets to economic conditions; and (iv) projected deterioration of bank portfolios and profitability under the baseline and adverse scenarios.

The stress test scenarios consider a baseline and an adverse post-COVID "recovery-at-risk" paths. The baseline scenario represents a V-shaped recovery, with a strong and rapid resurgence of growth, while the adverse scenario depicts a U-shaped recovery, with a persistent weakening of growth before it converges with the baseline scenario at the end of the test period. The cumulative difference between the gross domestic product (GDP) levels in the adverse scenario and the base scenario is on the order of 15 percentage points, or 2.2 historical standard deviations on average. This could be described as a "severe but plausible" scenario.[3]

The concentration tests assess the effect of a default by the main private debtors on bank portfolios. The FSAP team tested bank concentration risks by conducting a reverse stress test that evaluated the breaking point, i.e., the maximum number of cumulative large exposures that a bank can cover with its capital.

The stress test results indicate that the WAEMU banking system's recapitalization needs are moderate, but smaller banks and banks in certain member countries are vulnerable. Bank recapitalization costs due to shocks to economic growth and inflation are limited as a percentage of regional GDP—to between one and two percent, depending on the type of risk (credit, interest rate, or concentration), the scenario, and the degree of risk. The relatively small size of the banking sector as a percentage of regional GDP and the soundness of large banks explains the moderate system-

[1] This technical note was prepared by Romain Lafarguette, with the assistance of Zhuohui Chen. The main Python packages used for the stress tests are available at https://romainlafarguette.github.io/.

[2] See the 2022 WAEMU FSAP Technical Note "Systemic Risks and Macroprudential Policy Framework" (IMF 2022a) for stress tests focusing on contagion risks, and the Technical Note "Systemic Liquidity Analysis" (IMF 2022b) for stress tests focusing on liquidity.

[3] In the peak year of stress, the difference would reach 2.3 standard deviations from historical mean.

wide recapitalization cost. However, this cost could be higher in certain countries (especially for concentration risk) and around 30 small banks (out of a sample 100) are vulnerable to deteriorating macrofinancial conditions—in addition to about 20 banks that already do not meet the regulatory capital requirement.

The FSAP recommends increasing capital for fragile banks. The imposition of additional capital buffers for fragile banks is necessary, as is the strict application of concentration limits.

The FSAP suggests that the regulator should draw upon the statistical methods presented in this technical note to strengthen financial supervision. The Central Bank of West African States (BCEAO) could improve its bank monitoring framework by using risk modeling and statistical methods to identify the most vulnerable banks. Some of these methods are presented in this technical note. This technical note introduces three main technical innovations to help BCEAO experts: (i) design macro-financial risks scenarios using a risk-based model; (ii) group banks by clusters to conduct cluster analysis; and (iii) estimate the probabilities of default and the shocks impact on banks' ROA at different risk levels via quantile regressions. IMF technical assistance may be required to support the regulator in the rollout of these methods.

Table 1. WAEMU: Table of Recommendations

Recommendations	Authority	Priority[1]
Impose additional capital requirements within the Basel Pillar II framework to cover interest rate and concentration risks.	WAEMU Banking Commission (CBU)	ST
Address the problem of banks that do not meet regulatory solvency requirements via recapitalization or liquidation/resolution.	CBU	MT
Supplement the Central Bank of West African States' (BCEAO) stress test methodology with the macrofinancial risk models developed in this technical note. The scope includes (i) designing macrofinancial scenarios via a risk-based model; (ii) determining bank clusters to conduct analysis by risk clusters; and (iii) estimating the probabilities of default and the shocks impact on bank profitability at different risk levels via quantile regressions.	BCEAO	ST
Supplement the BCEAO's bank monitoring system with statistical early warning methods to identify banks most at risk.	BCEAO	MT
Publish a guidance note for banks on the preparation of stress tests.	BCEAO/CBU	ST

[1] ST=short-term (1–2 years); MT=medium-term (3–5 years).

INTRODUCTION

1. **The economic outlook for the West African Economic and Monetary Union appears favorable, albeit with significant risks.** Growth averaging 6.4 percent between 2012 and 2019 was stimulated by private investment, spurred by public spending and credit growth. Since growth fell to two percent during the public health crisis in 2020, the leading economic indicators predict a rebound with projected GDP growth of 5.7 percent for 2021. The IMF's projections assume a return to the pre-COVID growth path in 2022. Nonetheless, the deteriorating security situation (as already seen in Burkina Faso and Mali) and the risk of a resurgence of the COVID-19 pandemic, combined with the exhaustion of fiscal space, could compromise fiscal sustainability and external viability.[4] In addition, rising commodity prices and supply shocks on world markets could also impact inflation (which is already outside the BCEAO's tolerance band) and foreign reserves and, thus, lead to higher interest rates.

2. **The WAEMU banking sector has expanded considerably since the 2008 FSAP.** The size of the sector has almost doubled since 2008, with total banking assets of 51.3 percent of regional GDP in 2020 compared to 27.7 percent of GDP in 2008. Outstanding loans to the private sector increased by an average of 12 percent per year during 2010-2019, but still represent only 23 percent of GDP in 2020. Conversely, the share accounted for by government securities rose from 7.1 percent of assets in 2004 to 31 percent in 2020, thereby contributing to the sector's growth.

3. **Credit risk, which may be amplified by credit concentration, is the most important risk facing the banking sector.** The regional average of non-performing loans has fallen (11.2 percent in November 2021 compared to 20 percent in 2006), but this gradual improvement in portfolio quality and the persistently high level of NPLs at several institutions reflect a few significant pockets of credit risk. The concentration of assets may amplify the impact of a default on bank solvency. While large exposures to private borrowers is a long-standing phenomenon within WAEMU, exposure to sovereign risks has risen sharply since 2008 due to concentration of a few sovereign issuers in banks' portfolio.[5] Climate change may contribute to credit risk, but exposures to such risk are not monitored by supervisors, and rarely by banks.

4. **Interest rate risk has likely increased due to bank exposure to sovereign risks and their recourse to short-term financing from the BCEAO, that exposes banks to short-term policy rate increase.** Securities portfolios have relatively long maturities compared to bank resources (including increased recourse to short-term financing from the BCEAO), which exposes banks to reduced intermediation margins if interest rates increase—for example, against a backdrop of rising inflation.

[4] All states in WAEMU have reached a medium or high risk of debt distress according to the IMF's debt sustainability analyses. Sovereign ratings are below investment grade.

[5] For two-thirds of banks, exposure to large risks exceeded the Basel standard of 25 percent of capital in 2020.

5. Surplus capital to alleviate structural amplifiers of credit risk or meet emerging risks is limited. The capital ratio of WAEMU banks has increased during the last three years—from 10.5 percent in 2018 to 12.4 percent in June 2021. However, the capitalization of the sector is heterogeneous: 18 banks, representing 10.2 percent of banking assets, did not adhere to the solvency standards at end-June 2021. Certain banks are in long-standing violation of the rules. Furthermore, the absence of sovereign risk weighting reduces the overall capital requirements of banks. Finally, surplus capital levels are not commensurate with concentration, contagion, and interest rate risks.

MACROFINANCIAL SCENARIOS

6. IMF FSAP stress tests focus on severe yet plausible macrofinancial scenarios. Bank resilience is evaluated for credit risk and interest rate risk, by studying the dynamics of asset quality and profitability deterioration in the face of macrofinancial shocks. These shocks should be substantial to provide meaningful information on the resilience of banks when faced with a worst-case scenario, yet they should also be realistic to provide appropriate guidance for supervisors and policymakers. Thus, the IMF recommends that FSAP teams develop "severe but plausible" scenarios covering the relevant variables to study banking dynamics (Ong 2014).

7. The FSAP team has developed a new methodology for estimating macro-financial risks, designing specific "growth at risk" (GaR) and "inflation at risk" (IaR) models. The GaR and IaR methodologies anchor the magnitude of the shocks based on the tail of the empirical growth and inflation distributions respectively, rather than on a predetermined number of standard deviations (normally two) as done by the traditional IMF stress testing approach. These shocks are also conditional to a set of macrofinancial drivers, hence enabling a cogent narrative about the source of risks.[6] To address the considerable data constraints in developing countries, the risk models developed for the WAEMU FSAP are customized from the standard GaR model used for advanced countries.[7] These customized models take advantage of the statistical inference literature on small samples and noisy data, while retaining the general approach used for the advanced countries. The complete methodology, presented in Annex I, also features "recovery at risk" scenario designs that simulate different recovery paths and dynamics.

8. The "at risk" macrofinancial models capture varied complex risks and are used to project key macrofinancial variables. Unlike approaches based on a historical calibration—for example, considering shocks equal to two standard deviations—at-risk models are based on explanatory variables and project future distributions conditional on contemporaneous economic and financial variables. Projections are thus conditional on the most recent available observations.

[6] Some advanced economy FSAP teams have used complex structural models to design the scenarios. One example is the IMF Research Department's Global Integrated Monetary and Fiscal Model (see Anderson et al. 2015). These models, which are often Dynamic Stochastic General Equilibrium models, are not risk based as they are estimated around an equilibrium value and often only feature linear transmissions of shocks.

[7] For discussion on standard GaR models, see Adrian, Boyarchenko, and Giannone (2019); Adrian, Morsink, and Schumacher (2020); and Prasad et al. (2019).

This approach is particularly appropriate for the current COVID-19 crisis, where uncertainty has more to do with the dynamics of the post-COVID recovery than with the probability of a new exceptional shock superimposed on the existing crisis. Moreover, the at-risk models are useful for designing realistic stress test scenarios because they can project asymmetric distributions to reflect the balance of future risks more faithfully.

9. The explanatory variables used to model growth and inflation at risk are estimated using projection methods and cover a broad spectrum of macroeconomic variables. The statistical method extracts relevant information contained in several macroeconomic and financial variables into a single signal (Annex II). In the case of the growth-at-risk model, these groups of variables cover domestic financial conditions, private demand, public demand, external demand, environmental conditions, and agricultural production (Table 2; Figures 1.1, 1.2, and 1.3). These groups represent both the main drivers of growth and the sources of risk. They reflect quantitatively the FSAP risk assessment matrix. In the case of the inflation-at-risk model, the variables are financial conditions, inflation among trade partners, commodity prices, and agricultural production in the WAEMU (Table 3; Figures 2.1, 2.2, and 2.3).

Table 2. WAEMU: Composition of Synthetic Variables—GaR Model

Financial conditions	Private demand	Public demand	External demand	Agriculture and climate
Money market rate	Annual variation in private consumption	Variation in public consumption	Annual variation in imports	Climate-related disasters (droughts, floods, etc.)
Inflation	Private sector GFCF (gross fixed capital formation)	Public sector GFCF	Annual variation in exports	Maximum annual temperature variation
			Terms of trade	Annual production of cotton/coffee/cacao/rice

Source: IMF team.
Note: GaR refers to growth-at-risk.

Table 3. WAEMU: Composition of Synthetic Variables—IaR Model

Financial conditions	Inflation in trade partners	Commodity prices	WAEMU agricultural production
Money market rate	U.S. inflation	Variation in crude oil price per barrel	Annual variation in coffee production
Variation in nominal effective exchange rate	Inflation in euro zone	Food products price index on international markets	Annual variation in rice production
	Inflation in China		Annual variation in cacao production
	Inflation in Nigeria		

Source: IMF team.
Note: IaR refers to "inflation at risk."

10. The data reduction approach represents a good compromise between parsimony, interpretability, and the accuracy of small samples estimates. The use of synthetic variables has many advantages. First, the aggregating information reduces the number of explanatory variables in the regressions, increasing the degrees of freedom and reducing overfit and estimation noise associated with many model parameters. Second, synthetic variables parsimoniously capture the various facets of a common factor. For example, the agricultural and climate category consolidates the frequency of annual disasters, temperature variations, and the main agricultural products of the WAEMU into a single time series. Finally, the projection method used—projection to latent structure or PLS—is based on projections maximizing the common variance of the group of variables (see Annex II and Wold, Sjöström, and Eriksson 2001).[8] Synthetic variables filter the idiosyncratic noise of individual variables and thus retains only the common, more informative trend. The information gain is even more important as the original variables are quite noisy.

11. The FSAP at-risk models rely on a new methodology specifically adapted to small data samples, like those of the WAEMU. The at-risk models rely on a dual estimation, where the synthetic variables are used as explanatory variables. The first model regresses future growth to a one-year horizon on all the synthetic variables, adding a constant term and an autoregressive term (see Annex II and Figure 1.3 for growth and Figure 2.3 for inflation). The regressive model uses the Theil-Sen estimator (see Theil 1950 and Sen 1968), which is a simple estimator that is resilient to outliers and suitable for small samples. The second model is a dichotomous or logit model suited to

[8] Latent structures correspond to variables that are not directly observed. Instead, they are inferred through a mathematical model for other variables that are observed.

small samples (Firth 1993), in which the separation threshold is the Theil-Sen projected mean. This model estimates the balance of risks around the central projection: it measures the relative probability (odd-ratio) that future growth will be lower or higher than the Theil-Sen estimate (binary 0/1 model). Thus, the two-regression model estimates only two moments in the conditional distribution: the conditional mean (expectation) and the balance of risks around the mean (asymmetry). This approach is more parsimonious than the quantile regressions method used in Adrian, Boyarchenko, and Giannone (2019) and Prasad et al. (2019) for advanced economies, which is based on about ten quantile regressions. Finally, based on moments of the conditional distribution, the FSAP team fitted an asymmetric Gaussian distribution (Figures 1.4 and 2.5). The fit is made using the closed-form algebraic method, due to the simplicity of the specification of the asymmetric Gaussian function (Azzalini 2013). The final outcome is very similar to that of the canonical growth-at-risk model (Adrian, Boyarchenko, and Giannone 2019)—namely a projection of the conditional distribution of growth. However, the empirical strategy, inspired by the tools used in econometrics and biostatistics for small samples, is much more suitable for the WAEMU case.

