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Risk-to buffer: setting cyclical and structural banks capital requirements through stress tests

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Abstract

In this paper, we propose a new framework to jointly calibrate cyclical and structural capital requirements. For this, we integrate a non-linear macroeconomic model and a stress test model. In the macroeconomic model, the severity of the scenarios depends on the level of cyclical risk. Risk-related scenarios are used as inputs for the stress test model. Banks' capital losses derived from a scenario based on a reference level of risk are used to set the structural requirement. Additional losses associated with the current risk scenario are used to set the cyclical requirement. This approach provides a transparent method to strike the balance between cyclical and structural requirements.

Keywords: Financial vulnerability, macroprudential policy, non-linear models, capital requirements.

JEL Codes: C32, E51, E58, G01.

Non-Technical Summary

After the Global Financial Crisis, the Basel III regulation substantially raised bank capital requirements and introduced a distinction between *structural* and *cyclical* requirements. Structural requirements aim at making banks more resilient to risks related to structural features of the banking system (interconnection, design of the real estate market, etc.). Cyclical requirements cover risks deriving from the evolution of the financial cycle, i.e. excessive leverage and booming asset prices. In this context, Stress tests have emerged as a popular tool to calibrate both types of requirements. They consist in (i) designing an adverse economic scenario, (ii) computing bank capital losses under this scenario and (iii) calibrating capital requirements to cover those potential losses. However, if cyclical and structural requirements are calibrated using parallel stress tests based on similar scenarios, different requirements will end up covering the same type of vulnerability, resulting in a double counting of risk in capital requirements. For instance, an adverse scenario used for structural requirements including cyclical elements might lead to overlaps with cyclical requirements. Conversely, lack of communication could also lead to some risks not being covered by any of the requirements.

To clarify how to jointly set cyclical and structural requirements via Stress test, the paper introduces a conceptual framework called "Risk-to-Buffer". This framework leverages a non-linear macroeconomic model, generating macroeconomic scenarios whose severity depends on the level of cyclical risk. The use of risk-related scenarios in stress test exercises allows to establish a direct link between the cyclical risk level and the calibrated cyclical requirement. A structural requirement can be calibrated with respect to a standard risk level ("reference risk"). A cyclical requirement is then calibrated with respect to the to the current cyclical risk. Overall, the approach is developed in three steps:

1. Macroeconomic scenarios are generated based on a non-linear macroeconomic model, whose dynamics are amplified with the level of cyclical risks;

2. These scenarios are used as inputs in a stress test model to project banks' capital ratios. Higher-risk scenarios lead to larger capital losses;

3. Regulatory requirements are calibrated based on the projected losses. The reference-risk scenario is used to set the structural requirement level, and the additional losses due to the current cyclical risk scenario determine the cyclical requirement.

The paper also presents a practical illustration of this framework using a a multivariate non-linear macroeconomic model which can be used to generate risk-dependent scenarios. We estimate the model on the euro area and we identify a set of real and financial shocks. The debt service ratio (thereafter DSR) of non-financial private sector is used as a measure of cyclical risk. The DSR is defined as the share of income that firms and households use to repay their debt and is a measure of financial vulnerability. Estimations show that the responses of the economy to housing and output shocks are amplified under high cyclical risks. First, we simulate these two shocks to build the risk-related adverse scenarios. Second, in order to project banks capital losses under the different scenarios, we use a reduced-form stress test model. Third, we calibrate the cyclical and structural requirements according to the projected capital losses. In this way, we can calibrate a structural requirement and cyclical requirements for the different phases of the financial cycle (e.g. median risk, high risk).

Overall, the proposed Risk-to-Buffer framework aims at providing a formal mechanism to link the level of cyclical risk to the calibration of the cyclical requirement through stress tests, thereby reducing the risk of double counting and enhancing the effectiveness and transparency of capital regulation in the banking sector. The Risk-to-Buffer can be used to calibrate both micro and macro-prudential requirements. Also, the framework provides a transparent method to strike the balance between cyclical and structural requirements: it directly depends on the level of cyclical risk policymakers use as a reference to set the structural requirements. The lower this reference level of cyclical risk, the lower the structural requirement and the higher the role of the cyclical requirements.

Finally, this approach can provide a useful framework for the discussion over a "neutral" cyclical requirement, by providing a clear measure of the balance between structural and cyclical requirements.

1 Introduction

Since the global financial crisis, prudential authorities have substantially reformed the capital regulation framework for banks. A new set of rules, labelled the Basel III framework, have been introduced to strengthen banks resilience against risk.[1] To this extent, one of the novelties of Basel III consisted in introducing a distinction between: i) *cyclical requirements* that evolve with the financial cycle and ensure banks resilience against risks related to the evolution of financial conditions, ii) *structural requirements* remaining constant through the cycle and covering risks related to the structure of the banking system.[2]

Stress test models are key analytical tools used by competent authorities to set cyclical and structural requirements. Through a set of econometric and accounting equations, these models assess banks' resilience by projecting capital ratios under negative macroeconomic adverse scenarios. Authorities set capital requirements based on the banks' projected losses. However, a formal framework to map projected capital losses into cyclical and structural requirements is missing. Besides, if cyclical and structural requirements are calibrated using parallel stress test exercises based on similar scenarios, different requirements will end up covering the same type of vulnerability, resulting in a double counting of risk in setting capital requirements.[3] Lack of communication could also lead to some risks not being covered by any of the requirements.[4]

[1]The Basel Committee on Banking Supervision (BCBS) has agreed on a set of reforms concerning requirements for banks.

[2]Cyclical requirements are meant to ensure resilience in case of materialisation of the so-called cyclical risks: e.g. over-indebtedness of private agents causing massive deleveraging episodes or over-evaluation of asset prices triggering substantial downward correction of asset prices. The main example is represented by the Counter-Cyclical Buffer (CCyB), that is quarterly set by the macroprudential authorities in a counter-cyclical fashion. This requirement increases during the upward phase of the financial cycle when cyclical risks accumulate, and decreases when risks materialise, so that banks are less constrained in their credit supply and can support credit in the descending phase of the financial cycle. Besides, higher capital ratio levels allow banks to absorb losses, without enforcing general deleveraging.

