Risk-to-Buffer: Setting Cyclical and Structural Capital Buffers through Banks Stress tests*

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Abstract

In this work we present the Risk-to-Buffer: a new framework to jointly calibrate cyclical and structural capital buffers, based on the integration of a non-linear macroeconomic model with a Stress test model. The macroeconomic model generates scenarios whose severity depends on the level of cyclical risk. Risk-related scenarios feed into a banks' Stress test model. Banks' capital losses deriving from the reference-risk scenario are used to calibrate the structural buffer. Additional losses associated to the current-risk scenario are used to calibrate the cyclical buffer. We illustrate this approach through a calibration exercise on European banks.

Keywords: Financial vulnerability, macroprudential policy, non-linear models, macroprudential space, debt.

JEL Codes: : C32, E51, E58, G01.

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1 Introduction

The Global Financial Crisis has been a painful reminder of the economic costs associated to a fragile banking system, subject to default and acting procyclically, by reducing credit during periods of stress. As such, prudential authorities have substantially reformed banks capital regulation framework. They adopted a new set of rules, labelled Basel III, with the double objective of making banks more resilient and more countercyclical, i.e. building capital in good time and consume it during crisis to absorb losses rather than restricting credit. One of the novelties of Basel III consisted in introducing a distinction between: i) buffers which remain constant through the cycle and cover risks related to the structure of the banking system (structural buffers) and ii) buffers that evolve with the financial cycle and ensure banks resilience against risks related to the evolution of financial conditions (cyclical buffers).[1]

In practice, cyclical and structural buffers are often calibrated using banks stress test models. These models assess banks resilience through a set of econometric and accounting equations, projecting the evolution of bank capital and capital ratios (e.g. CET1 ratios) with respect to negative macroeconomic scenarios (so-called adverse scenarios).[2] Based on banks' projected losses, authorities set capital requirements so that, should the adverse scenario materialise, banks would have enough capital to absorb those losses and remain

[1]Cyclical buffers 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), which increases during the upward phase of the financial cycle when cyclical risks accumulate, and decreases when those risks materialise.

Structural buffers cover risks that do not evolve with the financial cycle. These buffers do ensure resilience of banks in periods of economic distress, but they do not cover losses deriving from financial cycle factors, i.e. cyclical risks, as agents' over-indebtedness and over-evaluation of asset prices. These buffers are set according to banks' structural long-term features and with a lower frequency with respect to the cyclical buffers. In practice, this category of buffers encompasses a wide range of different buffers, both microprudential (e.g. Pillar 2 requirements) and macroprudential, as such as the the Capital Conservation Buffer applied to the whole banking system or the G-SIB buffers, which is applied to important systemic institutions in order to cover the risk that their failure would mean for the entire financial system.

[2]Stress test usually focus on the evolution of Common Equity Tier 1 ratios (thereafter CET1 ratios). The CET1 is the most conservative form of bank capital, encompassing stocks and retained earnings. CET1 ratios are computed with respect to the Risk Weighted Assets, whose weights depend on the type of asset risk.

resilient.

However, a formal framework to map projected capital losses into cyclical and structural buffers is still missing. In particular, when cyclical and structural buffers are calibrated using different stress tests based on similar scenarios, different buffers might end up covering the same type of vulnerability, resulting in a double counting of risk in capital requirements.[3][4] Also, there is no agreement on a formal framework to map measures of cyclical risks into the adverse scenarios used to calibrate the cyclical buffers.

In this paper, we propose a new conceptual framework, the Risk-to-Buffer, to jointly calibrate cyclical and structural buffers through the use of stress tests. First, we use a non-linear macroeconomic model -which we call the Cyclical Amplifier- to generate adverse scenarios whose severity depends on the risk level. The Cyclical Amplifier is a Multivariate Smooth Transition regime switching model (Auerbach and Gorodnichenko (2013); Tenreyro and Thwaites (2016)) estimated through Local projections (Jordà (2005)). In this setting, a state variable, typically here a measure of cyclical risk, can amplify economic reactions. We produce a "reference" risk-scenario, based on a predetermined level of risk, and a "cyclical" risk-scenario based on the current level of risk. Second, a stress test model then projects banks' losses according to each risk level. The structural buffer is based on the losses obtained under the reference-risk scenario, whereas the cyclical buffer is based on the extra losses projected under the current-risk scenario, if any. Should the current risk level be lower than the "reference" risk (e.g. the one used to calibrate the structural buffer), the cyclical buffer would be set at zero. In this way, the sum of

[3] As an example at the European level, on one hand, stress tests are used for the calibration of structural buffers, as P2G buffers 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 are also a tool for the calibration of the Counter-cyclical buffers at national level.

[4] To this extent, policy makers have started to investigate the potential issues of overlapping between different buffers, calibrated through the stress tests losses. First, Bank of England clarified the use of stress test losses to calibrate the Counter-cyclical 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 at 2.5% at its minimum level, see the Final rule.

both buffers would not fall below the structural buffer, which acts as backstop on capital requirements. This method comes with four convenient features. First, structural and cyclical buffers clearly cover different expected losses, tackling the risk of overlap. The structural buffers act as a back-stop, while the cyclical buffers cover the extra risk due to current cyclical imbalances. Second, the level of cyclical buffer is mechanically linked to the evolution of cyclical risk. Third, this approach is very flexible and can accommodate any kind of state variables to capture cyclical risk, many structural identifications of the shocks and all sorts of stress tests frameworks. Fourth, the policy maker choice of the reference level of risk clearly strike the balance between structural and cyclical buffers: the lower this level, the larger the role of the cyclical buffer, which becomes positive once the actual level of risk is higher than the reference one. In particular, should the reference risk be below the median risk, this would imply that at when the current risk is at the median the cyclical buffer is positive,

We illustrate this approach with an example on buffer calibration for the Euro Area. First, we estimate the Cyclical Amplifier with a standard set of quarterly macroeconomic and financial variables. As state variable capturing cyclical risk, we use the 3-year change in the non-financial private sector credit-to-GDP ratio.In line with theoretical and empirical works (Jordà et al. (2013); Kiyotaki and Moore (1997)), results show that higher risk amplifies financial shocks as such as housing and spread shocks. We then use this Cyclical Amplifier to generate multiple adverse scenarios in which a fixed set of shocks hits the economy under different risk levels. In our application, we assume that a set of recessionary shocks hit the European economy at the beginning of our projection (housing shock, spread shock) initially causing a substantial drop in housing prices (-1.8%) and a increase in spread by 100 basis points. We produce a first scenario at a reference risk level (e.g. historical median) and a second scenario at some other risk level to capture the amplification role played by the cyclical risk. It appears that when the Credit to GDP ratio in difference is at its maximum, the effects on output are at least twice as large as the ones obtained under its minimum.