12. The FSAP considered two post-COVID recovery scenarios, inspired by historical sequences. The two scenarios—base and adverse—are estimated by making assumptions regarding the dynamics of the post-COVID recovery. The FSAP uses a dual approach to design the stress tests scenarios. First, the FSAP growth and inflation at-risk models, which follow the qualitative assessments in the Risk Assessment Matrix (RAM), project the conditional densities of growth and inflation, with clearly identified risk drivers and assumptions. The conditional distributions anchor the scenarios on the current risks faced by the WAEMU financial system. Second, the FSAP addresses the shape of the stressed path of GDP over the four-year stressed horizon.

13. A quantile transposition of past historical crises is used to realistically account for the inherent responsiveness of the regional economy. The base scenario relies on a "V-shaped" recovery, with a sharp upswing in 2022, consistent with the projections from the IMF's Article IV consultation. The sequencing of the "V-shaped" recovery is patterned after the episode of the Ivoirian crisis of 2011, which saw regional GDP rebounded very quickly starting in 2012. In contrast, the adverse scenario revolves around a slow "U-shaped" recovery of growth, modeled on the 1992 regional crisis, with growth beginning to recover in 2023 and converging on the base scenario at the end of the stress period. It combines risk factors identified in the RAM (Annex III), including a fiscal adjustment, recovery from the health crisis at the regional level, deterioration of the security situation, an external shock, and a climate shock. The climate shock was introduced in the macroeconomic model via shocks to a synthetic variable aggregating natural disasters, air temperature, and various agricultural products important to WAEMU economies (e.g., cacao, coffee, and rice). A granular approach that would directly target certain sectors or individual exposures to climate risk is not achievable due to the lack of granular data and limited direct exposures.

14. The team simulated the impact of a single country shock on WAEMU real GDP growth. The objective was to introduce into the adverse scenario the impact of possible security crises or socio-political troubles on real GDP growth. The country having the greatest impact on regional growth is Côte d'Ivoire, due to its high contribution to regional GDP. A shock affecting Côte d'Ivoire is accordingly included in the FSAP adverse scenario.

15. The magnitude of the shocks in the base and adverse scenarios was derived from the "at-risk" models. Econometrically, the sequencing of scenarios consists of estimating the sequence of percentiles in a historical crisis over a period of four years and evaluating these historical percentiles in the conditional distribution of the GaR model, as of end-2020. For instance, the 1992-95 GDP crisis is converted in quantile terms, based on the conditional projection as of 1991Q4 (sharp decline on the 3rd percentile, slow improvement in the 25th, 40th, etc., percentiles over time). Thus, while the shape or dynamic of the recovery is inspired by past crises (e.g., "V," U," or "L" shaped), the extent of the crisis depends on the conditional distribution estimated at the end of 2020. In other words, the same shock at the fifth percentile of the growth distribution may represent one percent in 1995 but two percent in 2020, as the underlying distribution has evolved. Constructing the scenarios in this way captures a plausible crisis dynamic (historically realized) that reflects recent macrofinancial conditions. This approach thus incorporates structural developments in WAEMU economies and current conditions, including the COVID-19 crisis.

16. The deterioration of regional GDP growth in the adverse scenario represents a cumulative shock of 15 percentage points (over four years) compared to the base scenario. This shock is equal to 2.2 annualized standard deviations of WAEMU GDP over the last 30 years. Thus, the magnitude of the adverse scenario is in line with FSAP practices, which rely on "severe but plausible" scenarios, where the adverse scenario is calibrated around a cumulative shock often falling between 2 and 2.5 historical standard deviations. In the case of the inflation-at-risk model, the dynamic of inflation is also estimated from the conditional distribution. The base scenario assumes that inflation is constant during the period and at the BCEAO target level of 2 percent. The adverse scenario sees inflation rise to the 95th percentile of the shocked conditional distribution—or inflation at 7 percent—after which it gradually returns to the BCEAO target at the end of the period (Figure 2.6).

17. The dynamic of the ancillary variables is estimated based on over-parametrized density models. In addition to growth and inflation, the scenarios for the stress tests must include factors that may impact bank credit portfolios and profitability (i.e., factors affecting their financial conditions). These ancillary variables are anchored to the main scenarios on growth and inflation using regressive models. Thus, for each percentage level of the growth and inflation dynamic, the model projects the corresponding level in the distribution of each of these ancillary variables. The distributions are obtained by direct adjustment of the historical data, and the selection of the best distribution family is made using Bayesian information criteria (Figures 1.5 and 2.4).

18. The scenario methodology is straightforward and informative and can be used by WAEMU authorities to strengthen their monitoring of financial stability. The FSAP has designed a base and an adverse scenario covering seven variables over a stressed period of four years. Figure 1.6 shows the dynamic of the principal variables and the cumulative difference between the base and adverse scenarios. These relatively complete set of macroeconomic scenarios can be derived simply from reduced form methods with macroeconomic data alone, without resorting to complex structural models, such as dynamic and general-equilibrium stochastic models. Hence, they enable supervisors to better monitor the banking sector. The scenarios can also be used as a reference for discussion with banks producing their own macroeconomic scenarios for their stress tests.

AGGREGATION THROUGH STATISTICAL CLUSTERING

19. Banks are grouped into four homogeneous clusters to identify typical bank profiles. Another FSAP innovation in stress tests is the use of statistical clustering methods to aggregate banks into clearly defined groups. This clustering allows asset profitability and portfolio deterioration projections to be estimated separately for each cluster, which avoids using a common panel estimation. Estimating projections for four differentiated clusters has the advantage of providing four sets of marginal effects for each explanatory variable. In contrast, panel estimation with fixed effects assumes that the marginal effects are identical for all individuals, and only the fixed effect (the intercept) is different. The homogeneous slopes of panel models assume that large banks have the same sensitivity to economic shocks as small, weak banks, all things being equal. In contrast, the clustering approach avoids this pitfall and provides estimates for different models for each group.

20. The bank clustering method uses a set of variables to capture bank profitability and solvency characteristics. The optimal number of groups (also called clusters) is determined by using the Ward metric[9] in a hierarchical aggregation model based on several features: total assets, bank capital as a percentage of total assets, the ratio of non-performing loans to total loans, and profitability. Thus, the algorithm aggregates banks gradually and calculates the ratio between the variance of features within the groups and the variance among the groups (intra versus inter variance). The result of this hierarchical aggregation is shown in a dendrogram (Figure 3.1). The team chose the optimum number of groups to minimize the intra variance (the groups are as homogeneous as possible) and to maximize the inter variance (the groups are as distinct from each other as possible). A review of a battery of statistical tests (Figure 3.2) determined that four clusters represent a good compromise between model parsimony, homogeneity, and separation of the groups. Projecting these four groups in a two-dimensional subspace allows visualization of the composition of different groups of banks (Figures 3.3 and 3.4). Annex IV explains the methodology in detail.

21. The results of the clustering method highlight distinct groups, clearly screening large banks from weak and under-capitalized banks. To give a clear intuition of the composition of the groups of banks, the FSAP team labels each group based on its average characteristics (Figure 3.4). For instance, one group may include large banks with significant market shares, while another group may include banks with insufficient capital and a high level of portfolio degradation. Thus, to simplify

[9] The Ward metric is presented in more detail in Annex IV.

and convey a clear message, groups are denominated as “large banks,” “weak banks,” “new banks” (small credit portfolio size and significant share of capital), and “medium-sized banks.”.[10]

CREDIT RISK

22. Projecting credit risk necessitates estimating the probabilities of default by taking into account macroeconomic conditions. In the frequentist framework, the probabilities of default (PDs) represent the proportion of bank loans deteriorating in response to macro-financial factors (decline in GDP, tightening of financial conditions, etc.). In principle, PDs depend on the type of borrower, the business sector, institutional components, and other factors. Estimating the PDs for different segments of bank portfolios thus requires high quality granular data for each institution. Besides granularity, these data should cover a sufficiently long period of time to measure the impact of economic and financial crises on the degradation of portfolios (Ong 2014). Unfortunately, such data are not available for the WAEMU. Thus, in the case of the WAEMU FSAP, the PDs are captured based on the first difference in the ratio of non-performing loans. In other words, the stock of loans first difference represents an aggregate flow at the bank level, and this is this flow that is modeled based on economic conditions, rather than the probability of default *per se*. This practice is recommended by the IMF in the event of data constraints (IMF 2015).

23. Conditional probabilities of default are estimated by type of bank and by level of risk, using a set of quantile regressions. The PD elasticities vis-à-vis the macro-financial variables are estimated using quantile regressions at risk levels set at 50, 75, and 90 percentiles. The quantile regressions are a tool robust to noisy data; they model the conditional quantiles of the dependent variable via linear specification. The explanatory variables of the quantile regressions include the macroeconomic variables projected in the scenarios (GDP growth, financial conditions, agricultural production, climate conditions, etc.) as well as bank-specific control variables (market share, profitability, etc.). The marginal effect of the macroeconomic environment on the dynamic of non-performing loans thus depends on the synthetic variable considered, the type of bank, and the level of risk. Figure 4.1 shows the results of the set of quantile regressions for each group of banks, for two levels of risk (50th and 90th percentile, respectively) isolating one particular regressor.[11] For the sake of clarity, the figure shows the marginal effect of a variation in GDP on the non-performing loans first difference, fixing the control variables at their 2020Q4 level. The estimation at different quantiles is crucial to capture different risk levels, particularly through the intercept coefficients. Parallel slopes across quantiles indicate linear effects for a particular regressor on a given cluster, but these don’t

[10] The sample covers both private and public banks, aggregated among the different clusters. However, there is no separate cluster for public banks because: (i) public banks are not of systemic relevance (they account only for about 10 percent of total assets); (ii) several of these public banks already necessitate restructuring and belong to the “weak banks” groups; and (iii) it is statistically more interesting to aggregate banks based on solvency metrics than on their ownership, which might not be the best criterion to assess risks on bank balance sheets.

[11] The quantile regressions include multiple regressors, but the 2D charts can only present the marginal impact of one regressor. However, the non-linearities can also occur in the other regressors, which are not shown for reasons of brevity, as the number of estimated coefficients is 2*10*3*4=240 reflecting the choice of the dependent variable (ROA/NPL), the number of regressors (10), the number of right-tail quantiles (3), and the number of clusters (4).

preclude other non-linear effects through other variables or via the intercept. The details of the estimation are available in Annex V.

24. An important methodological contribution of the quantile approach to bank clusters is to highlight heterogeneity on how banks' balance sheets react to shocks. The regression on the entire sample shows flat marginal effects ("horizontal slopes"), suggesting that there is no relationship between GDP and portfolio degradation. This effect is misleading: by distinguishing by bank cluster, coefficients appear with significant slopes that sometimes go in the opposite direction according to the type of bank (Figure 4.1). Thus, the medium-sized and large banks have an intuitive marginal GDP effect on non-performing loans: when GDP growth slows, the variation in non-performing loans increases. However, for new and weak banks, this effect is either null or even opposite, reflecting the noisy informative character of the data for these banks (which have very specific profiles in estimating PDs). Thus, estimating the elasticity of bank PDs overall the whole sample produces a misleading result—that the PDs are insensitive to GDP (on average). In fact, the results reflect a statistical artifact due to a composition effect on all banks rather than the elasticity of PDs *per se*.

25. The solvency test also evaluates the scenarios' impact on the return on bank assets. By using the same regressors and the same approach to measure variations in non-performing loans, the FSAP team looked at the marginal effects of macroeconomic and financial variables on the return on assets, by type of bank and level of risk (Figure 4.2). Here again, the elasticity varies sharply by type of bank, with large banks having the largest coefficients in absolute terms for almost all quantiles.

26. The new estimation methodology developed by the FSAP team modeled three sources of risk in the stress tests. The base and adverse scenarios, estimated via "at-risk" models, capture the macroeconomic or contextual risk. The introduction of capital ratios, loans as a share of total assets, and other variables unique to individual banks, helps incorporate financial risk. For example, under-capitalized banks are more at risk of experiencing an additional sharp degradation of their portfolios compared to better-capitalized banks. Finally, the idiosyncratic risk or "probability of default" is estimated by quantile regressions at different risk levels. Thus, while the marginal effect is quite small on average, it tends to increase with the level of risk. In other words, for a same level of GDP growth, there may be a risk that non-performing loans will increase more than in the average case. These PDs, estimated at different risk levels, represent the non-linear impact of crises on banking dynamics, where an average estimation assumes that the marginal effect on the PDs in times of crisis is the same as in normal times. Incorporating these three sources of risk offers a more complete view of financial stability risks than the traditional approach based on panel ordinary least squares (OLS) estimator with fixed effects.

27. The FSAP projected bank losses recursively over the stress horizon and inferred the capital ratio at the end of the period. Stress tests in a narrow sense, i.e., the projection of losses conditional on the macro-financial scenarios, derive naturally from the preceding stages. It is sufficient to recursively replace the value of the explanatory variables with their level in the two scenarios, and to iterate the first difference of non-performing loans and the return on assets over the stressed horizon. The stress test relies on two important assumptions: (i) the rate of losses on non-performing loans is constant at 75 percent, in line with the practices suggested by the Basel Committee in the absence of granular data on loss-given default; and (ii) the size of bank balance sheets is constant over the stressed period (no deleveraging), consistent with IMF practices and the difficulty of modeling the behavior of banks with respect to their loan volumes during crises. Simultaneously incorporating portfolio impairment and profitability variation allows projected earnings to be discounted from the provisions for non-performing loans, thereby reflecting the impact on flows and stocks. The projection methodology is presented in detail in Annex VI. Once losses are known, the capital ratios are computed under different recovery rates. The stress test uses positive cash flow to cover a portion of the cost for the provisions.