Structural requirements cover instead risks that do not evolve with the financial cycle. These requirements ensure resilience of banks in periods of economic distress, but they do not cover losses deriving from the financial cycle evolution. These requirements are set according to banks' structural long-term features and with a lower frequency with respect to the cyclical requirements. First, some requirements cover risks concerning idiosyncratic banks' features, i.e. microprudential structural requirements. Examples of those requirements are the P2G and P2R requirements, set by the Single Supervisory Mechanism (SSM) at European level. These requirements are calibrated considering the individual characteristics of banks (e.g. business model, internal governance). Macroprudential structural requirements are set considering the structural features of the banking system as a whole, as such as the Capital Conservation Buffer and the G-SIB buffers requirements. Their calibration does not evolve according the evolution of the financial cycle nor it is performed with quarterly frequency, opposite to the case for cyclical buffers.

[3]On one hand, stress tests are used for the calibration of structural requirements, as P2G set by the ECB on the basis of the results of the European Banking Authority (EBA) Banks stress tests. On the other hand, stress tests can also be used for the calibration of the countercyclical buffers (CCyB) at national level.

[4]To this extent, policymakers have identified the need to design frameworks to set different requirements via stress tests. First, Bank of England clarified the use of stress test losses to calibrate the Counter-cyclical

The "Risk-to-Buffer" conceptual framework In the first part of this paper, we present a new conceptual framework, the Risk-to-Buffer, to jointly calibrate cyclical and structural requirements. A non-linear macroeconomic model is used to generate adverse scenarios whose severity depends on the level of cyclical risk. Thanks to the model, we obtain a "reference"-risk scenario, based on a reference level of the cyclical risk, and a cyclical-risk scenario, based on the current level of the cyclical risk. Via the stress test model, we project banks' losses according to each risk scenario. We set the structural requirement based on the losses under the reference-risk scenario. The cyclical requirement is calibrated based on the (additional) cyclical risk losses. In this fashion, structural and cyclical requirements cover different types of vulnerabilities, addressing the risk of double-counting.

Our approach is articulated in three steps. First, we generate macroeconomic scenarios by using a non-linear macroeconomic model whose dynamics depend on the level of cyclical risk. We exploit this non-linear feature to generate several adverse scenarios in which the same set of shocks hits the economy under different risk levels. A first scenario is produced at a reference level of cyclical risk (e.g. minimum risk, median risk) to capture dynamics under a standard risk environment, and a second scenario is produced at the current risk level, to capture the amplification role played by the current cyclical risk.

In a second step, the different scenarios are used as inputs in a stress test model to obtain the corresponding capital ratio projections. Higher risk scenarios are associated with larger capital losses.

Third, the projected losses are used to calibrate capital requirements. The loss of the *reference risk* scenario is used to set the structural requirement, whereas the additional loss triggered by the current cyclical risk scenario sets the cyclical requirement. As such, this latter evolves with the level of cyclical risk. Should the current risk level be lower than the "reference" risk (e.g. the one used to calibrate the structural requirement), the cyclical requirement would be set to zero. In this way, the sum of both requirements would not fall below the structural requirement, which acts as a backstop for capital requirements. Importantly, the choice of the "reference risk" level directly affects the level of the structural requirement and in turn of the cyclical requirement: the higher the reference risk, the higher the structural requirement and the lower the space taken

Buffer and the PRA buffer in the Policy Statement — PS15/20, Pillar 2A: Reconciling capital requirements and macroprudential buffers, July 2020. Second, US Fed clarified the use of the stress Capital Buffer (SCB), as a buffer set based on the stress tests losses and integrating the previous Capital Conservation Buffer, which acts as a floor in setting the new SCB, set to 2.5% at its minimum level, see the Final rule.

by the cyclical requirement. As such, the Risk-to-Buffer framework offers a transparent way for policymakers to set the balance between the two types of requirements.

Application of the conceptual framework In the second part of the paper we provide a practical illustration of our framework.

First, we present the non-linear model through which we obtain the risk-dependent scenarios. This model is a Multivariate Smooth Transition regime switching model (Auerbach and Gorodnichenko (2013); Tenreyro and Thwaites (2016)) estimated through local projections (Jordà (2005)) by using quarterly observations of output, inflation, unemployment, the yield curve,[5] and housing prices for the euro area.[6] Thanks to its multivariate structure and to a Choleski decomposition, we identify a set of structural economic and financial shocks. The non-linear structure provides impulse responses that depend on the state variable. In the model, the latter is a measure of cyclical risk: the debt service ratio (henceforth DSR) of the non-financial private sectors (henceforth NFPS), i.e. firms and households. This ratio is computed as the fraction of income that agents use to repay their debt (Drehmann et al. (2015)). The DSR captures the degree of financial vulnerability of private agents: the higher the level, the lower the available cash flow to absorb adverse shocks. Overall, we find that shocks are amplified when the DSR is high.[7] To generate adverse scenarios mimicking the dynamics of a financial crisis, we assume that a set of recessionary shocks (housing shock and output shock) hits the European economy in each year of our projection. We calibrate the shock to match, under the maximum risk case, the severity of the GDP downturn considered in the 2018 EBA stress test, i.e. -7.8 percentage points in level deviation from the baseline scenario. We simulate these shocks under different risk levels and find that the impact of the adverse shocks substantially increases with the level of the DSR, i.e. with the cyclical risk.

Second, the simulated scenarios are used as inputs in a stress test model. In order to indirectly infer the elasticity of banks' capital with respect to GDP growth, we estimate a unique reduced-from regression estimated on the results of the European Banking Authority (EBA) 2018 Banks stress test exercise. This "indirect inference" approach can be interpreted as a two steps strategy.

[5] Spread between 10 years interest rate and short term rate

[6] A similar model estimated on the US is used in Couaillier and Scalone (2020) to estimate the how financial vulnerability affects the propagation of housing and credit shocks.

[7] For the sake of simplicity, in this work we focus on a unique measure of cyclical risks, but other measures of the cyclical risks could be used as state variable variable, as such as Credit-to-GDP gap (Borio et al. (2014)) or credit growth. In robustness exercises, we find that this type of amplification is there also when alternative risk measures are used. For robustness, different scenarios could be generated by using different cyclical risk measures.