In a second step, the different scenarios are fed into a mock stress test model to obtain corresponding CET1 ratio projections. Specifically, we recover elasticity of change in banks' CET1 ratio with respect to output growth provided in the EBA macroeconomic scenarios used in the EBA 2018 Banks Stress test exercise. Higher risk scenarios are associated with larger capital losses: under high risk the aggregate reduction of CET1 is more than tripled with respect to the case of low risk (respectively 5.7pp and 1.7pp); under median historical risk, the CET1 ratio depletion is 3.7 pp.

Third, those projected losses are used to calibrate regulatory buffers. The loss under the *reference risk* scenario provides the level of the structural buffer, whereas the additional loss triggered by the cyclical risk scenario sets the cyclical buffer. Using the historical median as the reference level of risk, the structural buffer would be equal to 3.7pp. Should the cyclical risk be at its historical maximum, the additional cyclical loss and thus the cyclical buffer would then be equal to 2pp. Instead, calibrating the structural buffer with the historical minimum level of risk would put the structural buffer at 1.7pp and, if the current risk is at maximum level, the cyclical buffer at 4pp. This alternative calibration would imply a a positive cyclical buffer of 2pp when risk is at its median.

Finally, our Risk-to-Buffer framework can be used to shed light on the interconnection between borrowers' based measures (e.g. prudential policy directly affecting indebtedness) and capital buffers. Indeed, borrowers' based measures can decrease the Credit to GDP ratio, leading to a reduction in the current cyclical risk. In our application, we find that a reduction of the state variable from its maximum to its 75th percentile triggers a reduction of 1pp in the calibrated cyclical buffer.

The Cyclical Amplifier complements the Growth-at-Risk model (henceforth GaR) that has become an influential tools for cyclical risk analysis over the past few years. The GaR is a *measure of systemic financial risk*, linking current macrofinancial conditions to the distribution of future GDP growth (typically focusing on the 5% quantile).Conversely, our

Cyclical Amplifier is a *tool to build adverse scenarios* depending on a measure of risk. As such, this approach allows for directly designing scenarios related to specific narratives (i.e. set of incoming shocks), an attractive feature for Stress tests.[5] Also, while the GaR focuses on one unique variable, namely output growth, the multivariate structure of the Cyclical Amplifier can provide adverse scenarios for the different economic variables policymakers may be interested in. Finally, by integrating the Cyclical Amplifier into the the Risk-to-Buffer framework, we provide a strategy to disentangle structural and cyclical buffers directly relating risk levels to calibrated buffers.
The reminder of this paper proceeds as follows. Section 2 frames our paper in the literature. In Section 3, we present the conceptual framework. In Section 4, we present the Cyclical Amplifier. Section 5 shows an application of the Cyclical Amplifier to the Euro Area. Section **??** houses the application of the Risk-to-Buffer framework to the Euro Area banks. Section 6 presents a comparison between our method and the Growth-at-Risk. Section 7 concludes.

2 Literature

In this work we join different streams of literature. First, Stress test literature has been developed to assess banks' resilience and calibrate buffers (Bennani et al. (2017); Budnik et al. (2019); Camara et al. (2015); Coffinet and Lin (2010); Dees et al. (2017); Henry et al. (2013)). All these papers provide analytical frameworks to test banks resilience during crisis time. As shown in Bennani et al. (2017); Dees et al. (2017) the results in terms of CET1 can be used to calibrate buffers. To this extent, our work provides a strategy to jointly set structural and cyclical buffers by showing a possible way to set buffers based on banks' projected losses.

[5]When running Stress test exercises, the narrative of adverse scenarios is often set according to the types of vulnerabilities identified at the moment of the exercises (e.g. deceleration in world demand, trade wars, asset over-evaluation in some specific sectors).

Second, non-linear macro models are estimated to assess the impact of financial vulnerability on the propagation of economic shocks (Aikman et al. (2016); Alpanda and Zubairy (2019); Barnichon and Matthes (2016); Carriero et al. (2018); Cheng and Chiu (2020); Couaillier and Scalone (2020)). In particular, through the use of empirical non-linear model, Barnichon et al. (2016); Carriero et al. (2018); Cheng and Chiu (2020) show that economic and financial shocks are amplified in crisis time. We contribute to this literature, by assessing how financial vulnerability affects the propagation of housing and spread shocks. According to our results, consistently with economic theory (Kiyotaki and Moore (1997)), financial shocks are amplified when agents are more financially vulnerable. Moreover, we show how such non-linear models can be integrated with a Stress test model in our Risk-to-Buffer framework.

Third, macroeconomic models are complemented with prudential authorities, either highlighting the key role of cyclical requirements as a stabilisation tool (Angelini et al. (2014); Angeloni and Faia (2013); Paries et al. (2018)) or assessing the costs and benefits related to the activation of capital buffers (Bennani et al. (2017); Clerc et al. (2015)). In particular, Clerc et al. (2015) show that structurally higher capital ratios stabilise the economy with respect to incoming economic shocks, whereas Angeloni and Faia (2013) show that mildly cyclical requirement reduce economic fluctuations. Our work provides a criterion to set cyclical buffers according to the evolution of cyclical risks for the alternative (and popular across central banks) calibration strategy based on Stress test models.

Finally, our non-linear framework relates to the influential Growth-at-risk model (henceforth GaR, Adrian et al. (2019); Prasad et al. (2019)). This approach links output responses to financial factors, taking into account the position of the economy in the business cycle and capturing tail risk. This model is often used to build adverse scenarios, whose severity depends on the level of financial conditions. By construction, the GaR is not linked to any particular type of shock, capturing unconditional tail risk. On the contrary, our Cyclical Amplifier allows the policymaker to design the shock of interest and generate adverse scenarios. This is a desirable feature for Stress tests, as policy makers are usually interested in assessing banks resilience with respect to the materialisation of specific risk scenarios (e.g. world demand slowdown, asset price downward correction for specific sectors).