28. The stress test projections show a significant effect of deteriorating economic conditions on the profitability of the banking system and its average capital ratio. The average return on assets in the banking system varies between 1.2 and -0.7 percent, based on the scenario retained and the level of risk (Figure 4.4). With an increase in non-performing loans of about 10-15 percentage points under the most unfavorable conditions, the average capital ratio in the banking system would fall by about six percentage points under the adverse scenario and the highest risk level (Figure 4.3). Fan charts 4.3 and 4.4 show that the impacts on the capital ratio and profitability vary substantially across quantiles, for a given scenario. For instance, the impact on the capital ratio under the adverse scenario varies considerably by quantile. For the medium quantile, risk-weighted assets (RWA) can vary by 1 percentage point (from 11 to 12 percent of RWA), while it can vary by 8 percentage points at the 90th quantile (from 4 to 12 percent of RWA). The large range at the 90th quantile reflects the idiosyncratic risk, as there is no reason to assume that the capital ratios projection should be at the median of the distribution in stressed time. The risk-level approach, reflected in the fan charts and operationalized via quantile regressions, allows policymakers to access the complex risks facing the WAEMU financial system.

29. The FSAP has identified 20 fragile banks and around 30 vulnerable banks. By examining the dynamics of banks at the individual level, it is possible to identify pockets of risk (Figure 4.5). Just under 20 banks, among the 100 included in the stress test, are already below the regulatory thresholds for capital under the most favorable conditions, i.e., under the base scenario and at median-level risk. It is important to note that, in nearly all cases, these fragile banks are already under-capitalized, even before the beginning of the stress test. They are already known to the supervisors. In addition to these 20 banks, there are around 30 vulnerable banks. These banks fall below the regulatory thresholds only under unfavorable conditions (i.e., adverse scenario and idiosyncratic risk levels at 75 percent). Under even more unfavorable conditions, with an extreme level of risk, a large majority of banks fall below the regulatory thresholds, but this outcome is quite unlikely due to the magnitude of the risk considered. This outcome helps identify sound banks—those resilient under the most unfavorable conditions. These are generally large, well-capitalized banks with quite limited credit portfolios compared to the size of their balance sheet.

30. The results of the solvency stress test indicate that the WAEMU banking system is relatively resilient, as measured by the recapitalization needs. The capital needed to recapitalize the banking system to meet the minimum capital requirement after a shock is moderate, in the order of 0.5 and 1.2 percent of regional GDP (Figure 4.6). The limited cost of recapitalization is due to the relatively small size of risk-weighted assets as a percentage of GDP, but also to the soundness of the large banks and the limited size of the loan portfolios of the weakest banks. The possible recapitalization needs are similar across countries—between 0.5 and 1 percent of regional GDP, except for Guinea-Bissau and Togo, for which the costs are closer to 3 percent of national GDP, due to specific vulnerabilities and the relatively larger size of the banking sector of these two countries.

INTEREST RATE RISK

31. The interest rate risk is captured by the sensitivity of bank return on assets to inflation and interest rates. The interest rate risk is modeled by the impact of inflation on the profitability of banks under different scenarios. Inflationary scenarios are estimated based on the inflation-at-risk model presented above, with a base scenario at 2 percent over the period and an adverse scenario rising to 7 percent before decreasing. Thus, the interest rate risk is globally captured by the impact of inflation and a tightening of financial conditions, as well as other control variables, on bank profitability and the evolution of their credit portfolios. Rather than directly modeling interest rate risk—complicated by the nature and the specificities of bank holdings (e.g., sovereign holdings)—the FSAP team decided to assess indirectly the interest rate risk via the impact on the returns on assets. This indirect modeling reflects the lack of granular data on securities portfolios and bank loans. Indirect assessment allows for a granular estimation of: (i) duration risk on securities; and (ii) the mismatch in the interest rate structure between bank assets and bank liabilities.

32. The methods for estimating and projecting the interest rate risk follow those used for credit risk. The interest rate risk stress test revolves around the estimation of regressions by type of bank and level of risk; the projections of profitability and portfolio degradation are also done recursively using the same working assumptions. The only difference is that the variable of interest is inflation instead of real GDP growth and that the scenarios derive from an inflation-at-risk rather than a growth-at-risk model. The approach used to measure credit risk is also used to measure the degradation of bank profitability as a function of inflation and increasing interest rates. The results of quantile regressions for the interest rate risk are presented in Figures 5.1 and 5.2, with features similar to credit risk in terms of the heterogeneity of marginal effects among the types of banks.

33. The results suggest that rising inflation and interest rate hikes play an important role in the portfolio degradation and the profitability of bank assets. Recursive projections of bank profitability and their non-performing loans makes it possible to infer bank capital ratios over the course of the stress test period. Ratios will depend on the severity of the scenarios and the level of risk. Thus, bank profitability is more at risk from inflation than from GDP growth, with an average level that can reach -1.5 percent under the most unfavorable conditions (Figure 5.3). Therefore, by incorporating the impact on the impairment of credit portfolios, the capital ratios of the WAEMU system could decrease by 2 to 8 percentage points according to the chosen scenario and level of risk (Figure 5.4).

34. The fragile and vulnerable banks exposed to credit risk are also exposed to interest rate risk. Following the same *modus operandi* as credit risk, the FSAP identified pockets of vulnerability in the WAEMU banking system (Figure 4.6). Although fragile and vulnerable banks face both credit risk and interest rate risk, the latter is a greater concern because of the impact of inflation on capital ratios. However, banks that are resilient to credit risk are also resilient to interest rate risk, suggesting that the problem has more to do with the inadequate capital level of these banks than the sensitivity of their portfolios to macro-financial conditions.

35. Like the results on credit risk, the impact of interest rate shocks on the recapitalization needed at the WAEMU level is limited. The amount of capital needed by banks to meet minimum capital requirements following an inflationary shock is moderate—in the order of 0.6 to 1.5 percent of regional GDP (Figure 5.6). This level is slightly more significant than for the credit risk, due to the stronger impact on profitability. Here again, the limited cost of recapitalization is due to the size of the banking sector as a percentage of regional GDP, but also to the soundness of large banks and the limited size of the credit portfolios of the weakest banks.

CONCENTRATION RISK

36. WAEMU banking assets are particularly concentrated. Figure 6.1 shows the distribution of the largest exposure (left) and the three largest exposures (right) as a function of capital.[12] The median concentration of the largest exposure represents about 50 percent of capital; for nearly two-thirds of banks, the three largest exposures exceed their entire capital (Figure 6.2).

37. WAEMU banks are often uncompliant with regulatory standards on exposure diversification. Figure 6.3 shows the distribution of banks in terms of the ratio between their first exposure and their capital. Under current regulatory standards, the largest exposure is limited to 55 percent of capital, and authorities plan to lower this threshold to 25 percent by 2024. Currently, more than one-third of banks are over the 55 percent limit and two-thirds are below 25 percent, This poses a risk to the stability of the banking system. Banks should reduce their exposures or substantially increase their capital—in the order of 5 percentage points of risk-weighted assets—or a combination of the two.

38. The FSAP team evaluated concentration risk using a reverse stress test. This static approach consists of estimating a continuum of scenarios in which banks' largest exposures deteriorate and cumulatively reach a "breaking point." This breaking point represents the number of cumulative non-performing loans that a bank can cover with its capital. The FSAP distinguishes two possible loss rates: a loss rate of 75 percent and a more conservative one of 100 percent. In addition, the analysis considers two coverage metrics: the entire capital and only the capital buffers. Ideally, it would be desirable that the capital buffers absorb the losses from the largest exposures. In this way, a bank would continue to be capitalized even in the case of the default of its largest borrower.

[12] This section considers large exposures to private borrowers. Sovereign exposures are not included.

Coverage with the full amount of capital necessitates recapitalization following the concentration shock.

39. More than 75 percent of banks have insufficient capital buffers to address their largest exposure. Figure 6.4 shows the results of the reverse stress test under different assumptions. Thus, while one-third of the banks cannot cover their largest exposure with their entire capital, more than 75 percent cannot do so with their capital buffer. Starting with the fourth cumulative exposure, more than half of banks exhaust all their capital. The impact is still more pronounced given a complete loss rate, with most banks exhausting their capital by the second cumulative exposure.

40. The capital needed to cover the concentration risk is moderate at the regional level but could be important for a few countries. The capital needed to bring banks back to the regulatory level (8.25 percent of risk-weighted assets), following a cumulative impairment of their one, five, and ten largest exposures, represents one, two, and three percent of regional GDP at end-2020, respectively (Figures 6.5 and 6.6). Again, the limited size of bank risk-weighted assets and the concentration of weaknesses among small banks limits recapitalization needs as a percentage of regional GDP. By country, the recapitalization needs range from 1.5 percent of national GDP for the largest and most diversified economy of the WAEMU (Côte d'Ivoire) to about 7 percent for Senegal and Togo (the largest banking sectors in term of national GDP).

41. The recapitalization needs are lower at the group level, due to increased diversification. The FSAP team also estimated the concentration reverse stress-test by consolidating bank exposure and capital buffers at the group level. Under this approach, the group can leverage on the capital of more solid banks to cover the capital shortfall of the weakest ones, assuming the same cumulative exposure defaults on all banks. In other words, all banks see their top 1, 2, 5, etc. exposures impacted within a group, and the capital of all these banks is pooled to face the concentration shock. Under this assumption, the capital needed to bring banks to their regulatory ratios fall by around 1 percentage points of regional GDP, due to increased intra-group diversification. The results are shown in Figures 6.5 and 6.6.

MEASURES AND RECOMMENDATIONS

42. Additional capital should be required for fragile banks to cover concentration risk. The imposition of supplementary capital buffers for fragile banks is necessary to strengthen their resilience to macrofinancial risks. Supplementary capital (imposed under Basel to address concentration risk) should be imposed beyond a minimum concentration threshold. The supplementary capital buffers should be a non-linear function of the degree of exposure and should incorporate the diversification of bank portfolios.

43. Supplementary capital should also be required to cover interest rate risk. The additional requirement, under Basel Pillar II, should be commensurate with the interest rate and maturity mismatches seen in bank balance sheets, which entails measuring them regularly.

44. The new tools presented in this note can assist BCEAO and CBU experts. The IMF team designed a new approach, drawing from small sample econometrics and biostatistics, to customize the models to the constraints of WAEMU data. The construction of macroeconomic scenarios via conditional distributions and the sequences of past crises provided realistic stressed dynamics that are similar to current macro-financial conditions. These scenarios—as well as the methodology—can be shared with banks for their own stress tests. The clustering methods enable supervisors to classify banks into various groups and to allocate more substantial resources to the supervision of groups with the weakest banks. Finally, projection methods by type of bank and by level of risk provide a more realistic dynamic of banks under stress. The results offer an interesting perspective on stress tests conducted internally by banks and can be used as the basis for discussions between supervisors and banks.

CONCLUSION

45. This technical note proposes a detailed analysis of the credit, interest rate, and concentration risks for WAEMU banks. The FSAP stress tests incorporated several risk factors: macroeconomic risk, which was captured by the "at risk" scenarios; financial risk, which was captured by the balance sheet projections of banks; and idiosyncratic risk, addressed by the quantiles projected. This multifactor approach offers policymakers a broad view of the risks weighing on financial stability.

46. The results of the stress tests indicate that the WAEMU banking system is relatively resilient to shocks to economic growth and inflation. The cost of recapitalization of banks as a percentage of regional GDP is limited. Solvency stress tests indicate that recapitalization costs range between 0.5 and 1.5 percentage points of WAEMU GDP for credit and interest rate risk, depending on the degree of risk and the scenarios considered. The recapitalization cost is higher for the concentration risk and amounts to two percentage points of WAEMU GDP. This limited cost is due to the relatively small size of the banking sector and the soundness of large banks in the region. However, this cost could be higher in a few countries due to the larger size of their banking sector (relative to national GDP and/or specific vulnerabilities). Moreover, around 30 small banks among the 100 tested are vulnerable to a deterioration in the macroeconomic situation—in addition to the 20 banks already below the regulatory thresholds at the current juncture.

47. The impact studies realized during the FSAP mission indicate that the high degree of concentration and insufficiently liquid banks are the main risks for the WAEMU financial system. The FSAP mission covered three types of stress-tests: (i) solvency stress tests, featuring credit, interest rate, and concentration risks (presented in this technical note); (ii) liquidity stress tests, covered in the IMF 2022 WAEMU FSAP technical note "Systemic Liquidity Analysis" (IMF 2022b); and (iii) contagion and interconnection stress tests, covered in IMF technical note "Systemic Risks and Macroprudential Policy Framework" (IMF 2022a). The solvency stress tests suggest that a realization of the concentration risk would require recapitalization of WAEMU banks by around two percentage points of regional GDP, while interest rate and credit risks would necessitate a recapitalization of between 0.5 and 1.5 percentage points of regional GDP, respectively. The recapitalization needs associated with a liquidity shock range between 0.3 and 2.1 percentage points of WAEMU GDP, while the contagion risk would trigger a recapitalization of up to 0.8 percentage point of regional GDP. Hence, concentration and liquidity risks dominate in the WAEMU financial system, while the contagion risk has the lowest impact.

48. The FSAP recommends increasing the capital of fragile banks and suggests that supervisors use the statistical methods of the FSAP to strengthen bank monitoring. The imposition of additional capital buffers for fragile banks is necessary as is the strict application of concentration limits. Moreover, the BCEAO can improve its bank monitoring framework by using the risk modeling presented in this note, as well as the statistical methods for identifying the most vulnerable banks.