In a first step (i.e. the EBA stress test), a set of accounting and econometric equations based on macroeconomic and (possibly confidential) banking data is used to simulate capital ratios under different macroeconomic scenarios. In a second step, the simulations coming from the complex model are used to estimate the elasticity of CET1 ratios to the macro-economic variables.[8] The single reduced-form equation model allows to create a transparent and direct link between the average CET1 ratio of the banking system as a whole, and the macroeconomic variables (e.g. GDP).[9] We find that under high risk the aggregate reduction of CET1 with respect to the starting point of the projection for European banks is equal to 3.8pp under High Risk, i.e. more than 6 times larger than under the Low Risk (0.6pp). Under medium risk, the CET1 ratio depletion would be 1.8pp.

Finally, we use the estimated losses to calibrate the requirements. In a first calibration approach, the structural requirement is set equal to the loss obtained with the DSR at its historical minimum (0.6%). When the current risk is at its maximum (median) level, the cyclical requirement is set to 3.2% (1.2%).

Should policymakers use the median historical risk as the reference level of risk, the structural requirement would be equal to 1.8%. In this case, when the current risk is at its historical maximum, the cyclical requirement is set to 2.0%, i.e. the additional loss deriving under the maximum risk scenario.

In the first calibration approach the relative importance of cyclical requirements is higher, providing more releasable requirements also when risks are not elevated yet or above the median.

Literature We join two streams of literature. First, banking models and stress test models have been developed assess banks' resilience and calibrate requirements (Bennani et al. (2017); Budnik et al. (2019); Camara et al. (2015); Coffinet and Lin (2010); Dees and Henry (2017); Henry et al. (2013)). Hirtle et al. (2016) develops a stress test model featuring a set of econometric equations linking macroeconomic and publicly available bank-level information to study the relation between macroeconomic variables and key elements of banks balance sheet and profits

[8]The Core Equity Tier 1, or CET1, is the purest form of bank capital, typically composed of common equity and retained earnings, and the one on which structural and cyclical buffers apply.

[9]In this work, we adopt a macroprudential perspective, focusing on the systemic dimension, i.e. setting homogeneous capital requirements across banks. In doing so, we set capital requirements with respect to the average banks' losses, obtained in a stress test model that does not take into account how idiosyncratic features of banks affect banks' balance sheet dynamics. The same approach could be applied to stress test exercises where idiosyncratic characteristics of banks (i.e. size, business models) affecting capital ratio dynamics, producing heterogeneous effects across banks (Hirtle et al. (2016)).

and losses. In our paper we indirectly infer this relation by using pseudo-data (simulations from the EBA stress test models). Jointly with a non-linear macro-economic model, this reduced-from stress test can be used to project the average banks capital shortfall under different risk-related macroeconomic scenarios, with the final goal to set cyclical and structural requirements.

Second, non-linear macro models are estimated to assess the impact of financial vulnerability on the propagation of economic shocks (Aikman et al. (2020); Alpanda and Zubairy (2019); Barnichon and Matthes (2016); Barnichon et al. (2016); Carriero et al. (2018); Cheng and Chiu (2020); Couaillier and Scalone (2020)). In our work, we detect non-linear amplification of real and financial shocks for the euro area, for which we find results overall consistent with economic theory (Guerrieri and Iacoviello (2017); Kiyotaki and Moore (1997)). The use of parallel scenarios is also considered in Parlatore and Philippon (2022), where the authors develop a framework to study the optimal design of the stress test scenarios, showing how parallel scenarios featuring different variance (and hence different severity) can be used to assess banks resilience and provide advice on the best policy. In our work, the severity of the scenario increases with the risk level, which amplifies the exogenous shocks thanks to the use of a non-linear macroeconomic model. This approach allows to map each risk level to a different capital requirement level.

The reminder of this paper proceeds as follows. In Section 2, we present the conceptual framework. In Section 3, we present the illustrative macroeconomic model and we report the estimated results. Section 4 houses the application of our model for calibrating requirements. Section 5 concludes.

2 The Risk-to-Buffer framework

In this section we introduce the conceptual framework. This framework maps the risk levels to their requirements, generating a formal link between: i) a reference risk level and the structural requirement; ii) a higher cyclical risk and the cyclical requirement. First, we show the logic behind the use of stress tests in setting capital requirements, highlighting the possible overlaps between different requirements when parallel stress tests are run. Second, we present how to link risk levels to scenarios used in stress tests, through a non-linear macroeconomic model. Third, we present how the different risk-related scenarios can generate risk-related losses to be mapped to capital requirements.

2.1 Stress test in requirement calibration

Banks' stress tests models are a set of econometric and accounting equations used to project banks' balance sheet variables (e.g. capital ratios, banks' profits) conditional on the evolution of a set of macroeconomic and financial variables (the macroeconomic scenarios):

$$Capital_{i,t} = g(Macro_t), \tag{1}$$

where $Capital_{i,t}$ is the capital ratio of bank i at time t, $Macro_t$ are the projection of macroeconomic and financial variables (baseline and adverse scenarios), $f()$ is the set of econometric and accounting equations of the Stress test model.

Macroeconomic variables $Macro_t$ are generated through a macroeconomic model $g()$ producing the macroeconomic and financial trajectories conditional on the assumed sequence of economic shocks $Shocks_t$:

$$Macro_t = f(Shocks_t). \tag{2}$$

In practice, policy makers test banks' resilience with respect to adverse macroeconomic scenarios.[10]

Since the goal of the policymaker is to ensure that banks will be capitalised enough in case of adverse scenario materialisation, the projected capital losses $Capital_{i,t}$ can be used to calibrate capital requirements $Buffers_{i,t}$:

$$Buffers_{i,t} = h(Capital_{i,t}). \tag{3}$$

In this work, for the sake of clarity, we assume that the each requirement is the same across banks ($Buffers_{i,t} = Buffers_t$) and is set equal to the average banks' final capital loss with respect to the starting point of the projection.[11]

Equations (1) and (2) can be used to re-write equation (3) as:

$$Buffers_t = h(g(f(Shocks_t))). \tag{4}$$

[10] Those scenarios usually mimic strong downturns, e.g. the global financial crisis (GFC) or the Euro-Area Sovereign debt crisis.