3 The Risk-to-Buffer framework

The Risk-to-Buffer framework presented in this paper maps two levels of cyclical risk to specific types of buffers, generating a formal link between: i) a reference risk level and the structural buffer; ii) the current cyclical risk and the cyclical buffer. First, we show the logic behind the use of Stress tests in setting capital buffers, highlighting the risks of overlapping buffers when using parallel Stress tests. Second, we present how to use a non-linear macroeconomic model to produce adverse scenarios dependent on cyclical risk. Those scenarios are then fed into a stress test model to produce cyclical risk-dependent capital losses used to calibrate cyclical and structural buffers.

3.1 Stress test in buffer calibration

When setting macroprudential capital buffers, policymakers aim at making banks resilient to adverse events, as such as financial crisis. A way to set the buffers consists in defining an adverse macroeconomic scenario, in order to assess how much capital banks lose in such case and to set the buffer so that banks hold enough capital to survive while absorbing the losses. Stress tests models emerge then as a key instrument to run this exercise.

Stress tests models are a set of econometric and accounting equations used to project banks' balance sheet variables (e.g. CET1 ratios, profits) conditional on the evolution of a set of macroeconomic and financial variables (the so-called macroeconomic scenarios, typically output, inflation, etc.):

$$CET1_{i,t} = f(Macro_t), \tag{1}$$

where $CET1_{i,t}$ is the CET1 ratios observed at time t for bank i, $Macro_t$ are macroeconomic and financial variables characterising the scenario and $f()$ is the set of econometric and accounting equations composing the model.

Macroeconomic scenarios are themselves generated through an economic model $g()$ producing the macroeconomic and financial trajectories conditional on an assumed sequence of economic shocks ($Shocks_t$) specified by the econometrician:

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

The macroeconomic scenario is fed into the Stress model, to project $CET1_{i,t}$ ratios for each bank $i = 1, ..., I$, conditionally on the macroeconomic scenario:

$$CET1_{i,t} = g(Macro_t). \tag{3}$$

In a last step, capital buffers $Buffers_{i,t}$ are set for each bank $i = 1, ..., I$, as a function of the CET1 ratios predicted by the stress test:

$$Buffers_{i,t} = h(CET1_{i,t}). \tag{4}$$

In this work, for the sake of clarity, we assume that buffers are the same across banks ($Buffers_{i,t} = Buffers_t$) and are set equal to the average banks' final CET1 loss with respect to the starting point of the projection. Should the adverse scenario materialise, banks could use the buffer to absorb the losses while remaining solvent.

Finally, Equations (1) to (4) can be rewritten as:

$$Buffers_t = h \circ g \circ f(Shocks_t) \tag{5}$$

An established methodology to link estimated bank losses to different types of capital buffers (typically structural and cyclical) is missing. Moreover, buffers can be calibrated by different institutions in parallel exercises, triggering the possibility of double counting the same risks (or neglecting some of them) when scenarios are too similar.[6][7]

3.2 Risk-to-Buffer: 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 3 years change in credit to GDP ratio in our application). We generate multiple adverse scenarios across different levels of risk:

$$Macro_t^{Risk} = f(Shocks_t, Cyc_t^{Risk}) \tag{6}$$

where Cyc_t^{Risk} is the state variable measuring the level of cyclical risk and the $Shocks_t$ is the fixed sequence of shocks, common across the different risk levels/scenarios.[8] Thanks to the non-linear features of the model, the severity of the scenario varies with respect to the state variable. If the state variable is a good measure of cyclical risk, higher risk scenarios

[6] As an example, if cyclical and structural buffers are set by using similar scenarios inspired by the Financial crisis, it is likely that both buffers are set to make banks resilient to the same type of downturn.

[7] Besides bank level microprudential buffers are typically set by the microprudential supervisor, while the macroprudential ones, which apply to a whole set of banks, are set by the regulator. For instance, a supervisor could take into account the high cyclical vulnerability of a country to design the adverse scenario used to calibrated microprudential buffers. This would create a risk of overlap with the cyclical capital buffer set by the macroprudential authority and meant to cover such cyclical risks.

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

will be associated to more severe output loss, e.g. featuring stronger amplification of economic and financial shocks.

A reference level of cyclical risk (e.g. the historical minimum risk, the median risk) is chosen to generate the reference risk adverse scenario: based on the losses under this scenario, we calibrate the structural buffer.

$$Buffers_t^{Structural} = h \circ g \circ f(Shocks_t, Reference\, Risk) \tag{7}$$

A second adverse scenario is produced based on the current level of cyclical risk. If this current risk is higher than the reference one, the adverse scenario is more severe and produces additional losses, based on which we can calibrate the cyclical buffer. If the current risk is lower than the reference one, the cyclical buffer is set at zero, so that the structural buffer acts as a back-stop on capital buffers,[9] while the cyclical buffer covers the amplified losses due to current level of risk.

$$\begin{aligned} Buffers_t^{Cyclical} = max\Big(&h \circ g \circ f(Shocks_t, Current\, Risk) \\ &- h \circ g \circ f(Shocks_t, Reference\, Risk),\, 0\Big) \end{aligned} \tag{8}$$

This framework is flexible enough to adapt to different policy maker's preferences regarding the reference risk level. The lower this level, the smaller will be the structural buffer and the larger the role of the cyclical buffer

Figure 1 provides an illustration of the Risk-to-Buffer. A given set of shocks is used to produce three risk-dependent scenarios: low risk (blue), the median risk (yellow) and the current risk (red). Should the policymaker set the structural buffer using the median historical risk level as the reference level, she would set the structural buffer equal to the losses under this scenario, while the cyclical risk would cover the additional loss related to the current level of risk (first bar). If the policy makers wants to cover all the losses

[9]In the current regulation no buffer is set to be negative. In the setting, this zero lower bound translates into a buffer equal to zero in case the current rate would go below the median level.