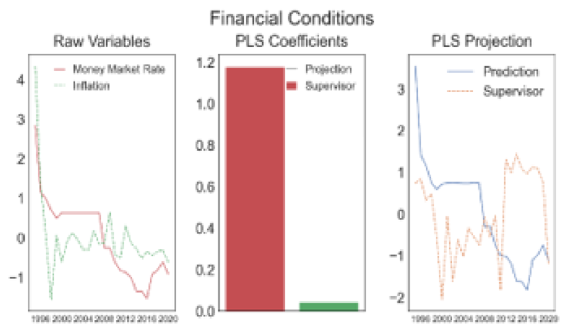
49. The WAEMU FSAP has proposed several technical improvements on the stress-testing methodology that can be useful to BCEAO financial stability experts. The WAEMU FSAP team introduced several innovations to improve the solvency stress tests used during IMF FSAPs. First, the team used customized small-sample risk models to anchor the scenarios based on risk factors (as identified in the Risk Assessment Matrix), factoring current macrofinancial conditions and designing recovery-at-risk paths. Second, the clustering analysis allowed banks to be grouped into statistically determined clusters, yielding cluster-specific PD and ROA elasticities. Third, these elasticities are not only cluster-specific, but also risk-specific, as they are estimated at different risk levels. This approach considerably improves upon linear panels-based methods, where the elasticities are common for all banks, up to the fixed effect, with a linear marginal effect (the behavior during crisis time is assumed to be similar as during normal times). Finally, the stress test projections incorporate both balance sheet and profitability shocks simultaneously. Each type of shock is conditional on past risk-based projections, thereby providing fan-chart stress tests. The risk models used in this FSAP inform simultaneously on the three sources of risk faced by the WAEMU financial system (macro-environment, financial, and idiosyncratic risks). These new methods are extensively discussed in this technical note and its appendixes.

50. While the new methodology developed for the WAEMU FSAP introduced several innovations, it shares some caveats with traditional IMF stress tests. First, these stress tests do not incorporate the potential feedback loops of the financial system on the real economy. For instance, the deterioration of bank balance sheets can amplify contractions in GDP during the stressed period. This caveat, however, might be less pronounced for WAEMU economies since macrofinancial linkages tend to be weaker in low-income countries than in other regions. Second, some transmission channels might be misidentified due to limited data granularity. For instance, the WAEMU FSAP didn't have access to bank portfolio decompositions, and it was necessary to model the impact of interest rate hikes through a profitability model. The duration risk and interest-risk mismatches on bank balance sheets are not *directly* accounted for, but only *indirectly* through their overall impact on profitability. The overall impact could be more or less pronounced depending on how these structural mismatches have increased over time. Third, the FSAP team assumed constant balance sheets (no deleveraging) during the stressed period. This is a common assumption among

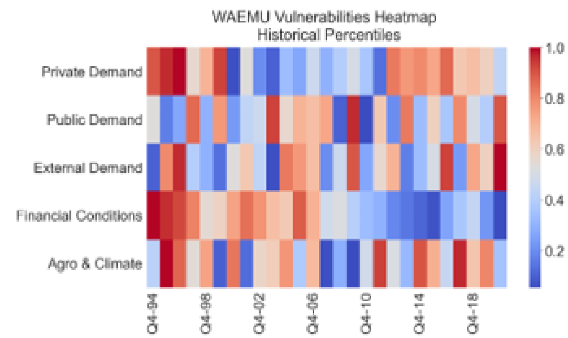
IMF FSAPs due to the difficulty of estimating a behavioral model for bank lending during crisis. This assumption is somewhat acceptable in the sense that it introduces a conservative bias, consistent with the goal of stress testing, as banks could deleverage to improve their capital ratios. Finally, the WAEMU FSAP team worked under the assumptions that WAEMU financial institutions will resist during a crisis: the model features risk-free sovereign assets (WAEMU governments will pay back their debt) and fixed exchange rates, consistent with the FCFA/EUR peg maintained by the BCEAO. However, extreme-tail shocks could force a de-pegging or lead some governments to default on their domestic debt, profoundly shaking the WAEMU financial system. While these risks have low probability, they are difficult to model in a standard stress test because of the lack of historical benchmark. Hence, in accordance with IMF "severe but plausible" scenarios, extreme shocks are not considered for the WAEMU.

Figure 1. Scenarios—Growth at Risk

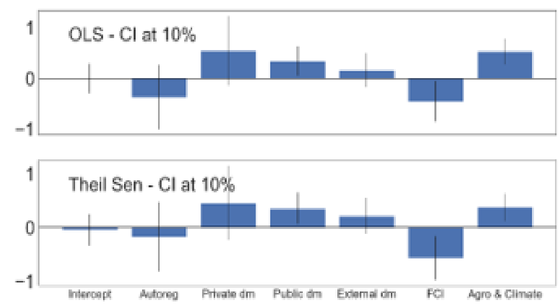
1. Synthetic variables – demand components, financial conditions, climate and agriculture – are estimated via Partial Least Squares.[15]



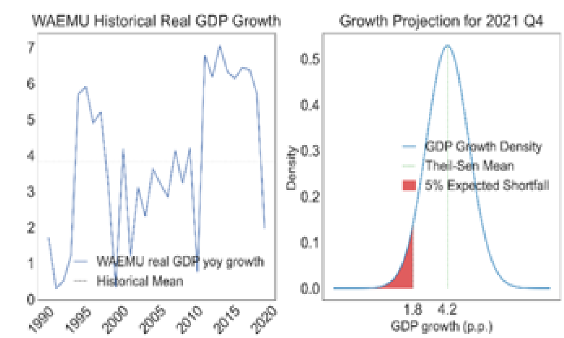
2. These synthetic variables capture multifactorial risks on WAEMU growth.



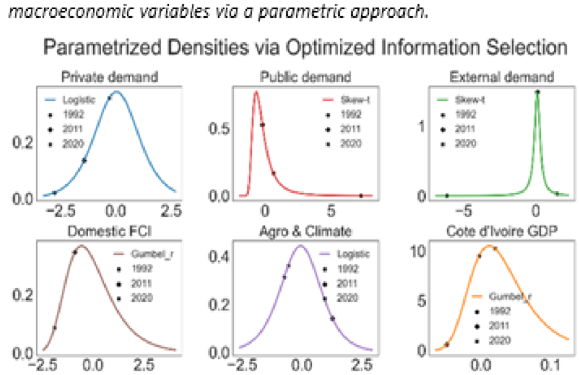
3. These synthetic variables are used as explanatory variables to project future WAEMU GDP growth, one year ahead.



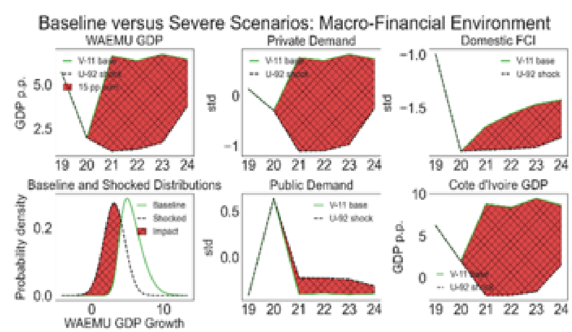
4. The future GDP growth density is obtained through the projections. Density modeling identifies risks to future GDP growth.



5. Satellite models generate the distributions of the ancillary macroeconomic variables via a parametric approach.



6. The FSAP determines the V and U-shape scenario of the main macro-financial variables over the stressed period.

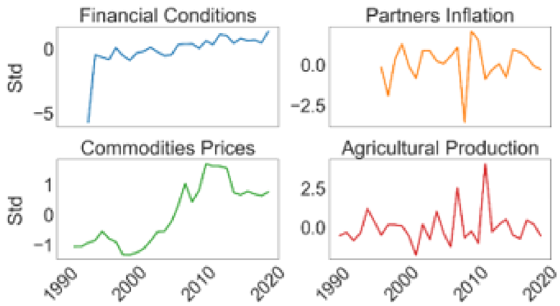


Sources: BCEAO data and computations by IMF staff.

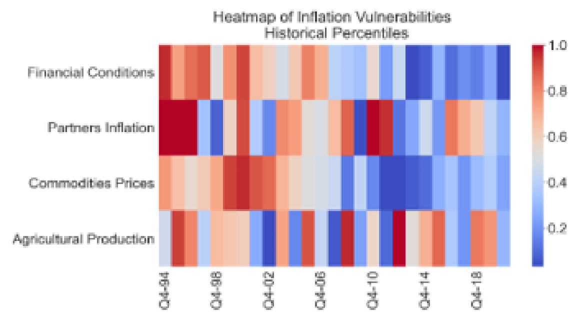
Note: Autoreg = auto-regression; CI: confidence interval; OLS: ordinary least squares.

Figure 2. Scenarios—Inflation at Risk

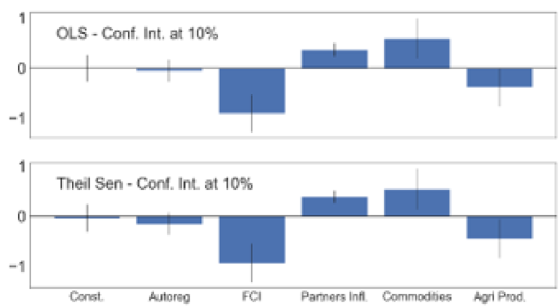
1. The synthetic variables reflect the WAEMU inflation drivers.



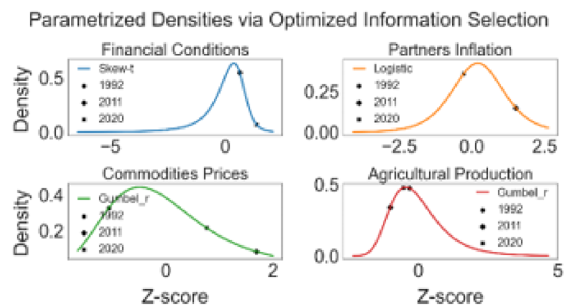
2. These synthetic variables capture the multiple sources of inflationary risks for the WAEMU.



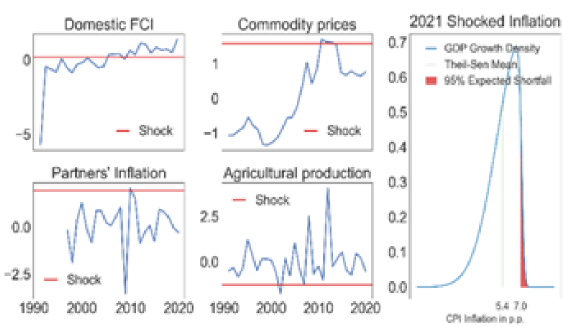
3. These synthetic variables are used to project future inflation, one year ahead.



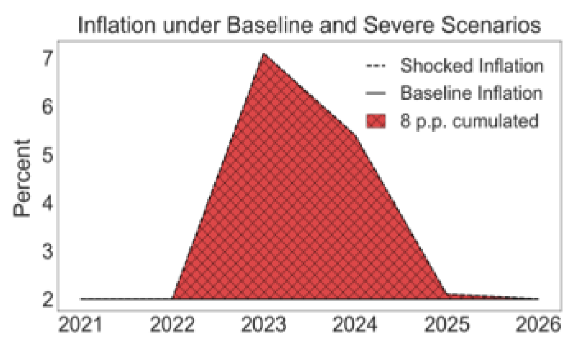
4. The inflation shocks are derived through the parametrized densities of the regressors.



5. Multiple shocks on financial conditions, commodity prices, partners' inflations and agricultural production translate into a shocked inflation density for the WAEMU.



6. The baseline scenario assumes inflation constant at the BCEAO target of 2 percent, while the adverse scenario considers an inflation upshoot at the 95th quantile of the shocked distribution.

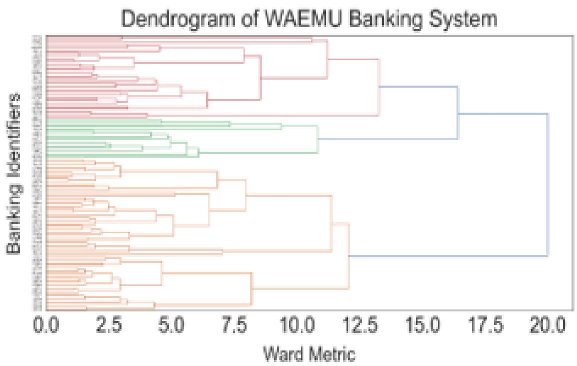


Sources: BCEAO and IMF staff computations.

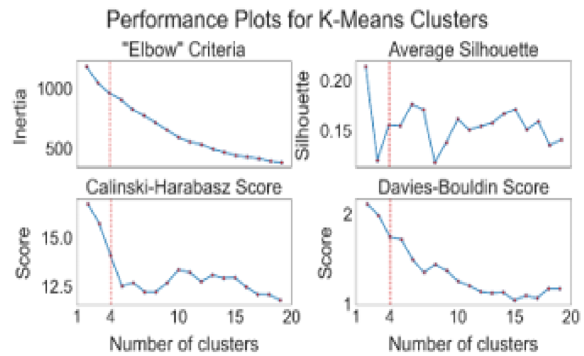
Note: Const. = constant; Autoreg = auto-regression; FCI =Financial Conditions Indicator; Agri. Prod. = agricultural production

Figure 3. Bank Clustering

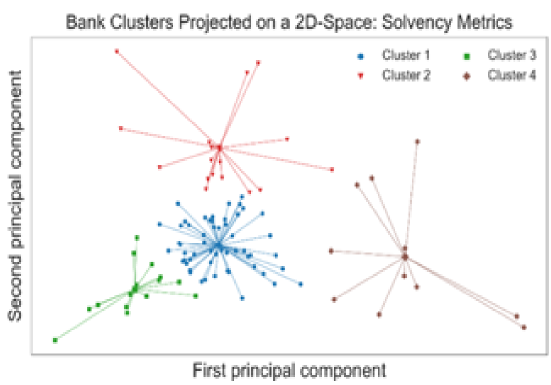
1. The set of WAEMU banks are aggregated by a hierarchical method, to try different partitioning combinations.



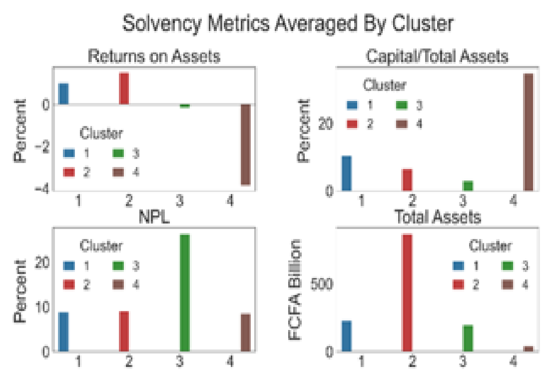
2. The number of clusters is determined through statistical criteria. The FSAP team decided to use four clusters.