[11] Alternative mapping functions could be considered, e.g. computing shortfalls with respect to some exogenous fixed levels.

This standard approach, widely used in policy-making, may raise key issues. First, the stack of capital requirements is composed of multiple requirements: how to map the whole projected losses into multiple requirements is not formalised in the standard approach. Second, since requirements can calibrated by different institutions through parallel exercises, different requirements can potentially overlap and cover the same type of risks.[12]

2.2 Generating scenarios related to the level of risk

In our framework, adverse scenarios are generated through the use of a state-dependent macroeconomic model. The state variable of the model is a measure of cyclical risk (e.g. the level of private indebtedness). By using always a fixed set of economic shocks, we generate multiple adverse scenarios across different levels of risk (e.g. low risk, medium risk, high risk):

$$Macro_t^{Risk} = f(shocks_t, Cyc\,Risk_t) \tag{5}$$

where $Cyc\,Risk_t$ is the state variable measuring the level of cyclical risk and the $shocks_t$ is the fixed sequence of shocks, common across the different scenarios.[13] Thanks to the non-linear features of the model, the severity of the scenario varies with respect to the cyclical level. If the state variable is a good measure of cyclical risk, the high risk scenarios will be associated to a more severe output reduction, e.g. featuring stronger amplification of economic and financial shocks, in line with the theoretical literature on the *financial accelerator* (Bernanke et al. (1996); Kiyotaki and Moore (1997)) and the empirical literature on such amplifications (Aikman et al. (2020); Carriero et al. (2018); Jordà et al. (2013)).

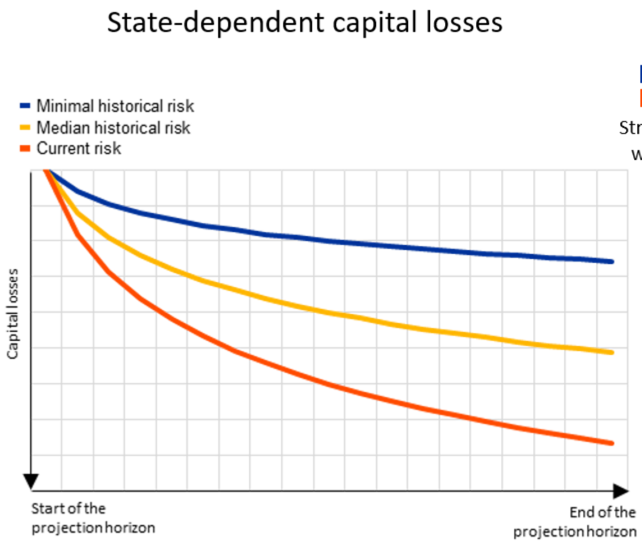
2.3 A capital loss for each risk level

Figure 1 illustrates the use of the adverse scenarios in the stress test (equation 1) to provide capital ratios projections ($capital_{i,t}^{Risk}$) and map them into capital requirements. The left panel shows the expected impacts of a given economic shock under different level of cyclical risks. For illustration purpose, we focus on three cases: low, medium and high risk scenarios, gener-

[12] For example, some requirements are fixed at international level (e.g. Capital Conservation buffer), other requirements are fixed at national levels (Counter-cyclical buffers). Besides microprudential requirements are typically set by the microprudential supervisor at the bank's level, whereas the macroprudential requirements apply to a whole banking system and are set by the regulator.

[13] A study on how to choose shocks is beyond the scope of our work. In practice, shocks are selected in light of risk analysis.

Figure 1: Illustration of the methodology



Note: The methodology is based on the use of multiple scenarios generated with the same set of shocks in different states of the economy. Dynamics are state dependent: the low risk (blue), the median risk(yellow) and the high risk (red) scenarios have different severity. Stronger severity scenarios will cause larger capital losses. The structural and cyclical requirements are then set with respect to those scenarios. First, depending on their preferences, policymakers set the structural requirement to cover the losses under the "reference" risk scenario, e.g. the minimum risk level (right hand side bar) or the median risk level (left hand side bar). Second, the cyclical requirement is set to cover the additional losses related to the current risk level.

ated using the historical minimum, median and maximum of the state variable. Higher risk is associated with more severe scenarios and, hence, larger capital losses.

2.4 From capital losses to requirements

Finally, the losses generated by the stress test are used to calibrate the requirements. The structural requirement is set equal to the losses obtained under the reference risk:

$$Buffers_t^{Structural Risk} = h(g(f(Shocks_t, Reference\, Risk). \tag{6}$$

The cyclical requirements is set to the level of additional losses generated under the current risk level:

$$\begin{aligned} Buffers_t^{Cyclical Risk} =& h(g(f(Shocks_t, Current\, Risk)) \\ & - h(g(f(Shocks_t, Reference\, Risk). \end{aligned} \tag{7}$$

When the current cyclical risk evolves, the cyclical requirement changes in line with the level of cyclical risk. If the current risk goes below the reference level, the cyclical requirement will be set to zero. Conversely, if the current level attains its historical maximum, the cyclical risk requirement will be equal to the additional shortfalls generated under the most severe scenario. The choice of the reference risk level depends on the policy-maker's preference. In this work we consider two alternative settings (right panel of Figure 1). In one setting, the policymaker chooses the minimum risk as the reference risk. In this case, the policy maker wants to cover all the losses deriving from the risk amplification by using the cyclical requirement (the red part in the right bar of Figure 1, whereas the structural requirement (the blue part) would be equal to the loss under the low risk scenario. In this case, under the medium risk (akin to a "neutral" state of the economy), the cyclical requirement is positive, e.g. in this case the "neutral" cyclical requirement is positive.[14]

In the second setting, the reference risk is the median level. In this case, all the losses obtained under medium risk are covered by the structural requirement. According to this setting, the cyclical requirement covers only the additional losses generated by a risk level higher than the median.

Under the first setting, the cyclical component of the total requirement space is more relevant. In this setting, authorities have more fire-power to counter-act the negative effects of risk materialisation by releasing a higher level of cyclical requirement.

The next two sections provide an illustration of this framework, based on European data and a reduced-form stress test model.