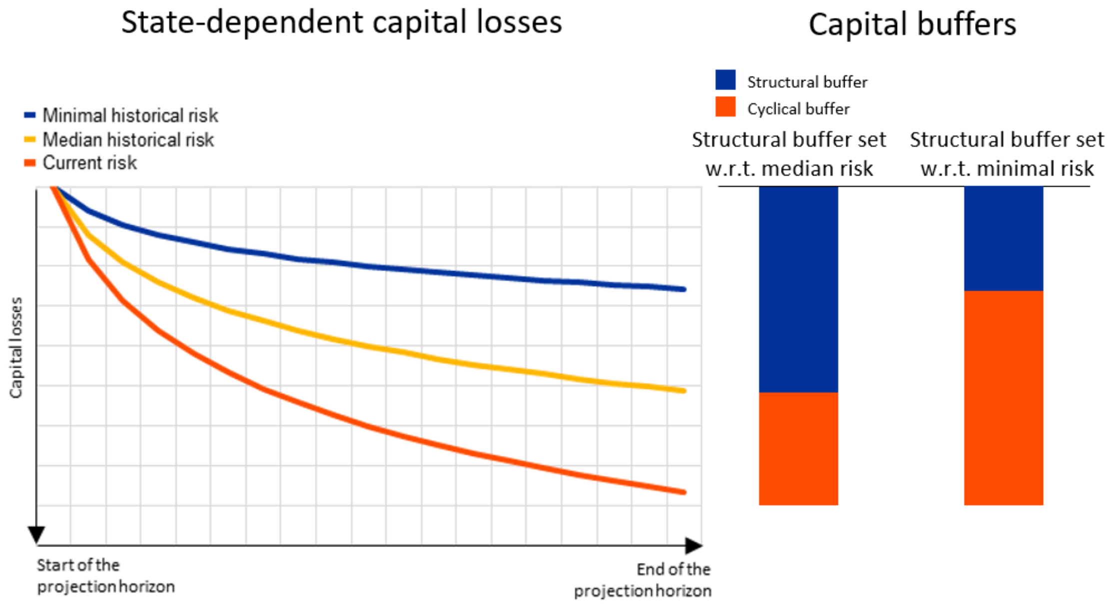

Figure 1: Illustration of the Risk-to-Buffer.
Note: The chart illustrates the Risk-to-Buffer approach. Thanks to the state-dependent nature of the Cyclical Amplifier, the same set of shocks produces different scenarios at different levels of cyclical risk: the low risk (blue), the median risk (yellow) and the current risk (red). The policymaker chooses the level of the reference risk used to calibrate the structural buffer, while the cyclical buffer covers the additional losses (if any) due to the current level of risk.

deriving from the amplification generated by cyclical risks through cyclical buffers, she can choose to set the structural buffer based on the low risk scenario, where there is not amplification. This reduces the level of the structural buffer and increases the cyclical buffer (second bar). In particular, at median risk (i.e. when the financial cycle is at its steady-state level), the cyclical buffer would be positive, introducing the notion of a "positive neutral rate" for the cyclical buffer.[10]

4 The Cyclical Amplifier

The Cyclical Amplifier is the non-linear econometric model through which we can design risk-related scenario. We use a Multivariate Smooth Transition Regime Switching Model (Auerbach and Gorodnichenko (2013); Tenreyro and Thwaites (2016)), estimated by using

[10]To this extent, in the United Kingdom and some Euro Area jurisdictions, the neutral "equilibrium" level of the Counter-Cyclical buffer is set at positive values.

Local Projections (thereafter LP) by Jordà (2005).[11]

The non-linear structure allows to estimate impulse responses whose dynamics depend on the regime of the economy. In particular, the model allows smooth transition from one regime to another, producing different dynamics for each level of risk included from the historical minimum (Low) Risk to the maximum (High) risk.

For each period $t = 0, ..., T$, horizon $h = 0, ..., H$, with n the number of endogenous variables and p the number of lags, our econometric setting is:

$$\begin{aligned} Y_{t+h} = \; & F(z_t)(\alpha_h^H + \Sigma_{\ell=1}^{p} \beta_{h,\ell}^H Y_{t-\ell}) \\ & + (1 - F(z_t))(\alpha_h^U + \Sigma_{\ell=1}^{p} \beta_{h,\ell}^U Y_{t-\ell}) \\ & + u_{h,t}, \end{aligned} \tag{9}$$

where Y is the $(n, 1)$ vector of endogenous variables, z is the scalar interaction variable and $u_{h,t}$ is the $(n, 1)$ vector of errors at horizon h at time t. The state effect is driven by $F(z_t)$, that is the scalar function governing the transition between the high and the low regime. $F()$ is used to normalize the state variable z_t 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} more dependent on the first (second) line of Equation (9). As standard, the transition function is the logistic transformation of the original z_t:

$$F(z_t) = \frac{1}{1 + exp\left(-\theta\left(\frac{z_t - v}{\sigma_z}\right)\right)} \tag{10}$$

where θ is the smoothing parameter governing the smoothness of the transition from one state to another[12], v determines the part of the sample spent in either state[13], and σ_z is the

[11]The econometric technicalities are inherited from Couaillier and Scalone (2020), where the same approach is used to assess how financial vulnerability affects propagation of financial shocks in the US economy.

[12]The higher θ, the faster $F(z_{c,t})$ goes toward 0 and 1, i.e. converging to dummy-regime switching.

[13]$z_t > v$ is equivalent to $F(z_t) > 0.5$. Defining v as the $p - th$ percentile 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.

standard deviation of the observed state variable. Both θ and v are generally calibrated (Auerbach and Gorodnichenko (2013)). In the literature, it is standard to define v as the historical median of the original state variable, so that the resulting state spends half of the time in both regimes. In our benchmark specification, we set $\theta = 3$ (Franz (2017); Tenreyro and Thwaites (2016)).

Thanks to the multivariate setting we can adopt standard shock structural identification procedures as such as Choleski decomposition or sign restrictions. In this regard, Plagborg-Møller and Wolf (2021) formally established that the standard VAR identification methods can be equivalently used in a multivariate LP context. The identified shocks are then used in the scenario design.