3. The FSAP team projects the clusters in a 2-D subspace to display the dispersion of banks inside each cluster.



4. The clusters are well segregated, with different average profiles per cluster, between solid and weak banks.

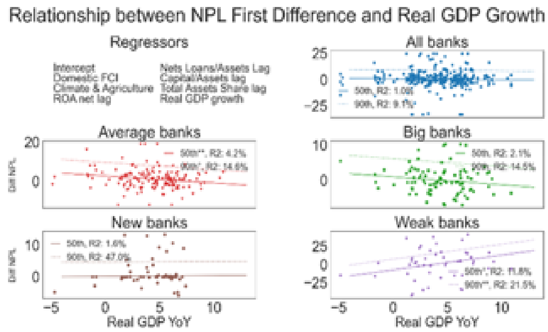


Sources: BCEAO and IMF staff computations.

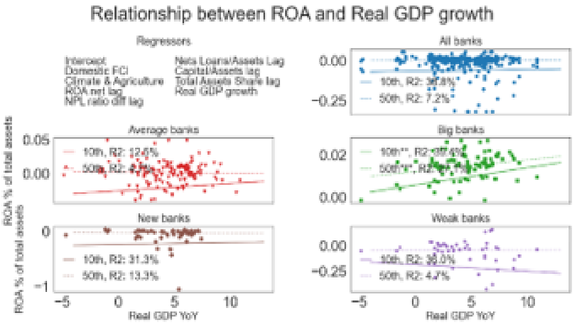
Note: NPL = non-performing loan.

Figure 4. Credit Risk

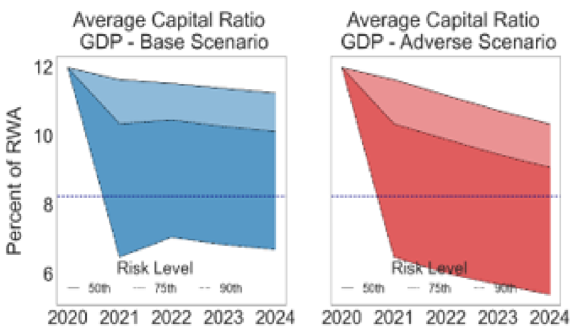
1. The probabilities of default are estimated on each cluster and for each level of risk, using quantile regression.



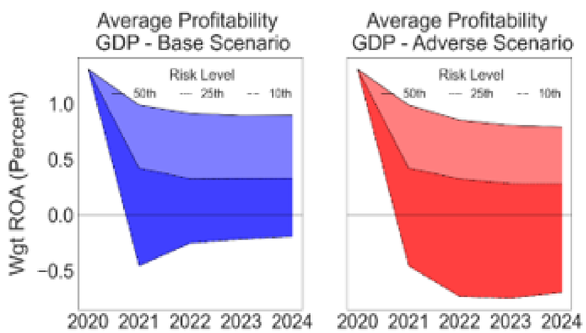
2. Likewise, future returns on assets are projected via quantile regressions, with GDP as one of the main regressors.



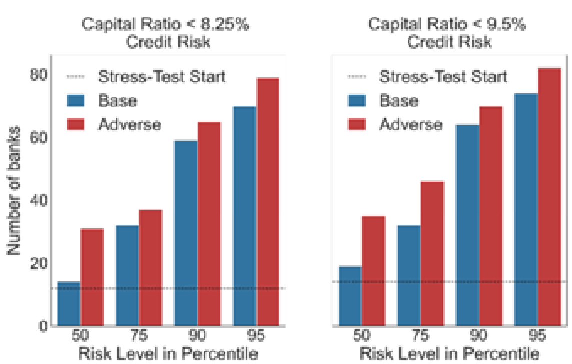
3. Under the adverse scenario and considering the highest risk, capital ratios could collapse by up to 6 p.p.



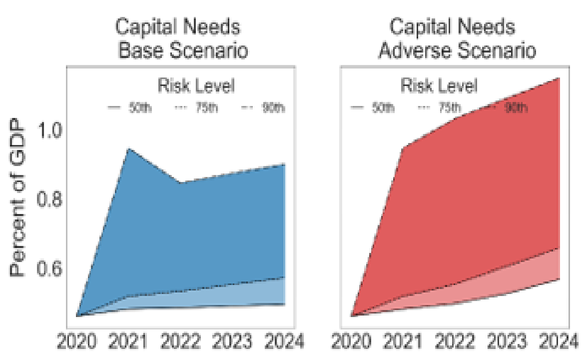
4. Under the adverse scenario, the ROA could contract by up to 2 p.p., depending on the risk level considered.



5. Around 20 banks are identified as fragile, while 30 others are vulnerable to a severely degraded macroeconomic environment.



6. The capital needs for the WAEMU region remain limited, with capital needs around 1 p.p., even under the adverse scenario.

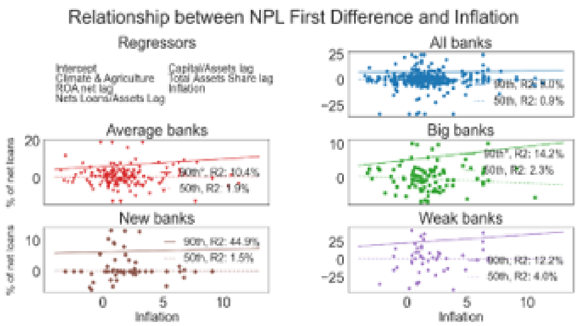


Sources: BCEAO and IMF staff computations.

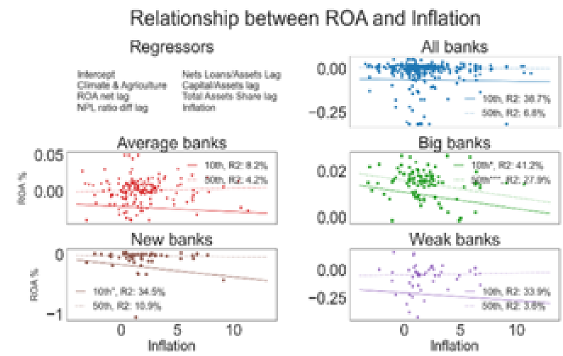
Notes: FCI = Financial Conditions Indicators; NPL = non-performing loans; ROA = returns on assets; RWA = risk-weighted assets; YoY = year-on-year. Risk level is defined as 50^{th}, 75^{th} and 90^{th} percentiles.

Figure 5. Interest Rate Risk

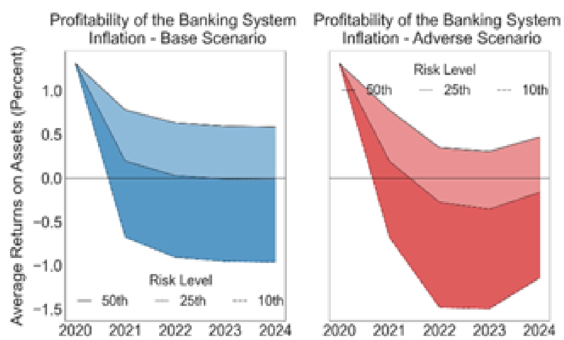
1. The probabilities of default are modeled as a function of inflation risk. The methodology is similar as the one used for credit risk.



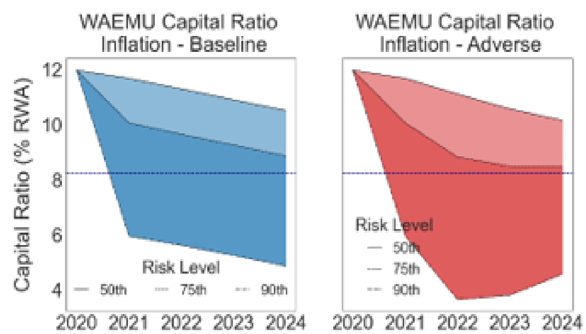
2. Likewise, the ROA is projected on inflation and a set of control variables.



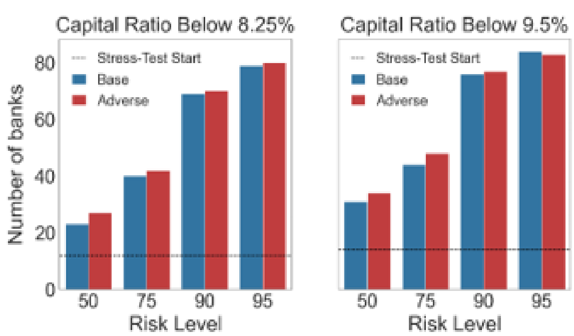
3. Under the adverse scenario, the ROA could contract by up to 2.5 p.p., depending on the risk level considered.



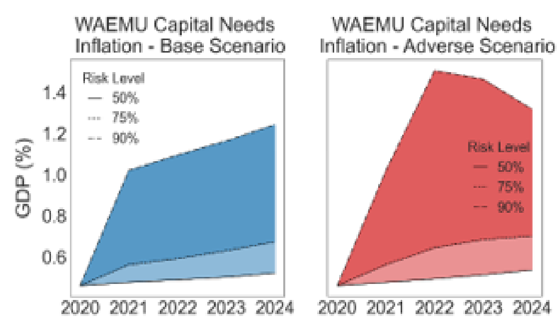
4. Under the adverse scenario and considering the highest risk, capital ratios could collapse by up to 8 p.p.



5. The same banks are vulnerable to interest rate risk as those that are vulnerable to credit risk.



6. The capital needs for the WAEMU region remain limited, with capital needs around 1.5 p.p., even under the adverse scenario.

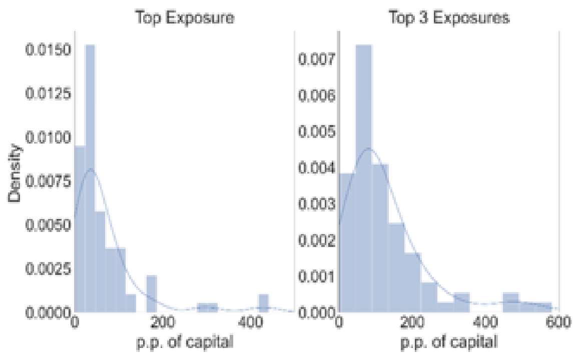


Sources: BCEAO and IMF staff computations.

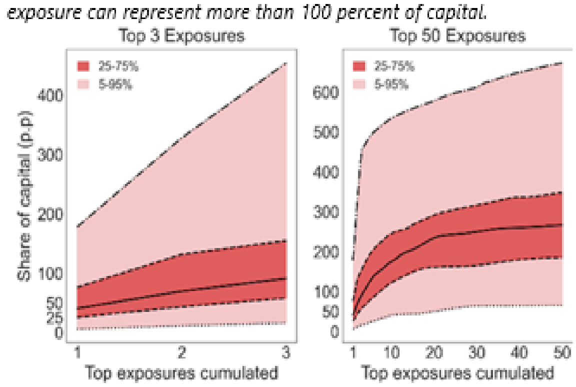
Note: NPL = non-performing loans; ROA =returns on assets; RWA =risk-weighted assets. Risk level is defined as 50th, 75th and 90th percentiles.

Figure 6. Concentration Risk

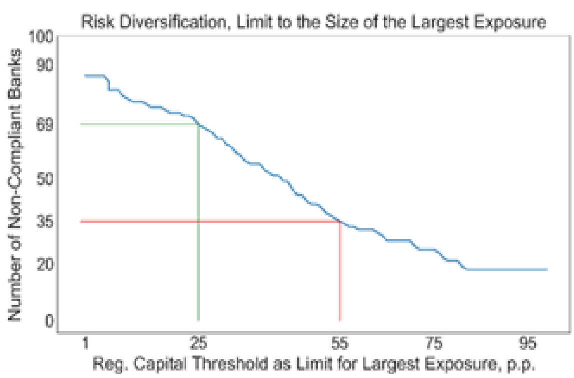
1. The largest exposures represent an important share of capital...



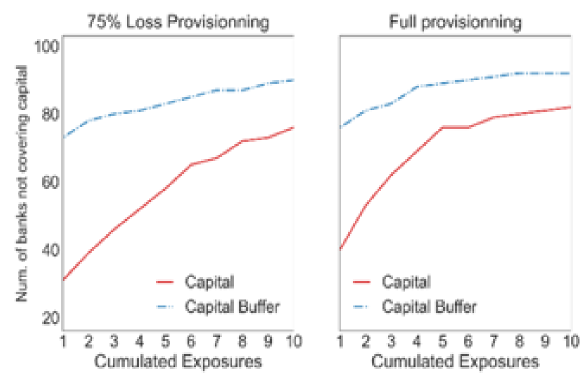
2. ...with a strong heterogeneity across banks, where the largest exposure can represent more than 100 percent of capital.



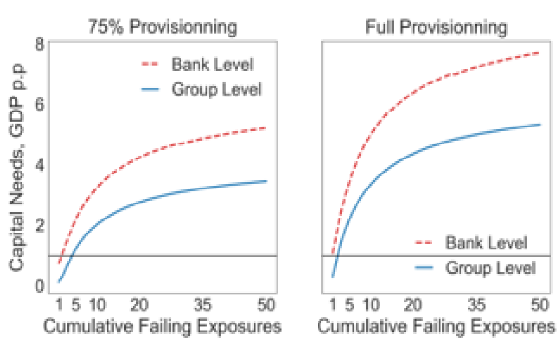
3. Two thirds of banks are unable to comply with the new norm that the largest exposure cannot exceed 25 percent of capital.



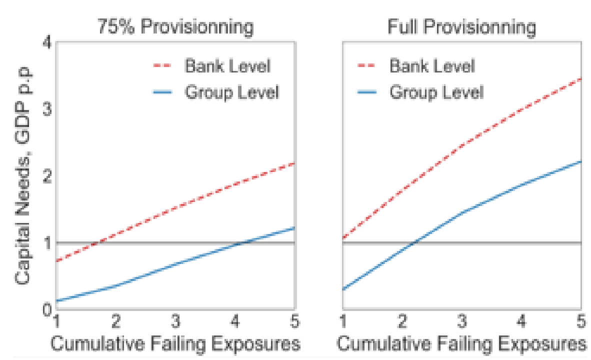
4. Most banks cannot absorb losses on their top three exposures with their capital.