3 Illustration: the non-linear macroeconomic model

In this section, first, we present the non-linear econometric model. Second, we present the data and the interaction variable used in the benchmark estimation. Third, we present the impulse responses produced by the model, focusing on the two shocks included in the model (i.e. housing shock and output shock). In doing that, we highlight the substantial state effects related to level of cyclical risk: both housing and output shocks are more recessionary under high cyclical risk. This feature of the model allows producing scenarios, that, given the same set of initial shocks,

[14] To this extent, in the United Kingdom and some euro area jurisdictions, the neutral level of the Counter-Cyclical buffer is set to positive values.

are more severe under high risks. Such scenarios are used in the stress test exercise to calibrate the structural and the cyclical requirement.

3.1 The econometric model

The macroeconomic model is a Multivariate Smooth transition regime switching model (Auerbach and Gorodnichenko (2013); Tenreyro and Thwaites (2016)), estimated by using Local Projections (thereafter LP) by Jordà (2005).

In such a model, a state variable transitions between two polar regimes, affecting the effect of shocks on the economy. More specifically, for each period $t = 0, ..., T$, horizon $h = 0, ..., H$, with n the number of endogenous variables, p the number of lags, our econometric setting is:

$$
\begin{aligned}
Y_{t+h} = \; & F(z_{t-1})(\alpha_h^H + \Sigma_{\ell=1}^{p} \beta_{h,\ell}^H Y_{t-\ell}) \\
& + (1 - F(z_{t-1}))(\alpha_h^U + \Sigma_{\ell=1}^{p} \beta_{h,\ell}^U Y_{t-\ell}) \\
& + u_{h,t},
\end{aligned}
\tag{8}
$$

where Y_t is the $(n, 1)$ vector of endogenous variables at time t, z_{t-1} is the scalar interaction variable at time $t - 1$ and $u_{h,t}$ is the $(n, 1)$ vector of errors at horizon h at time t. The state effect is given by $F(z_t)$, that is the scalar function governing the transition between the high and the low regime. This function is used to normalize the state variable in a scalar included in the interval $[0, 1]$ and increases in z_t. Higher (lower) values of z_t will correspond to $F(z_t)$ closer to 1 (0), making Y_{t+h} depending more on the first (second) line of Equation 8. As standard, the transition function is the logistic transformation of the original z_t:

$$
F(z_t) = \frac{1}{1 + exp\left(-\theta\left(\frac{z_t - v}{\sigma_z}\right)\right)}
\tag{9}
$$

where θ is the smoothing parameter governing the smoothness of the transition from one state to another[15], v determines the part of the sample spent in ether state[16], and σ_z is the standard deviation of the observed state variable. Both parameters are generally calibrated (Auerbach and Gorodnichenko (2013)). We set c at the historical median of the original state variable, so that the resulting state spends half of the time in both regimes. Our baseline specification

[15] The higher θ, the faster $F(z_t)$ goes toward 0 and 1, i.e. converging to dummy-regime switching.

[16] $z_t > v$ is equivalent to $F(z_t) > 0.5$. Defining v as the $p - th$ quantile of the historical time series of z_t forces $F(z_t)$ to spend $p\%$ of the time below 0.5, i.e. in the low regime.

uses $\theta = 3$ (Tenreyro and Thwaites (2016)), but our results are robust to a large range of other calibrations.

We construct confidence intervals using the block-of-blocks bootstrap approach, following Kilian and Kim (2011), in order to account for the autocorrelation in time series.[17].

3.2 Estimation of the macroeconomic model

In our benchmark specification, the model is estimated on euro area aggregate data (EU19) using a sample going from 2002 Q1 to 2019 Q2. The specification includes: output (GDP), inflation (HICP), unemployment rate, short-term rate (3-months EURIBOR), house prices, the spread between the 10 years government rate and the risk-free rate. Rates are reported in levels, whereas the other variables are expressed in percentage quarterly variations.[18] The process has one lag and the model is estimated for 12 quarters ahead.

The state variable to capture agents' vulnerability is the Debt Service ratio (DSR) of the Non-Financial Private Sector, as computed by Drehmann et al. (2015):

$$DSR_t = \frac{D_t}{Y_t} \frac{i_t}{1 - (1 + i_t)^{-m}}, \tag{10}$$

where Y_t is income, D_t is debt, i_t is the effective lending rate, m is the average maturity. The DSR is the fraction of revenue that agents have to pay in the current period in order to repay a debt of m maturity in equal portion.[19] A higher DSR implies that agents are overall more vulnerable to economic and financial shocks. As such, the same negative economic shocks are expected to have more adverse consequences when the aggregate DSR increased, as agents are more likely to be in financial distress.

We apply a Choleski decomposition to identify economic and financial shocks.[20] We order

[17]We construct all possible overlapping tuples of m consecutive dates in the matrix Y of endogenous variables, along with the corresponding block of regressors for each selected dates, at each horizon of regression. We then draw in this set of blocks to construct the bootstrapped time series. We set $m = 5$ in line with Horowitz (2019)), in that m should be proportional to $n^{1/3}$. We thus select blocks of five consecutive dates to build the bootstrap time series. In a robustness exercise, we also apply the bootstrap-after-bootstrap method, which corrects for bias in bootstrap estimates (see Kilian (1998); Kilian and Kim (2011))

[18]Our estimation results are robust to the use of shadow short term rate (Wu and Xia (2016)).

[19]The use of Debt Service Ratio allows directly capturing different key dimension of financial vulnerability as such as the evolution of the cost of debt, the amount of debt in the economy and the capacity to repay the debt via income. This indicator expressed in difference is widely used in macroprudential analysis to detect the build-up of cyclical risks (Lang et al. (2019))

[20]Structural identification is not mandatory to design adverse scenarios, which can also be produced through reduced form shocks. Nonetheless, providing a structural interpretation to the set of shocks can help to interpret the non-linear dynamics found in the model.

variables as follows: output, inflation and unemployment rates, policy rate, spread and house prices. In this way financial variables react on impact on the macroeconomic variables, whereas these latter take one quarter to react to financial shocks. This is consistent with financial variables reacting typically faster than macroeconomic ones. The short term rate is ordered after the unemployment rate, so that monetary policy reacts on impact to output, inflation and unemployment rate. This ordering is overall standard and in line with Aikman et al. (2020); Cesa-Bianchi (2013); Goodhart and Hofmann (2008). The sign of the responses and the state dependent amplifications are strongly robust to alternative Choleski ordering.