We construct confidence intervals using the block-of-blocks bootstrap approach, suggested for LP by Kilian and Kim (2011) to account for the autocorrelation in time series.[14]

5 Application on the Euro Area

In this section we present an application of our Risk-to-Buffer to the Euro Area. First, we present the data and the interaction variable used in the estimation of the Cyclical Amplifier. Second, we estimate the Cyclical Amplifier, uncovering important amplifications when risk in high. Third, we use the Cyclical Amplifier to design adverse scenarios focusing on a sub-set of structural shocks (i.e. housing shock and spread shock). Fourth, we feed those adverse scenarios in a very simplified stress test to produce capital losses. Finally we map those losses to capital buffers.

[14]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 (2018)), 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))

5.1 Cyclical Amplifier: Specification and data

In our benchmark specification, the model is estimated on euro area aggregate data (EU19) using a sample going from 2002 Q1 to 2019 Q2. As shown in the Appendix, results are qualitative similar if we estimate the model on a panel EU countries exploiting country-level data. The benchmark specification includes: Output (GDP), Inflation (HICP), Unemployment rate, the Short-term interest rate (EURIBOR 3-months), Real House prices, the Spread between the 10 years government rate and the short term interest rate. Rates are reported in levels, whereas the other variables are expressed in percentage quarterly variations. Our estimation results are robust to the use of shadow short term rate (Wu and Xia (2016)) instead of the observed short term rate. The process has two lags and the model is estimated for 12 quarters ahead.

The state variable is the total Credit-over-GDP ratio of Non-Financial Private Sector expressed in 3 years difference. The Credit over GDP is a measure of indebtedness of the economy. By expressing the series in its difference, we get rid of its long run trend related to low frequency structural changes. Moreover, the indicator expressed in difference is widely used in macroprudential analysis to detect the build-up of cyclical risks (Lang et al. (2019)). A higher Credit-to-GDP ratio difference means that agents expanded their debt more than output, increasing financial vulnerability. As such, the same negative economic scenario is expected to have more adverse consequences when the Credit to GDP ratio increased.

In this application we focus on a unique and simple indicator of cyclical risks. Nonetheless, as shown in the Appendix, our empirical results are qualitatively robust to the use of other measures of cyclical risks, as such as the Debt Service Ratio (Drehmann et al. (2015)) and the Credit-to-GDP gap (Borio et al. (2002)).

We apply Choleski ordering to identify economic and financial shocks, in order to give a structural interpretation to the set of shocks that we use in the adverse scenario design.[15]. We order variables as follows: Output, Inflation and Unemployment rates, Short term interest rate, Spread and House prices. The short term rate is ordered after the unemployment rate, in order for monetary policy to react to Output, Inflation and Unemployment Rate. This ordering is consistent with financial variables reacting faster than macroeconomic ones and is line with Aikman et al. (2016); Cesa-Bianchi (2013); Goodhart and Hofmann (2008). Importantly, the sign of the responses and their state amplifications are strongly robust to alternative Choleski ordering.

5.2 Cyclical Amplifier: Results

We focus on the two financial shocks that will be used in the scenario design: a Spread shock and a Housing shock.

The housing shock can be interpreted as an exogenous variations in housing preference in line with Guerrieri and Iacoviello (2017) pushing demand and house prices up. In the following quarter, this increase is transferred to the rest of the economy. In Figure 2, we report the impulse responses of our six endogenous variables with respect to a one standard deviation expansionary housing shock for two states of the economy: a Low Risk case (green line) corresponding to the case of $F(z) = 0$ and High Risk case (red line, $F(z) = 1$). Under high vulnerability, the response to a housing shock is positive and statistically significant for the whole projection horizon, with a maximum increase of 0.5% two years after the shock arrival. Conversely, under low vulnerability, the response of output is not statistically significant for the first year, it becomes positive in the second part of the projection but remains substantially smaller with respect to case of high vulnerability. An important state effect is also found for unemployment. Under the High Risk regime, the maximum effect on unemployment is statistically significant (-0.2pp) as

[15]This step is not mandatory to design adverse scenarios, which can also be produced through reduced form shocks. However, providing a structural identification may become necessary in case the macroeconomic model is also used in the macrofinancial feedback loop to amplify banks' distress through financial shocks in the so-called second round of Macroprudential Stress tests (Budnik et al. (2019))

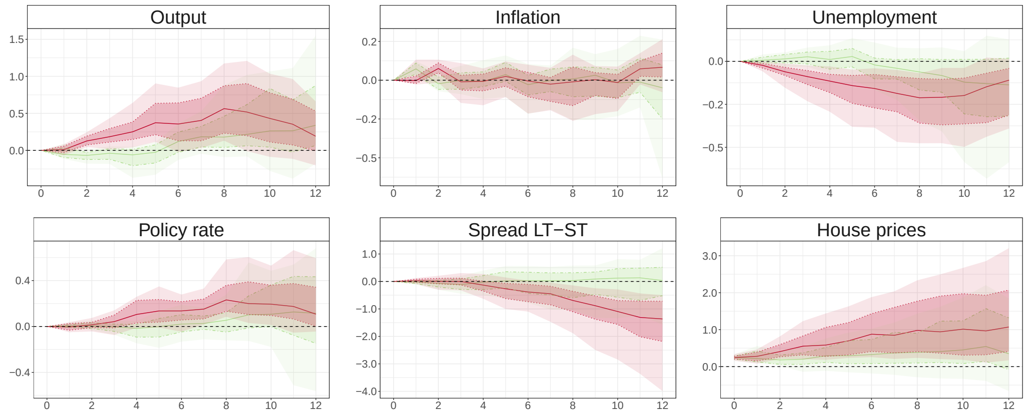

Figure 2: Impulse responses of our endogenous variables to a housing shock.
Note. The responses of output growth, inflation and house prices are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (green) lines are the impulses when leverage is high (low). Shaded areas represent the 67% and 90% confidence intervals.

opposed to the response under the low regime, whose effect is from two times to three times smaller. Consistently, the reaction of monetary policy is statistically significant under high risk and twice as large as the one of the low risk. The shock triggers a statistically significant flattening of the yield curve under the high risk: one year after the shock, the spread decreases by 1pp, whereas the effect is not statistically significant under low risk. As showed by Guerrieri and Iacoviello (2017), housing shocks can feature important non-linear effects. The price of housing directly affect the worth of collateral that agents can provide to guarantee their ability to pay back their debt. A decrease in house price can therefore directly affect the borrowing capacity of agents by reducing their spending and amplifying the initial fluctuation. This financial accelerator effect (Kiyotaki and Moore (1997) played by debt and housing is expected to grow with agents' indebtedness. In a similar application estimated on the US economy (Couaillier and Scalone (2020)), we find that high vulnerability amplifies housing shocks.