5. At the regional level, capital needs would exceed one percent of GDP to cover at least the first exposure. At the group level, recapitalization needs are lower due to increased diversification.



6. Two p.p. of WAEMU GDP are necessary to cover the top five exposures. The recapitalization needs are lower by one percentage point by assuming that exposures are consolidated by groups.



Sources: BCEAO and IMF staff computations.

Table 4. WAEMU: Financial Soundness Indicators

	2016	2017	2018 [1]	2019	2020
	(Percent, unless otherwise indicated)				
Solvency ratios					
Regulatory capital to risk weighted assets	11.3	11.7	10.5	11.5	12.4
Tier I capital to risk-weighted assets	10.3	10.8	9.7	10.6	11.4
Provisions to risk-weighted assets	10.1	9.8	7.5	7.6	7.4
Capital to total assets	5.8	6.3	6.8	6.6	7.1
Composition and quality of assets					
Total loans to total assets	52.2	54.1	55.7	56.2	52.3
Concentration: loans to 5 largest borrowers to capital [2]	101.9	89.8	82.6	86.1	72.0
Sectoral distribution of loans					
Agriculture	3.2	3.9	4.6	3.0	3.0
Extractive industries	1.6	1.5	1.7	1.7	1.8
Manufacturing	15.5	16.2	15.1	14.3	13.0
Electricity, water and gas	4.9	5.6	5.6	4.6	4.7
Construction	10.8	9.8	10.6	11.2	10.2
Retail and wholesale trade, restaurants and hotels	26.7	26.8	27.7	25.9	26.5
Transportation and communication	9.9	11.6	10.5	11.3	10.8
Insurance, real estate and services	7.2	7.2	6.8	7.2	8.4
Other services	20.1	17.4	17.5	20.8	21.7
Gross NPLs to total loans	13.8	13.9	12.4	11.4	11.0
Provisioning rate	65.5	63.6	65.3	63.3	67.2
Net NPLs to total loans	5.2	5.5	4.7	4.5	3.9
Net NPLs to capital	47.2	48.0	38.2	38.3	29.0
Earnings and profitability					
Average cost of borrowed funds	2.9	2.5	2.4	0.7	0.9
Average interest rate on loans	9.8	8.4	7.6	7.1	7.6
Average interest margin [3]	6.9	5.9	5.2	6.4	6.7
After-tax return on average assets (ROA)	1.3	1.3	1.2	1.3	1.2
After-tax return on average equity (ROE)	20.2	17.6	14.6	15.3	13.9
Noninterest expenses/net banking income	58.5	58.3	60.5	58.9	58.1
Salaries and wages/net banking income	25.6	25.0	25.9	24.8	25.1
Liquidity					
Liquid assets to total assets	27.1	27.3	27.8	26.0	24.4
Liquid assets to total deposits	42.3	42.3	42.4	38.7	35.5
Total loans to total deposits	89.5	92.0	92.2	90.2	82.2
Total deposits to total liabilities	64.1	64.5	65.7	67.1	68.7
Sight deposits to total liabilities [4]	34.4	34.7	35.1	35.8	37.1
Term deposits to total liabilities	29.7	29.8	30.6	31.4	31.5

Source: BCEAO.

[1] First year reported in accordance with Basel II/III prudential standards and the new banking chart of account.

[2] Indicators do not account for the additional provisions required by the WAEMU Banking Commission.

[3] Excluding tax on bank operations.

[4] Including saving accounts.

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Annex I. "At-risk" Models on Small, Noisy Samples

1. The FSAP uses two types of "at-risk" models, "growth at risk" and "inflation at risk," to design adverse scenarios for GDP growth and inflation. Modeling risk through explanatory variables generates scenarios that are both plausible—with a "narrative"—and dependent on a risk level. Thus, the severity of the scenarios is anchored on a risk quantification (for example, 5 percent), which is supported by explanatory variables referring to the risk assessment matrix for the WAEMU (Annex III).

2. The FSAP had to develop a new methodology as the risk models currently used at the IMF are not suitable for small and "noisy" samples likes those of the WAEMU. In effect, the GaR (growth at risk) approach initially developed by Adrian, Boyarchenko, and Giannone (2019) and taken up by the IMF teams in many countries (Prasad et al., 2019) is based on estimation methods requiring at least 60 to 80 observations, or 15 to 20 years of quarterly data. The WAEMU's long-term macroeconomic data are annual and cover only 20 years, or three to four times fewer observations than required for the usual risk models.

3. The FSAP has thus used methods from so-called robust econometrics and from biostatistics, which are very well-suited to small samples, to construct new risk models appropriate for the WAEMU's data. The samples in biostatistics are often much more limited than in economics, and biostatisticians have developed very well-honed tools to address these problems. Some econometricians have also examined the problem of estimating small samples to create a class of adapted models called "robust" models; see McKean (2004) for a presentation.

4. Two distinct models are thus used to capture two conditional moments of the distribution of the dependent variable. The first model is a called the Theil-Sen model (Theil 1950; Sen 1968), which is a regression model improving the OLS estimator to make it more accurate for estimation on small samples and, particularly, robust to outliers. The Theil-Sen model has a level of tolerance to outliers of 29 percent (Peng, Wang, and Wang 2008), which means that it delivers an estimation where the variance of the estimator is limited, even with nearly one-third of aberrant or extreme observations.

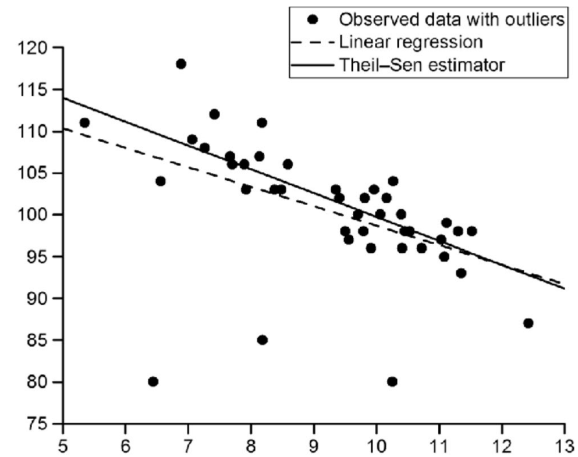
5. The Theil Sen model estimates the conditional average, like a classical OLS estimator. The specification of the Theil-Sen model is like the one of an OLS:

$$y_{t+h} = \alpha + \beta^{TS} X_t + \epsilon_t^{TS}$$

Where $y_{t+h}$is the real GDP growth in $t+h$, X_t a vector of conditional variables, α the intercept and ϵ_t^{TS} the residuals of the Theil-Sen regression.

Thus, for the conditional values of the explanatory variables vector (also called the conditioning vector), the conditional average of the dependent variable is simply given by $y_{t0} = \hat{\alpha} + \hat{\beta}^{TS} X_{t0}$, as in a classical OLS estimator.

6. The conditional mean is estimated using a Theil-Sen estimator. A "jackknife" Theil-Sen estimator—one that systemically removes one observation at a time from the initial sample—is constructed. For example, if the sample contains 20 observations, it creates 20 subsamples of 19 observations, with a different observation removed from the original sample at each iteration. It then estimates a classical OLS regression on each subsample, thus obtaining 20 values for each coefficient. The Theil-Sen estimator is the average of these 20 values, i.e., the average of the OLS coefficients estimated on each of the subsamples. It is thus highly robust to outliers, to the extent that the impact of such observations is diluted in the estimators for each subsample. Taking the median makes it possible to reduce the impact of coefficients that are too extreme. It is important to note that the Theil-Sen estimator is not a quantile regression estimator (in contrast to those used in Annex VI). It is a conditional average estimator wherein the estimation strategy is based on a median, but the quantity of interest is not the conditional median, but rather the conditional mean, as in a classical OLS estimator.



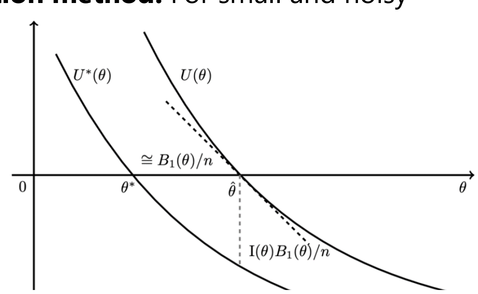
Note: Difference between MCO and Theil-Sen estimator.
Source: Scikit-Learn documentation.

7. The second model used by the FSAP, the "Firth Logit" model (Firth1993), is a logistic regression model with penalized likelihood. Like the classical logistic model, the Firth model estimates the binary probability of an event. For example, "what is the probability that WAEMU growth will be higher than three percent next year?" This probability may be coded as a binary 0/1 indicator, taking 1 if the event occurs and 0 if it does not. In the case of the growth-at-risk or inflation-at-risk models, the event is thus coded as being dependent variable y_t, higher than a given value $\bar{\bar{y}}$. Thus, the specification of the Firth model is written as a classical logistic model.

$$\mathbb{P}[y_{t+h} > \bar{\bar{y}} | X_t] = \alpha + \beta^{LR} X_t + \epsilon_t^{LR}$$

Where $y_{t+h}$is the real GDP growth in t+h, $\bar{\bar{y}}$ a given growth threshold, X_t a vector of conditional variables, α the intercept and ϵ_t^{LR} the residuals of the logistic regression.

8. Here again, Firth's innovation relies in the estimation method. For small and noisy samples, or samples with a very weak degree of separation (a lot of 1 and little 0, for example), the classic logistic estimator is biased. Firth shows that by modifying the likelihood function (the logistic models are estimated based on maximum likelihood) and by introducing a penalizing term, it is possible to eliminate the estimation bias (Firth 1993). This is thus an estimator particularly well suited to small, noisy samples like the WAEMU macroeconomic data.



Note: Log-Modified Likelihood.
Source: Firth (1993).

9. The FSAP uses the Firth model to estimate the balance of risks around the average projection of growth or inflation. The Firth model is estimated by taking as the separation value the Theil-Sen projection of the dependent variable. Thus, the logistic model evaluates the probability that the distribution of growth (or inflation) is less than or more than the average value predicted by the Theil-Sen model. For example, if the Theil-Sen model projects mean growth of four percent for the next year, the Firth model will report on the probability that growth will be higher than four percent. In other words, the Firth model estimates the balance of risks around the central tendency.

10. The Theil-Sen/Firth dual model thus estimates two moments in the conditional distribution of the variable of interest and the third moment is obtained based on a parametric assumption. The first statistic is the conditional expectation estimated by the Theil-Sen model $\mathbb{E}[\boldsymbol{y_{t0+h}}|X_{t0}] = \hat{\alpha} + \hat{\beta}^{TS}X_{t0}$, while the second is the asymmetry of the distribution, obtained as the cumulative density estimated at the conditional mean[1] $\mathbf{F}(\boldsymbol{y_{t0}}|\boldsymbol{X_t}) = \hat{\alpha} + \hat{\beta}^{LR}X_{t0}$. These two statistics are not sufficient to parametrize a distribution, as the second order moment is missing, i.e., the variance. Estimating the conditional variance on a very limited sample is discouraged, as the estimators of conditional variance need quite a lot of information to estimate heteroskedasticity (as in the case of an ARCH/GARCH model, for example). Thus, the FSAP decided to make the simplifying but realistic assumption that the variance is unconditional, and equal to the residual variance of the Theil-Sen estimation (i.e., heteroskedasticity is assumed to be constant over the course of time). This approach also addresses a recurring problem of projection models, i.e., that the variance of the projection tends to increase with the projection's horizon. With constant heteroskedasticity, there is no inflation in the variance. Thus, under this assumption, the FSAP obtains three conditional moments: the expectation (Theil-Sen projection), the variance (constant heteroskedasticity, derived from Theil-Sen), and the skewness (obtained from the Firth logistic model).

11. The team parametrizes an asymmetrical Gaussian distribution from the three estimated moments, thus offering a complete risk model. The FSAP decided to further stabilize the projection by using an over-parametrized fit, where the distribution is assumed to follow an asymmetric Gaussian process.[2] This assumption is realistic, insofar as an asymmetric Gaussian distribution naturally encompasses both the standard normal distributions and the asymmetric ones. This approach retains a high degree of generality, while conserving simplicity. It presents the most interesting metrics for economists (central tendency, interquartile range, and balance of risks). The choice of an asymmetrical Gaussian rather than another asymmetrical distribution is constrained by the number of moments. To estimate an asymmetric Student distribution,[13] four moments are needed (including the kurtosis), which, due to the very limited size of the sample, is unfeasible. Another approach consists of using non-parametric distributions, like kernels, but again, the very limited size of the samples makes this approach unsuitable. Finally, a major advantage of the asymmetric Gaussian distribution is that it provides simple analytical relationships between

[1] This quantity is not directly a measure of asymmetry. However, in the case of an asymmetrical Gaussian distribution, it is possible to infer the asymmetry coefficient from $\mathbf{F}(\boldsymbol{y_{t0}}|\boldsymbol{X_t})$ via a simple bijective transformation.

[2] See Azzalini (2013) for the formal derivation of the asymmetric distributions.

[13] For example, as developed in Adrian, Boyarchenko, and Giannone (2019).

moments, cumulative density, and parameters (Azzalini 2013). This property greatly simplifies the distribution fit on conditional moments, as the parameters are derived manually in closed algebraic form and not through optimized approximation as in Adrian, Boyarchenko, and Giannone (2019) or Prasad et al. (2019). This property offers a relatively straightforward and very precise methodology.

12. Shocks are simulated in the "at-risk" models by shocking the synthetic variables obtained by PLS (see Annex II). The density model used by the FSAP can be used to study the impact of specific shocks on the conditional distribution of GDP. This approach studies the impact on the entire distribution, i.e., the central tendency, the tails of the distribution, the balance of risks, the values at risk, etc. The shocks simulation is obtained in reduced form and without identification, as there are so far no identified growth-at-risk models available in the literature.