In the estimated model, shocks are overall amplified under high risk. We report the impulse responses of the two shocks that are used to build the scenarios in Section 4: the housing shock and the output shock.

Figure 2 reports the impulse responses with respect to a one standard deviation recessionary housing shock for two states of the economy: a Low Risk case (blue line) corresponding to $F(z) = 0.1$ and High Risk case (red line, $F(z) = 0.9$).[21] Under high vulnerability, the response of output to a housing shock is negative and statistically significant for most of the projection horizon, with a peak effect of -1.3% two years after the shock arrival. Conversely, under low vulnerability, the response of output is not statistically significant and close to zero for the whole projection horizon.[22] Consistent non-linear dynamics are detected for unemployment, policy rate and the yield curve.

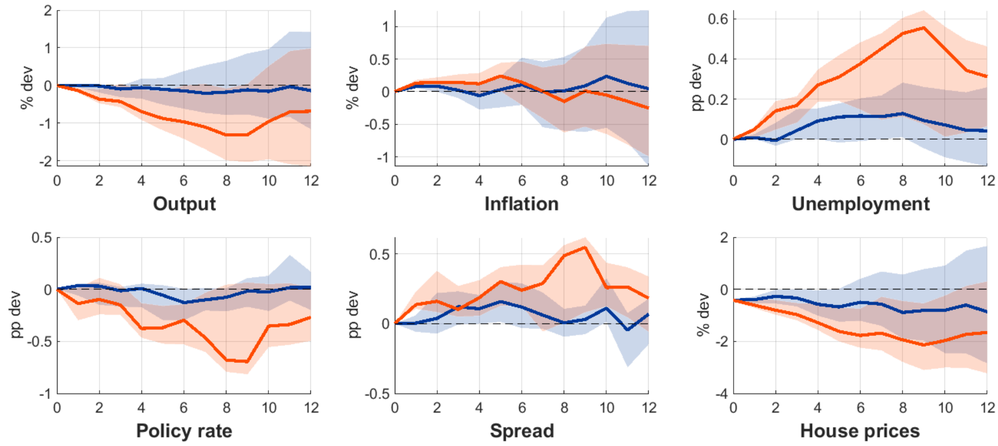
Figure 3 reports the responses of the economy to a recessionary one-standard-deviation output shock. When risk is low (blue lines), the shock has a negative effect on output only at the beginning of the projection horizon. Besides the effect is not statistically significant starting from the second period after the shock arrival. Under high risks (red lines), the effect is statistically significant for half of the projection. Similar non-linear dynamics are found also for unemployment and house prices, whose increase is statistically significant under the high risk case. Under low risk, in line with the responses found for output, the effect on unemployment and house prices fades away very quickly.

Overall, those results confirm that higher cyclical risk amplify initial exogenous shocks, resulting in more adverse scenarios. In the application, we use this model to build adverse scenarios,

[21] The housing shock can be interpreted as an exogenous variation in housing preference in line with Guerrieri and Iacoviello (2017).

[22] In a similar application on the US economy (Couaillier and Scalone (2020)) we also find that high vulnerability amplifies housing shocks.

Figure 2: Impulse responses to a Housing shock



Note: the responses of output growth and inflation and house prices are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (blue) lines are the impulses when risk is high (low). Shaded areas represent the 90% confidence intervals.

project bank losses and calibrate capital requirements.

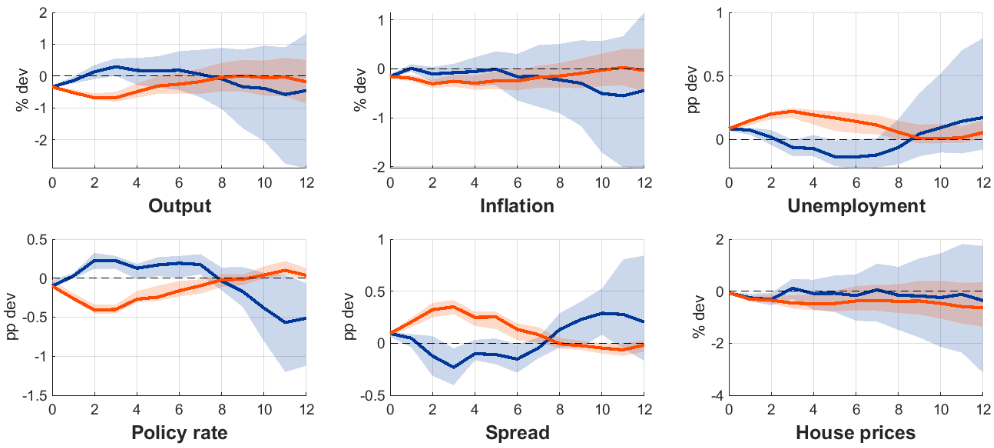
4 Illustration: an application on European banks

First, to have a transparent stress test model, we estimate a reduced form regression capturing the impact of GDP growth on banks' CET1 ratio, based on the results of the 2018 EBA stress test exercise. Second, we use our macroeconomic non-linear model to generate risk-dependent adverse scenarios for the European economy. Third, we feed the different adverse scenarios in our stylised stress test model, to compute CET1 losses for each scenario. We focus on three different risk levels: low risk (minimum DSR), medium risk (median DSR) and high risk (maximum DSR). These scenarios and their related CET1 losses are our reference points to calibrate cyclical and structural requirements. Finally, we map those losses into capital requirements, discussing also the impact of the choice in "reference risk" level.

4.1 A indirect stress test model

In order to project CET1 ratios conditional on macroeconomic scenarios, we adopt a reduced-form modeling strategy, in line with standard models in the stress testing tradition (e.g., Budnik et al. (2019); Dees and Henry (2017)). We indirectly infer the elasticity of CET1 ratios with respect to economic activity, based on the results of the 2018 EBA stress exercise. This allows

Figure 3: Impulse responses to an Output shock



Note: the responses of output growth and inflation are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (blue) lines are the impulses when risk is high (low). Shaded areas represent the 90% confidence intervals.

us to build and run an extremely simple stress test model while relying on a real life stress test exercise. We use this estimated equation as stylised stress test model to show a concrete application of our Risk-to-Buffer framework.