In Figure 3, we report the responses of the economy to a recessionary one-standard-deviation spread shock. In our identification, the spread shock is an exogenous increase in spread which has immediate impact on house prices whereas the effect on output, inflation and unemployment rate arrives with one lag. In line with Musso et al. (2011), this shock

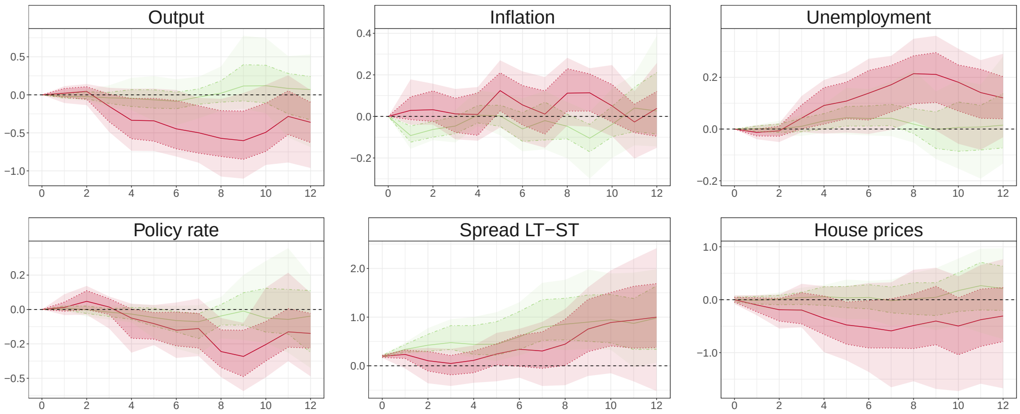

Figure 3: Impulse responses of our endogenous variables to a spread shock.
Note. The responses of output growth, inflation and house prices are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (green) lines are the impulses when leverage is high (low). Shaded areas represent the 67% and 90% confidence intervals.

can be interpreted as a credit supply shock. When risk is low (green lines), an increase in spread of 0.4pp will trigger a non statistically significant negative effect on output across all the projection. Under high risk, the effect becomes statistically significant since the third quarter: output reacts negatively and will be around -0.5% lower with respect to the initial level after two years since the shock arrival. Consistently with the evolution of output and spread, under low risk, unemployment moderately increases while at the end of the projection, the final effect is not statistically significant. Under high risk, unemployment increases substantially and is statistically significant after the second quarter: the effect will be from two to eight times as large as the effect under low risk depending on the horizon.

Importantly for our application, this type of non-linear effects featuring housing and spread shocks allow obtaining scenarios whose severity increases with the level of initial risk.

5.3 Scenario Design

Equipped with the estimated Cyclical Amplifier, we can prepare the adverse scenarios. First, the central (or baseline) scenario is usually what is considered, at the time of the exercise, as the most likely trajectory of macroeconomic and financial variables. In our case, we use a fictitious scenario where Euro Area output constantly grows at 2% annually. Second, the adverse scenarios feature the evolution of macroeconomic and financial variables going through an economic downturn.[16] We design our adverse scenarios by assuming two recessionary shocks simultaneously hitting the economy at the beginning of the projection: a 4 standard deviations spread shock; ii) a -4 standard deviation housing shock. On impact, shocks trigger an increase of the spread shock equal to 100 basis points whereas housing prices substantially decrease (-1.8%). This initial set of shocks is propagated onto the different horizons through the local projection coefficients estimated in the macroeconomic model (Equation (9)). Different initial Credit to GDP ratio differences are considered, and associated to different transition variables $F(z_t)$ thanks to the transition function (Equation (10)): we run four scenarios with $F(z_t)$ equal to 0, 0.5, 0.75 and 1.[17]

In Figure 4, we report the impulse responses of the endogenous macroeconomic variables with respect to the different cases. Overall, this type of scenario produces a severe recession, featured by a strong fall in output and a downward correction of house prices. However, output, unemployment and house prices experience a much stronger variation in the high risk state: nine quarters after the shock arrival, the fall in output and the jump in unemployment are respectively three and four times larger than in the low risk state, while house prices experience a steeper fall in the high risk state (five times stronger with respect to what obtained under low risk). The effect on the policy rate, which decreases in all the scenarios, is three times larger in the high scenario with respect to the low risk. Overall, consistently with those state effects found in the previous section, state effects

[16] In our case, we aim to obtain scenarios whose magnitudes are comparable to the ones featuring standard Stress test exercises (EBA Stress Test scenarios or CCAR - US Fed Stress tests)). These scenarios often try to mimics financial crisis dynamics (Cerra and Saxena (2008); Jordà et al. (2013)). As example, for the euro area, the last three EBA exercises presented a deviation of GDP growth between 7 and 8 pp between adverse and baseline scenarios.

[17] By using the transition function for EA economy these values correspond to historical values of respectively -6.5%, 7.5%, 11.7% and 17.7%.