To obtain a shocked distribution, it is sufficient to change the conditioning vector by applying a shock to one or more of the synthetic variables (often by shocking the synthetic variable by one or two standard deviations):

$$\mathbb{E}[\boldsymbol{y_{tS+h}}|X_{tS}] = \hat{\alpha} + \hat{\beta}^{TS}X_{tS} \text{ where } X_{tS} = X_t + \left[0,\ \ldots,\ \Delta X_j,\ \ldots,\ 0\right]$$

$$\textit{Often } \Delta X_j = 1 \text{ or } 2\ std(X_t)$$

Where $y_{tS+h}$is the shocked real GDP growth in $t+h$, $\bar{\bar{y}}$ a given growth threshold, X_{tS} a vector of shocked-conditional variables, α the intercept and $\hat{\beta}^{TS}$ the estimated coefficient of the Theil-Sen regression.

After projecting the conditional shocked mean, the FSAP team estimates the Firth model and adjusts the conditional Gaussian distribution as in the non-shocked estimation.

13. In conclusion, this annex has presented a new type of "at-risk" model for small samples. This model offers the same depth of interpretation as classic "at-risk" models but is based on methods that are far more adaptable to small samples estimation. This approach, as well as the entire empirical strategy presented in this note, expands the statistical toolbox of the BCEAO. The Python codes used in this exercise are available at https://romainlafarguette.github.io/software/.

Annex II. Estimating Synthetic Variables by Partial Least Squares

1. **The synthetic variables used in the growth-at-risk and inflation-at-risk models are obtained through data reduction based on a set of variables.** The common trend of several variables with the same "theme" (see the complete list in Tables 2 and 3) are extracted through partial least squares regression (PLS; see Wold, Sjöström, and Eriksson 2001). PLS is a supervised data reduction approach, while the Principal Components Analysis (PCA) is an unsupervised data reduction algorithm.

2. **The PLS estimator models the covariance between two datasets, named Y and X, based on the latent structure of the underlying data.** The latent structure is obtained by projecting both the Y and X matrices on a vectorial lower-dimension subspace, such that the covariance between the projections of Y and X in this new subspace is maximized. Contrary to an ordinary least square estimator, which projects Y on the subspace of X, the PLS estimator uses an intermediate step—the latent structure—to deal with multicollinearity in the X space. The PLS method is useful for analyzing data with numerous multicollinear variables that are potentially noisy and may even have incomplete observations. While the OLS estimator becomes less effective as the degree of multicollinearity among the explanatory variables increases, the precision of the PLS estimator increases. Hence, data reduction through PLS is particularly appropriate for aggregating a large number of collinear data X, with an objective: maximizing the correlation with a supervisor variable Y.

3. **Unlike an OLS estimator that projects Y over the subspace of X, the PLS estimator maximizes the covariance between *Y* and *X* in a latent structure.** This latent structure makes it possible to circumvent the problem of multicollinearity by choosing a more appropriate vectorial subspace than the X space. The algorithm constructs the weights, loads, and scores as linear combinations of the original variables.

The PLS algorithm breaks down the Y and X matrices as follows:[1]

$$X = TP'_X + E_X$$

$$Y = UP'_Y + E_Y$$

where,

- P'_X and P'_y are the scores of X and Y, respectively. They represent the latent structure.
- T and U are the loadings on X and Y, i.e., the projection of X and Y on the latent structure.
- E_X and E_Y are the error terms, assumed to be independent and identically distributed random variables.

[1] The presentation of the algorithm follows the one provided by Wold, Sjöström, and Eriksson (2001).

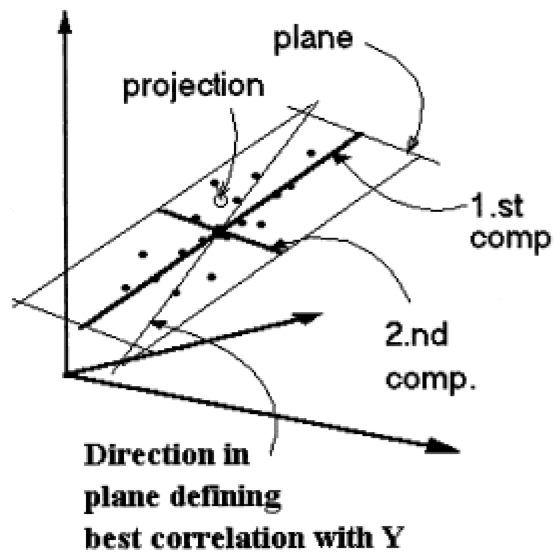
- The X-scores T form a linear combination of the original X matrix. The coefficients of this linear combination are called the $T = XW$ weights.

4. **The PLS algorithm estimates the scores and loadings recursively, as a function of the number of components chosen.** The components in a PLS are conceptually similar to those of a PCA. They represent recursive orthogonal projections, with the first component explaining most of the covariance between *Y* and *X*, the second being orthogonal to the first component and explaining most of the remaining covariance, and so on.

5. **An important aspect of the PLS estimator is that the *T* scores of *X* are good predictors of *Y* when they are projected on the latent structure of *Y*.** Thus, it is possible to break down $Y = TP'_Y + F$ (for a formal proof, see Delaigle and Hall 2012). Thanks to this mathematical property, the PLS score of *X* is an appropriate predictor for *Y*:

$$Y = XWP'_Y + F = XB + F$$

6. **The PLS approach combines two objectives.** The PLS estimator offers a dimensionality reduction of the *X* matrix in a certain vectorial subspace, where the *X* scores are well correlated with the *Y* matrix. In other words, the PLS extracts a reduced *X* signal while ensuring that this signal is well correlated with the projection of *Y* in the latent structure.



Note: Geometric representation of the PLS estimator.

Source: Wold, Sjöström, and Eriksson 2001.

Conceptually, the PLS projection can be understood as a classic linear projection (like an OLS) but on a latent structure rather than on the standard vectorial subspace of X, as shown in the adjacent figure.

7. **In the WAEMU FSAP, the team used only the first principal component of the PLS estimated on each group of variables.** This approach has advantages by providing a simple way to interpret each principal component as the best representation of a group of variables. It is more difficult to interpret two principal components, because two principal components represent different linear combinations of a single set of variables, with a different explanatory power. In addition, as these synthetic variables (the principal components of each group) are used in second stage regressions, it is easier to use only one component per group rather than two (which would inflate the number of regressors and nullify the advantage of using a data reduction method).

8. **The FSAP uses as supervisor future real GDP growth (the Y matrix) for the GaR model and future inflation for the IaR model.** The X variables are listed in Tables 2 and 3, with details in the body of the text. The supervision variables are chosen for being precisely the dependent

variables of the at-risk models. In this way, the coefficients of the linear combinations optimize the predictive power of the models by maximizing the covariance with the dependent variable. This approach does not create endogeneity problems as the dependent variable is a future variable (one-year ahead) that cannot influence in return the contemporaneous variables.

Thus, unlike a PCA, where the aggregation of variables is unsupervised and depends only on the projection of the *X* matrix variance, the PLS offers clear supervision that improves interpretability and increases the predictive power of the models. This is the reason why the WAEMU FSAP is using a PLS approach.

Annex III. Risk Assessment Matrix

WAEMU: Risk Assessment Matrix		
Risk Origin	**Relative Probability/Horizon**	**Expected Impact if Realized**
RAM 1: A lethal and highly contagious local outbreak of COVID-19 leads to subpar/ volatile growth	**High** **Short to medium term** The region's low vaccination rates raise the probability of reimposing containment measures, leading to weaker economic growth, worsened fiscal situation, and elevated debt sustainability concerns.	**High** New costly containment measures at the national level, including large-scale lockdowns, lead to a contraction in private sector demand that cannot be redressed by the public sector due to limited fiscal space. The slowdown in economic growth leads to a deterioration in banks' asset quality. The impact is exacerbated by weaknesses in the WAEMU's health system.
RAM 2: A systematic deterioration of the security situation in the region	**Medium** **Short to medium term** An intensification of security incidents in the region and spillovers across member countries can slow economic activity and impair public finances and policy implementation more broadly.	**High** The deterioration in the security situation impairs domestic demand (public and private sector) of one or two countries of the union, with spillovers to other member countries. The slowdown in economic growth leads to a deterioration in banks' asset quality.
RAM 3: De-anchoring of inflation expectations in the U.S. and/or advanced European countries leading to a rise in interest rates and risk premia	**Medium** **Short to medium term** A sustained rise of inflation and an unanchoring of U.S. inflation expectations could prompt an early U.S. monetary policy tightening. The repositioning of global market players would lead to tighter global financial conditions and higher risk premia for frontier markets, with negative consequences for capital inflows and official foreign reserves in the WAEMU.	**High** Member countries lose global market access due to a deterioration in global conditions or rising doubts about debt sustainability. An inability of the regional government debt market to absorb fiscal demand leads to a decline in foreign reserves and an interest rate spike. An accelerated fiscal correction dampens public sector demand. Higher interest rates and crowding out of private sector demand leads to credit contraction, which exacerbates the decline in private sector demand. The slowdown in economic growth leads to a deterioration in banks' asset quality. The interest rate increase squeezes banks' margins.
RAM 4: Rising and volatile food and energy prices	**High** **Short to medium term** Raw material prices rise more than expected due to pent-up post-pandemic demand and supply disruptions. Uncertainty leads to a bout of volatility, particularly in oil prices, with resultant fiscal implications, given the WAEMU's status as a net oil importer.	**Medium** An accelerated fiscal correction could dampen public sector demand and spill over to private sector demand. The contribution of external demand to GDP growth declines or turns negative. The rise in inflation and the drop in foreign reserves due to the increase in raw material prices lead to higher interest rates and lower private sector demand. The slowdown in economic growth leads to a deterioration in banks' asset quality. The interest rate increase squeezes banks' profitability.
RAM 5: A rise in the frequency and intensity of natural disasters related to climate change	**Medium** **Short to medium term** Climate change could negatively affect agricultural production and exports, increase the need for subsidies, and reduce the population's standard of living.	**High** Reduced yields on food crops dampen growth due to lower net exports. The asset quality of banks with agricultural exposures is impaired directly as yields drop. Government exposure guarantees pass the losses to the public sector. Use of subsidies to offset climate impact diverts resources from more productive uses and reduces the growth impact of public expenditure. The small size of exposures dampens the impact.

Annex IV. Grouping Banks by Statistical Clustering

1. **The FSAP uses clustering methods to group banks together in homogeneous distinct groups, based on their characteristics.** The objective of the aggregation is two-fold. First, grouping together similar banks makes it is possible to estimate predictive models for homogenous groups of banks, which increases the information available for parametric estimation, while minimizing idiosyncratic heterogeneity. Given the lack of historical experiences, this approach represents a good compromise between panel models and individual models. . Secondly, each group has a representative synthetic bank (the centroid of the group) that can be used to impute missing values for banks belonging to the same group ("clustered-based hot deck imputation"). In addition, clustering methods correspond to the first stage of scoring models (where groups of banks have a score associated with one of their characteristics, for example, being at risk of bankruptcy). Scoring methods could be used by the supervisors to select the weakest banks and conduct more in-depth inspections, thus optimizing the resources used in supervision.

2. **The optimum number of clusters is determined by a data clustering algorithm known as hierarchical classification.** The FSAP team used a standard approach from the literature (Tibshirani and Hastie, 2016) to determine the optimal number of groups. The algorithm calculates the Ward distance between two clusters recursively, beginning with clusters with one individual (each bank is its own cluster). The Ward distance is defined as the square of the Euclidian distance on the vectorial subspace of the variables—or features—of the banks. The variables are presented in the Statistical Clustering section in the body of the text. The Euclidean metric is:

$$d_{ij} = d(\{X_i\},\{X_j\}) = \|X_i - X_j\|^2$$

It proceeds to aggregate all the pairs of clusters two by two and retains the combinations that minimize the intra-cluster variance after aggregation. Thus, the pairs of clusters retained are those that match up the most similar banks. The algorithm is then calculated recursively on the aggregated groups to produce at each stage a new clustering of data with fewer groups than before, ultimately ending up with a single group. The results of the algorithm are presented in a dendrogram (Figure 3.1) and suggest that a breakdown in four or five groups is appropriate (corresponding to a Ward metric of around 12.5) as it is located just before the leap in variance in groups located below the dendrogram. In other words, choosing three rather than four groups drastically increases the intra-cluster variance, while choosing four groups instead of five (or five groups instead of six) entails a limited intra-variance increase. The result is an appreciable gain in parsimony.

3. **A battery of diagnostic tests confirms the choice of four clusters.** For each clustering possible under the Ward metric, the FSAP team calculated different diagnostic metrics: the breakdown of the inertia of the initial point cloud, the silhouette (report of intra and inter variances), and two scores (Calinski-Harabasz and Davies-Bouldin). Tibshirani and Hastie (2016) present these metrics in detail. The choice of four clusters is thus confirmed with a good silhouette ratio and correct scores, while the inertia criterion does not distinguish any optimal clustering. Technically,

choosing five clusters would also be acceptable, but for reasons of parsimony, the team preferred four clusters.

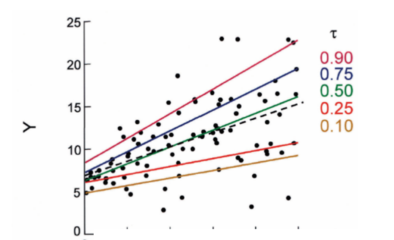
4. The projection of clusters in a reduced sub-space suggests that two groups are very homogeneous, while the other two are more disparate. To provide an idea of the shape of the clusters, the team performed dimensionality reduction based on a PCA applied to all the banks with the same variables as those used in the hierarchical clustering method. To simplify the representation, only the first two components were retained (choosing three would generate a three-dimensional figure that would be difficult to read). Figure 3.3 shows this breakdown and suggests that clusters 1 (blue) and 3 (green) are relatively homogeneous, while group 2 (red) and 4 (brown) are more dispersed.