This strategy can be framed in two steps. In a first step, granular models based on a set of economic and accounting equations are used to compute the relation between banks balance sheet and a set of explanatory variables (macroeconomic and bank idiosyncratic variables). In this step, banks confidential information is also considered. This set of equations is then used to simulate the evolution of CET1 ratios under macroeconomic scenarios (the EBA stress test exercise). In the second step, a reduced-form equation is estimated based on the first-step simulations to recover the relation between GDP and the CET1 ratios, resulting from the complex interaction of macroeconomic and bank level information coming out of the original set of models. With respect to a direct use of the original stress test model, this approach allows to obtain a more direct and transparent link between GDP and CET1 ratios, without the need to rely on confidential banking data. Second, the approach is particularly fit for our case where the relevant information are the projected average CET1 ratios of the banking sector as a whole, which are used to guide on the evolution of macroprudential structural and cyclical requirements.[23]

[23] Another option would be to run a stress test model by using publicly available data, as done by Hirtle et al. (2016). This approach consists of building a model with a set of econometric equations linking banks balance sheets items onto macroeconomic and bank variables. In this case, the link between macro variables and the final

Based on the results of the 2018 EBA stress test exercises, we estimate an equation linking the annual difference in the CET1 projections $\Delta CET1\,ratio_{t,i}$ for each bank i of country j to $\Delta GDP_{t,j}$, i.e. the annual growth rate of GDP, and country level control variables $X_{t,j}$:[24]

$$\Delta CET1\,ratio_{t,i,j} = \alpha_j + \beta \Delta GDP_{t,j} + \gamma X_{t,j} + \varepsilon_{t,i,j}. \tag{11}$$

Our dataset contains the 33 largest euro area banks at the moment of the exercise and we consider the data in both the baseline and adverse scenarios.[25]

Table 1 houses the results. A reduction of -1% in GDP is associated to a reduction of -0.46pp of the CET1 ratios. The result is strongly significant in statistical ($p < 0.01$) and economic terms. It is also stable across different specifications.

4.2 Bank losses under different scenarios

We consider a baseline scenario and an adverse scenario. As baseline scenario, we assume a constant real GDP annual growth equal to 1.8% for each year.[26] To build the adverse scenario, we assume that output and housing recessionary shocks hit the economy at the beginning of each year of the projection. The use of these two shocks is consistent with the experience of the stress text exercises, where a mix of real and financial shocks is usually simulated to generate a sizeable economic downturn. In our case for each scenario, both shocks feature the same standard deviation (2.1), calibrated such that, under the high risk scenario, the economy ends up -7.8pp lower than in the baseline scenario, matching the recession size for the euro area in the

CET1 ratios would be derived by composing the results from the different equations. This would allow to run a model based on publicly available information and still be able to highlight the heterogeneity within the banking sector. Since we focus on the average evolution of the CET1 in the banking system, we adopt the two steps approach, which is able to directly provide us with the elasticity linking the macro scenarios to the overall CET1 shortfall of the banking system. Should the exercise tackle more microprudential calibration, a direct stress test would better fit our purpose, since we would need to assess how the macroeconomic environment interacts with the idiosyncratic features of the banks via the balance sheet structure, the relative importance of the single item and the micro explanatory variables.

[24] For the official document presenting the 2018 macroeconomic scenarios, please see here. EBA 2018 stress test results are available here.

[25] The exercise features two scenarios, each one spanning for three years. First, a baseline scenario is in line with the official European projection for macroeconomic variables. Second, an adverse scenario features an important drop in asset prices and house prices, triggering a strong recession and reaching its maximum amplitude in the second year.

[26] The baseline scenario is usually in line with the central forecast of macroeconomic and financial variables. The adverse scenario features the evolution of macroeconomic and financial variables featuring an economic downturn. Stress test adverse scenarios often try to mimics financial crisis dynamics (Cerra and Saxena (2008); Jordà et al. (2013)). As an example, for the euro area, the EBA exercises run between 2014 and 2018 presented a deviation of GDP growth for the euro area between 7 and 8 pp between adverse and baseline scenarios.

Table 1: Reduced form stress test model

Dependent Variable:			$\Delta CET1$		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
GDP	0.4602***	0.4950***	0.5255***	0.5039***	0.5137***
	(0.0556)	(0.0716)	(0.0796)	(0.0784)	(0.0803)
INF		-0.1889	-0.0820	-0.1508	-0.0433
		(0.1286)	(0.1406)	(0.1587)	(0.3383)
SPR			0.5816	0.8188*	0.8614*
			(0.4140)	(0.4543)	(0.4987)
EUR				-0.4936	-0.5120
				(0.3243)	(0.3321)
UNE					0.0682
					(0.1524)
Fixed-effects					
Country	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	198	198	198	198	198
R^2	0.32701	0.33228	0.33562	0.33903	0.33994
Within R^2	0.30620	0.31163	0.31508	0.31859	0.31953

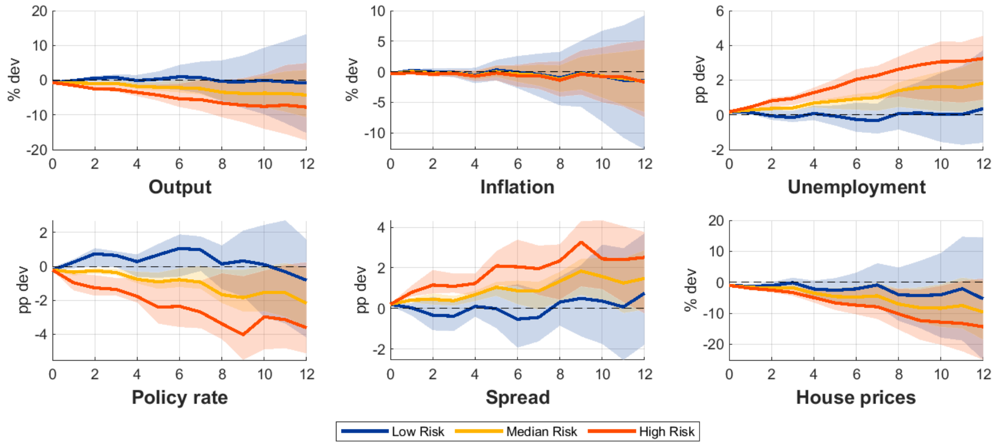
Note: The Table reports the results of the estimation of Equation 11. Robust standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

adverse scenario of the 2018 EBA stress test. On impact, these shocks trigger an initial decrease in output and in house prices, respectively by -0.70% and by -1.8%. Shocks are propagated on the different horizons through the local projection coefficients estimated in the macroeconomic model (Eq. 8). In order to obtain the risk dependent scenarios, we consider three different initial levels of the state variable $F(z_t)$: 0, 0.5 and 1.