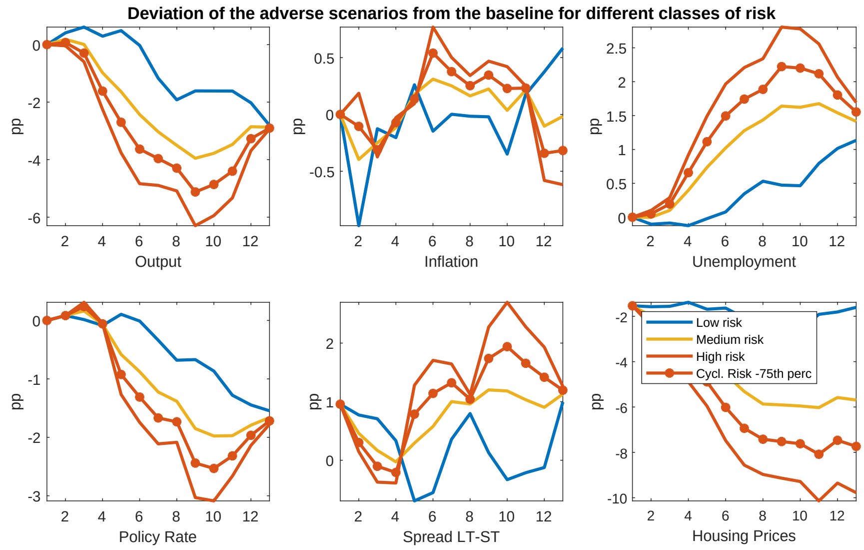

Figure 4: Deviation of the adverse scenarios from the baseline scenario. Note. The deviation between central and adverse scenario corresponds to the sum of the impulse responses of the macroeconomic variables to the set of housing shock (-4 standard deviation), spread shock (4 standard deviation shock). Impulse responses are obtained for the low risk scenario (blue), medium risk scenario (yellow) and high risk (red) for the three years of projections. Variables are reported in percentage points.

are in line with economic theory (Guerrieri and Iacoviello (2017); Kiyotaki and Moore (1997)) in that cyclical risk (e.g. indebtedness) plays the role of financial accelerator of the economic and financial shocks.

In order to compute the adverse scenario, these impulse responses are added to the central scenario[18].

5.4 Projecting bank capital losses with a stress test

In order to project CET1 ratios conditional on macroeconomic scenarios, we need a model which estimates the CET1 elasticity with respect to the macroeconomic variables. We adopt a reduced-form modeling strategy, in line with standard models in the stress testing tradition (e.g., Budnik et al. (2019); Dees et al. (2017)). Instead of using real data, we estimate this relation on the results of the 2018 EBA Stress exercise. We use this estimated

[18] In theory it would be possible to use, as central scenario, the unconditional forecast of the macroeconomic model used to generate the adverse scenario. In practice, central banks choose their official forecasts as central scenario for the sake of consistency.

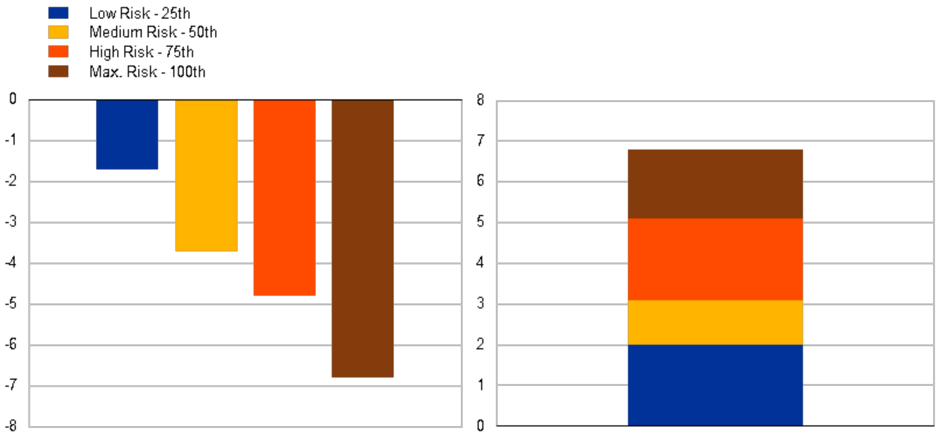

Figure 5: CET1 and Buffers. Note. Aggregate CET1 ratios variation for three years of the projection are reported on the left hand side in % ratios. The buffer corresponding to each losses are reported on the right hand side. These buffers are the reference to set structural and cyclical buffer. If the medium risk is our reference buffer, the medium buffer will be equal to the sum of the blue and yellow bricks. If the current risk is at its maximum level, the cyclical buffer will be equal to the sum of the dark red and light red bricks. If the transition variable decreases to its 75th percentile, the cyclical buffer will be set equal to the light red brick.

equation as a stylised Stress test model to show a concrete application of our Risk-to-buffer framework while relying on an elasticity found in an existing stress test exercise. We simply estimate the elasticity of CET1 to output growth in the EBA 2018 stress test, mimicking a back-of-the-envelop simplified stress test exercise.[19][20][21]

The estimated relation between GDP and CET1 ratio is as follows:

$$\Delta CET1\, ratio_t = -0.87 + 0.45 \Delta GDP_t. \tag{11}$$

[19]In our work, since we focus more on systemic resilience and on macroprudential buffers, we do not consider the effects related to individual banks' variables (size, business type, individual expositions), that are key to obtain heterogeneous variations across banks in standard Stress test models. A possible top-up of this work could be to use a standard Stress test model that considers individual characteristics of banks to obtain CET1 depletion for each bank of the sample. This variation could be particularly useful in the calibration of microprudential buffers (e.g. P2G buffers). Abad-González et al. (2018); Apergis and Payne (2013); Kolari et al. (2019) study how macroeconomic and individual variables affect the results of Stress test models and find overall find that idiosyncratic banks' features play a key role in determining the outcome of the Stress test.

[20]The EBA exercise i) is based on a wide set of accounting and econometric equations, ii) includes a set of additional constraints that ensure sufficient severity and realism in the EBA results. Our reduced form estimation does not allow heterogeneous elasticity across countries.

[21]For the official document presenting the 2018 macroeconomic scenarios: here. EBA 2018 Stress test results are available here

	Central	Low Risk	Med Risk	$F(z_t) = 0.75$	High Risk
t+1	0	0.2	-0.7	-1.2	-1.7
t+2	0	-0.5	-2.5	-3.4	-4.4
t+3	0.1	-1.7	-3.7	-4.7	-5.7
Struct-Benchmark	3.7	3.7	3.7	3.7	3.7
Cycl -Benchmark	0	0	0	1	2
Struct-Alternative	1.7	1.7	1.7	1.7	1.7
Cycl -Alternative	0	0	2	3	4

Table 1: CET1 losses with respect to the their starting point in percentage differences according to the different risk levels for the three years of the projection. If the reference risk is the medium risk, the structural buffer will be equal to the loss under Medium risk (3.7pp). In the fourth line we report the values of the cyclical buffer (Cycl-Benchmark) under the different risk levels, obtained as difference between the respective CET1 loss and the medium risk loss. In the alternative calibration (Cycl-Alternative), the reference level is the low risk. The structural buffer would be equal to 1.7pp. When the current risk is below the reference risk, the cyclical buffer is set at 0.