5. The analysis of the average features by cluster suggests distinct profiles. Figure 3.4 shows the average of variables by cluster. Thus, cluster 3 (green) is the group with the strongest rate of non-performing loans, nearly null profitability, a small balance sheet, and very limited capital. To simplify and provide an idea, the team called this group "the weak banks," which are clearly under-capitalized banks with very degraded portfolios. Cluster 2 (red) aggregates the banks with the largest asset size, the best profitability, and a limited rate of non-performing loans. Cluster 2 is thus the group of large banks. Cluster 4 (brown) is very special: it consists of very small banks, with very few assets, few non-performing loans, a very high capital-to-assets ratio, and very negative profitability. These are newly created banks, with very small balance sheets primarily consisting of capital and very few loans, which explains the stagnant profitability. Finally, Cluster 1 (blue) includes the largest number of banks, with average characteristics on each variable. In other words, these are "medium-sized banks" with the most homogeneity.

Annex V. Stress-testing via Quantile Regressions

1. **The conditional probabilities of default and profitability are estimated by type of bank and by level of risk, based on a set of quantile regressions.** In evaluating both credit risk and interest rate risk, the team must project the probabilities of default and the banks' profitability as a function of macroeconomic and financial variables. Whereas most stress tests conducted by the IMF use OLS panel estimations (see Ong 2014), the FSAP team decided to use another approach that consists of estimating quantile regressions on clusters of banks.

2. **Quantile regressions are a robust tool to model conditional quantiles with noisy data.** While an OLS estimator estimates the conditional mean of the dependent variable, quantile regressions estimate the conditional quantile. The approach is realized by the appropriate choice of the regression's objective function (called the "check function" in the literature on quantile regressions), for which the estimator asymptotically converges to the conditional quantile. A detailed explanation of the methodology is available in Koenker and Hallock (2001). To provide a graphic idea, where an OLS estimator adjusts all the points on average (dotted in the adjacent figure), the quantile regressions estimator estimates the slope of the quantile coefficient at a given level of the distribution of the dependent variable (for example, the tenth percentile of the dependent variable distribution, in red). The advantage of the quantile regression approach for stress tests is that it captures the idiosyncratic risk of the probabilities of default and profitability, i.e., the risk that these variables are not at the level of their average value, but rather in the tails of their distribution.



Graphical OLS and quantile regression representation. Source: IMF staff.

3. **The explanatory variables of quantile regressions include the macroeconomic variables projected in the scenarios, but also control variables specific to the banks.** For each cluster, the IMF team estimated two separate estimations—for the return on assets (ROA) and the flow of non-performing loans (ΔNPL_i). The regressions represent a future projection and thus the return and the flow of non-performing loans are taken at *t+1*. This approach also eliminates possible endogeneity simultaneity bias.

- $Q(ROA_{i,t+1}, q) = \alpha^q_{R,C} + \boldsymbol{\beta^q_{R,C}Macro_t} + \boldsymbol{\gamma^q_{R,C}BankControls_{i,t}} + \epsilon^q_{i,t}, \quad \forall\, i \in C$
- $Q(\Delta NPL_{i,t+1}, q) = \alpha^q_{N,C} + \boldsymbol{\beta^q_{N,C}Macro_t} + \boldsymbol{\gamma^q_{N,C}BankControls_{i,t}} + \epsilon^q_{i,t}, \quad \forall\, i \in C$

With:

- $\boldsymbol{Macro_t}$: macroeconomic clusters vector, reflecting the base/adverse scenarios (i.e., GDP, inflation, domestic financial conditions, climate change, agricultural production, etc.).
- $\boldsymbol{BankControls_{i,t}}$: individual banking variables vector (i.e., past profitability, non-performing loans level, capital ratio, bank's market share, etc.).
  - *q:* quantiles level, reflecting different levels of risks
  - *C*: cluster related to bank *i*

4. **The coefficient vectors α_C^q, β_C^q, and γ_C^q are cluster- and quantile-dependent.** The coefficients are estimated based on standard quantile regressions on each cluster. The advantage of estimating by cluster is to obtain cluster-dependent coefficients, based on simple quantile regressions rather than panel quantile regressions, which are much more complicated to estimate. Because quantiles are non-linear, there is no direct equivalent to the fixed effect OLS estimator for quantile regressions. This approach addresses the problem of slopes homogeneity of the classic panels, while using limited granular data. Figures 4.1 and 4.2, which show non-performing loans and profitability, respectively, present the coefficients for GDP growth (with the other explanatory variables being fixed to their late 2020 level) for quantiles, medians, and ten percentiles, for each cluster.

5. **The projection of profitability and non-performing loan flows thus incorporates three sources of risks.** First, the macroeconomic risk, deriving from the base/adverse scenarios, is captured based on the coefficients of the $\boldsymbol{Macro_t}$ variables vector. Second, financial risk, representing the impact of the very characteristics of the banks' balance sheet on the evolution of profitability and non-performing loans is incorporate through the coefficients of the $\boldsymbol{BankControls_{i,t}}$ variables vector**.** Finally, the idiosyncratic risk representing the "PDs at risk" and "profitability at risk" is captured by the different quantile coefficients. It represents the risk that these variables will fall in the tails of their distribution rather than at their conditional average value.

6. **The quantile approach used by the FSAP for the stress tests is innovative on several levels.** Stress tests are often estimated by OLS and omit the idiosyncratic risk, which is crucial in a time of crisis. During a crisis, is unlikely that profitability and non-performing loans will have the same dynamic as in normal times. Cluster estimation generates different elasticities by type of bank and thus obtains more realistic estimations that avoid composition effects.

Annex VI. Recursive Dynamic Projection Model

1. **Banks' solvency is calculated during stress tests using recursive projections done one-by-one, for each bank.** Thus, the team incorporates the evolution of profitability and the PDs to project the profitability and non-performing loans flows in the next period, based on a set of regressors. The conditioning vector represents the explanatory variables vector evaluated on a given date. This evaluation considers the scenario, but also the banks' characteristics and the lagged variables from the previous period. The conditioning vector is thus conditional at date *t*, and is expressed as: $[Macro_t|Scenario_{Base,\ Adv}, BankControls_{i,\,t}]$.

2. **The projection is realized by replacing the quantile regression coefficients with their estimation and by evaluating the conditioning vector recursively.** Thus, for each type of bank (cluster), the team projects the conditional quantile of profitability and non-performing loans:

- $\forall q,\ \hat{Q}\big(ROA_{i,\,t+1},\ q\big) = \widehat{\alpha_R}^q + \widehat{\boldsymbol{\beta_R}}^{\boldsymbol{q}}\boldsymbol{Macro_t} + \widehat{\boldsymbol{\gamma_R}}^{\boldsymbol{q}}\boldsymbol{BankControls_{i,\,t}}$
- $\forall q,\ \hat{Q}\big(\Delta NPL_{i,\,t+1},\ q\big) = \widehat{\alpha_N}^q + \widehat{\boldsymbol{\beta_N}}^{\boldsymbol{q}}\boldsymbol{Macro_t} + \widehat{\boldsymbol{\gamma_N}}^{\boldsymbol{q}}\boldsymbol{BankControls_{i,\,t}}$

3. **Net losses are calculated for each level of risk (quantile) by subtracting from the projected profitability the provision for non-performing loans, assuming a rate of loss at 75 percent.** Profitability during the current period may also serve to absorb a portion of losses on the loan portfolio. In contrast, in the case of negative profitability, these flow losses are added to the losses on the loan portfolio.

- $\boldsymbol{Losses}: \widehat{ROA}\ - \mathbf{1}\big(\widehat{\Delta}NPL > 0\big) * 0.75\,\widehat{\Delta}NPL$

4. **Capital and regulatory ratios are projected for each level of risk, subtracting net losses from capital using a transition equation.** An important assumption of stress tests is that the size of the banks' balance sheet remains constant during the stress period (no deleveraging). It is challenging to estimate a behavioral model that projects the volume of loans granted by banks; thus, the FSAP's working assumption is that this volume remains constant. This is common practice in IMF FSAP stress tests and can be justified by the fact that banks cannot suddenly reduce the size of their balance sheet without exacerbating the economic crisis and then losing even more in profits.

- Capital transition equation: $capital_{t+1} = capital_t\ - 1(Losses < 0) * Losses$
- Regulatory ratio transition equation: $\frac{capital_{t+1}}{RWA_{t0}} = \frac{capital_t\ -1(Losses<0)*Losses}{RWA_{t0}}$

5. **The projections are then iterated by updating the conditioning vector based on past scenarios and projections.** An important aspect of recursive projections in a density model involves the choice of risk level for determining the conditioning vector. It would be unrealistic to use a high level of risk (95 percent) at each stage, i.e., a level that assumes banks suffer an extreme idiosyncratic shock at each period. To proceed to the next stage, the team retained the median value of the projected variables as the starting point for (i) ROA (ii) ΔNPL and (iii) $\frac{capital_{t+1}}{RWA_{t0}}$. In contrast, the projection of conditional quantiles for each period produces the fan charts for credit risk (Figures 4.3 and 4.5) and rate risk (Figures 5.3 and 5.5).

Annex VII. Matrix of Banking Sector Stress Tests

WAEMU: Matrix of Banking Sector Stress Tests		
Domain		**Assumptions**
1. Institutional perimeter	Institutions included	• 99 banks (almost all); several very small banks with insignificant activity or missing data were excluded.
	Market share	• More than 95 percent of banking sector assets in the region.

	Data and baseline date	• 2000–2020 (macro data), 2010–2020 (banking data).
		• Reference date: Q4 2020.
		• The bank-by-bank data provided by the authorities include historical series over about ten years for:
		   • balance sheets, P&L statements, equity, credit breakdowns, and securities holdings.
		   • credit risk (e.g., doubtful debts), concentration risk (for deposits and loans), interest rate risk, foreign exchange risk, and liquidity risk.
		   • macroeconomic data (e.g., interest rates, inflation, and climate index) from leading sources (e.g., Bloomberg, Haver, IMF) are used to model macroeconomic linkages.

2. Risk propagation channels	Methodology	• A macroeconomic growth-at-risk model projects the future distribution of real GDP growth as a function of current macrofinancial conditions. The propagation of risks to WAEMU growth is captured by nonlinear density estimators, with shocks transmitted nonlinearly across the GDP distribution. The FSAP team developed a density projection model specifically adapted to low-income countries, with estimation methods that are robust to measurement errors and accurate for small samples. • The 99 banks are divided into four groups via statistical learning methods and form clusters that are homogeneous in terms of asset quality, size, capitalization, and asset returns. The conditional distribution of doubtful debts explained by the macroeconomic variables is estimated separately for each group to predict the rise in the probabilities of default (PDs) under each macroeconomic scenario and risk level. • The loss recovery assumptions are *ad hoc*, due to the lack of adequate historical data. • The stress test of bank credit portfolios was conducted via a balance sheet method—including estimation of the PDs, calculation of default losses, and equity absorption. It assumed a static balance sheet size and composition during the stressed period. The WAEMU FSAP team innovated by using statistical learning methods for processing noisy data and addressing the issue of small sample size.

WAEMU: Matrix of Banking Sector Stress Tests		
Domain		**Assumptions**
		• The same methodology has been used to estimate an inflation-at-risk model and its impact on banks' capital.
	Satellite models	• Based on growth-at-risk and inflation-at-risk estimates, and the stress paths over a three-year horizon, the team used a series of satellite models to infer the dynamic of macroeconomic variables of interest (interest rate, inflation, etc.).
	Stress testing horizon	• Four years (2021–24).
3. Tail shocks	Scenario analysis	• The FSAP constructed a baseline scenario and an adverse scenario. • Due to the current COVID-19 crisis, the scenarios entail a recovery-at-risk, modeling the risks of a slow U-shaped recovery and a rapid V-shaped recovery. • The baseline scenario is aligned with the IMF's latest *World Economic Outlook* and is consistent with WAEMU's Article IV. • The adverse scenarios are structured dynamically as a function of: (i) the macroeconomic shocks of the Article IV report's Risk Assessment Matrix (RAM); (ii) historical crisis paths in the WAEMU; and (iii) the level of assumed risk (e.g., value at risk of 5 percent).
	Sensitivity analysis	• The stress test of concentration risk is conducted by a sensitivity analysis with *ad hoc* tests of defaults of largest borrowers and withdrawals of largest depositors.

4. Risks and buffers	Risks/factors assessed (How each element is assessed, assumptions made)	• The FSAP models:
		  • A set of macrofinancial shocks derived from the Article IV report (external demand shock, worsening of the COVID-19 pandemic, climate change, deterioration of international financial conditions, etc.).
		  • Propagation of shocks emanating from each country of the monetary zone to the region.
		  • The modeling of shocks is nonlinear and dynamic, with the shocks corresponding to points in the distributions of GDP, inflation, and associated macroeconomic variables.
		  • The shocks are calibrated based on the unconditional distribution of the explanatory variables.

	Behavioral adjustments	• Bank balance sheet compositions and sizes are assumed to be static over the entire stress period. • Dividend distributions are only permitted for banks that meet the regulatory capital requirements and have positive profits.

WAEMU: Matrix of Banking Sector Stress Tests		
Domain		**Assumptions**
5. Regulatory and market-based standards and parameters	Calibration of risk parameters	• The risk parameters are estimated via density models using structural relationships and estimated distributions conditional on the macrofinancial conditions at the reference date. This approach permits time series modeling of relationships, while also accounting for the already exceptionally strong shock of COVID-19. • The risk paths are calibrated—in distribution percentiles—on the WAEMU's crises of 1982, 1994, and 2011, which enables different recoveries (U-shaped and V-shaped) to be captured.
	Regulatory, accounting, and market-based standards	• Use of regulatory ratios and minimum capital requirements imposed by the BCEAO as IMF stress test standard.
6. Reporting format for results	Output presentation	• A decline in banking sector capital during the stress period, under different scenarios. • Number of banks and share of banking sector assets of banks whose capital falls below the regulatory minimum. • Recapitalization needs in percent of GDP.