Overall, these shocks produce a fall in output and a downward correction of house prices, as reported in Figure 4. Concerning the output, thanks to the non-linear structure of the model, at the end of the simulations, the high (median) risk scenario downturn is about eight (four) times larger in the low risk state, in deviation from the baseline. Similarly, the increase in unemployment and spreads and the fall in house prices are larger the higher the cyclical risk. In reaction to this larger economic deterioration, the central bank reduces more the policy rate under the high risk scenario. In order to compute the adverse scenario, the deviations reported in Figure 4 are added to the baseline scenario.[27]

[27] For the baseline scenario, an option would be to use the macroeconomic model to use the unconditional forecasts of the macroeconomic model as baseline scenario. In practice, central banks choose the official forecasts

Figure 4: Low risk, Median Risk and High Risk scenarios - level deviations



Note: Deviation from the starting point. The responses of output growth and inflation are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (blue) lines are the model dynamics when risk is high (low). Yellow lines report the model dynamics under median risk. Shaded areas represent the 90% confidence intervals.

By using our indirect stress test model of Equation (11), we obtain the projections of the CET1 ratios under the the risk-related adverse scenarios. As shown in the left panel of Figure 5, the higher the cyclical risk, the higher the CET1 loss, as higher risk scenarios are associated to larger GDP downturns. Under the low risk scenarios, the CET1 ratios deteriorate by -0.65pp. This depletion increases to 1.83pp in the median risk scenario and to 3.83pp in the high risk one. The latter is in line with the depletion of 3.95pp in the EBA stress test featuring the same severity in terms of final level deviation.[28]

4.3 Calibration of requirements

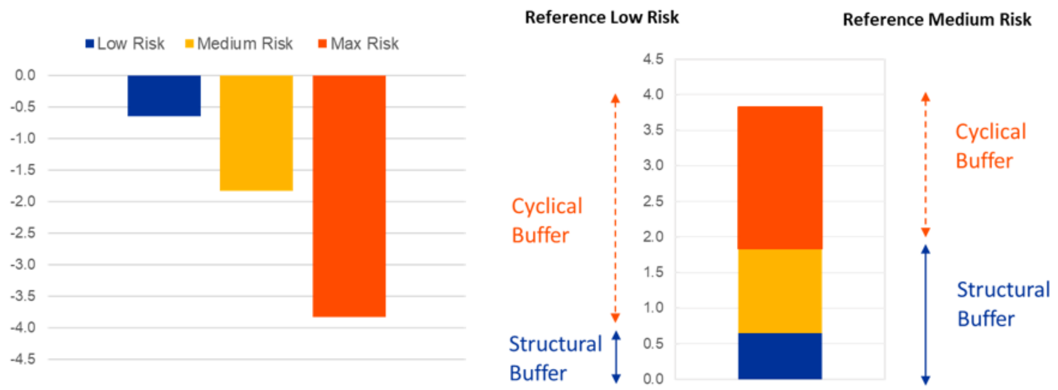
We use the projected capital losses to set cyclical and structural requirements. For illustrative purpose, we consider two options, as illustrated in the right panel of Figure 5.

In the first option, the structural requirement is set to match the loss in the minimum risk scenario, i.e. 0.6%. If the current cyclical risk is at its median (high) level, the cyclical requirement will be equal to 1.2% (3.2%). In particular, this implies a strictly positive cyclical requirement when the economy is at its historical median level of cyclical risk, resulting in a so-called "positive neutral rate". In the second option, the reference risk corresponds to the median cyclical risk, implying a structural requirement equal to 1.8%. As such, when the DSR is at its historical

as baseline scenario for the sake of consistency.

[28] The results for the EBA stress test can be found here (Fully loaded CET1 ratios - restated).

Figure 5: CET1 projected losses and requirements



Note: Aggregate CET1 ratios variation for three years of the projection are reported on the left hand side in percentage points. The requirements corresponding to each case are reported on the right hand side. Results for the low, median and high risk scenarios are reported in blue, yellow and red respectively. On the right hand side, for each risk we report the additional contribution the to the CET 1 losses (pp level). These contributions are used to set structural and cyclical requirements in the right hand panel of the chart.

maximum and results in a loss of 3.8pp, the cyclical capital requirement would be set at 2.0%, whereas it would be set at zero when the DSR is at (or below) its historical median.

Those two options show how the choice of the reference cyclical risk level transparently maps into different structural vs cyclical requirements balance. This choice depends on the preference of the policy-makers for time-varying requirements (cyclical) vs permanents ones.

5 Conclusion

This paper proposes the Risk-to-Buffer, a conceptual framework to jointly calibrate cyclical and structural requirements with stress test models. For this, it relies on a state-dependent macroeconomic model in which adverse scenarios are amplified when the cyclical systemic risk is high. The structural requirement is then calibrated on the capital losses due to a "reference" level of cyclical systemic risk. When cyclical systemic risk is above the reference risk, the cyclical requirement is calibrated on the additional losses due to the current risk.

This approach can also be applied to rich stress tests exercises featuring bank-specific characteristics, leading to bank-specific capital requirements. Additionally, it provides policymakers with a transparent way to strike the balance between the two types of requirements, depending on what they consider to be the "reference" level of systemic risk and their preference for releasable requirements.

Finally, this approach can provide a useful framework for the discussion over a ”neutral” cyclical requirement, by providing a clear measure of the balance between structural and cyclical requirements.

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