Details on the estimation of the mock Stress test models are housed in the Appendix.

The four adverse scenarios presented above are used in our stylised Stress test model (Equation (11)), to obtain the projection of the CET1 ratios for each scenario. Since the model does not consider individual variables among the regressors, the elasticity is homogeneous across banks. The variations of CET1 ratio for each bank will ultimately depend on the macroeconomic scenario, which we assume to be common across all the economies.

In Table 1, we report the projected variation of CET1 ratios as difference with respect to the starting point in percentage points levels, obtained for the banks of our sample. Under the central scenario, the average CET1 ratio remains stable around the initial starting point along the whole projection. Under the adverse scenarios, results deteriorate for the three years of the projection. As it also appears from Figure 5, the higher the risk, the higher the loss, in that higher risk scenarios are associated to larger GDP downturns. The loss in terms of CET1 ranges between 1.7 (low risk scenario, $F(z_t) = 0$) and 5.7pp (high risk scenario, $F(z_t) = 1$)).

5.5 Buffers calibration

We use the projected variations as reference points to set cyclical and structural buffers. For calibration, we assume that the policy maker wants to make sure that the buffers cover the risks-related losses predicted in our model, so that if risk materialises, banks will cover those losses with the corresponding buffer. The policy maker needs to choose which risk-level will be used to set the structural buffer. To this extent, we consider two options. In the first option, the structural risk corresponds to the median risk level, meaning that the median historical value of the 3-year change in credit to output ratio represents the equilibrium level. In the second option, we set the structural risk at the minimum risk level, meaning that any additional CET1 loss deriving from cyclical amplification will be covered by the cyclical buffer.

Let us first consider that the the policy makers decides to set the structural buffer equal to the loss in the median risk scenario. In our application, the structural buffer would be set equal to 3.7 percentage points (CET1 loss at t+3 in the Medium Risk scenario in Table 1). The cyclical buffer would be defined as the difference between the losses obtained under the current risk scenario and the part of the loss already covered by the structural buffer.[22] As such, when the state variable is at its maximum, given the loss of 5.7pp, the cyclical capital buffer is set at 2 pp, whereas it is set at zero when the state variable is at (or below) its historical median. Should the Credit to GDP ratio 3 years difference fall from its maximum to its 75th percentile, the cyclical buffer would be reduced to 1pp.

We now consider the case where the policymaker, in order to increase the role of the cyclical buffer, decides to set the structural buffer according to the minimum risk level. In our application, the structural buffer would be equal to 1.7 (CET1 loss at t+3 in the Low Risk scenario in Table 1), whereas the cyclical buffer would be equal to the rest of the loss associated to the cyclical risk. In this case, if the current cyclical risk is at its median (high) level, the cyclical buffer will be equal to 2pp (4pp).[23]

At the median risk level, the cyclical buffer would cover around half of the total prudential space. In practice, since the Global Financial Crisis the cyclical components of the total capital buffers (e.g. the CCyB) in Europe have covered substantially less than half of the

[22]When the cyclical risk goes below the median risk, the cyclical buffer hits its zero lower bound.

[23]In this case, the medium risk cyclical buffer could be considered a "neutral" positive buffer, i.e. the value of the cyclical buffer in equilibrium.

total macroprudential buffers. As such, depending on the preferences of policymakers, this example calls for the build up of a larger macroprudential space through a rebalancing toward more cyclical buffers. This would allow authorities to: 1) have stronger space against the negative amplification mechanisms related to the materialization of cyclical risks (e.g. inversion of the cyclical cycle); 2) act more timely in case the cyclical buffers are set at a higher frequency.[24]

Thanks to the role played by indebtedness in affecting scenario severity, our application allows also to study the interaction between borrowers' based measures, as such as Debt Service to Income (DSTI) limits and Loan-to-Value (LTV) caps directly limiting agents' indebtedness and capital requirements. According to Table 1, if we assume that the authority activates borrowers' based limits, so to slow the increase in credit to GDP ratio and push down the transition variable from its maximum to its 75th, the cyclical buffer would be reduced by 1pp. Overall, this exercise highlights two main points. First, borrowers' based measures affect the evolution of cyclical risks and their activation has a direct effect only on the calibration of the cyclical buffer. Second, through our approach, this direct link can be quantified, providing a transparent tool to assess such interactions.

6 A comparison with the Growth-at-Risk

Since the seminal work by Adrian et al. (2019); Prasad et al. (2019)), the Growth-at-Risk approach (henceforth GaR) has become widely popular in assessing cyclical risk and, in turn, to inform on buffer calibration. In this approach, a set of quantile regressions model the link between output growth and economic and financial variables. The quantile regression structure allows to obtain dynamics which change across the different phases of the business cycle. In this way, the model allows to obtain skewed output forecast and

[24]To this extent, the Bank of England's Financial Policy Committee (FPC) announced that it would pursue a 1 percent default Counter-cyclical buffer for normal times - BoE (2016) from 'The Financial Policy Committee's approach to setting the counter-cyclical capital buffer', Policy Statement, April.

quantify the tail risks of the economy (typically at the 5th percentile).[25] In Stress test, the model is used to tailor the severity of Stress test adverse scenarios according to the current risk flagged in policy analysis.[26]

The Cyclical Amplifier and the GaR differ along at least two dimensions. First, in GaR the severity of the output loss in the adverse economic scenario does not depend on the scenario narrative but only on the way through which the level of cyclical risk affects the output forecast distribution. Instead, in the Cyclical Amplifier, the narrative and the shocks chosen to produce the scenario influence the type of amplification produced. In this sense, the GaR and the Cyclical Amplifier can be complementary. If the authority wants to be agnostic about the type of risk materialising, then the GaR determines a tail risk without the need to define a narrative. If instead the authority wants to assess banks resilience with respect to a particular type of risk (e.g. house price correction, trade wars, etc.), the Cyclical Amplifier allows to take into account how cyclical risks amplify the set of incoming shocks. This feature is key given that cyclical risks can have heterogeneous amplification effects on the different shocks.[27]

A second difference concerns the way through which the two approaches produce the complete set of macroeconomic and financial variables in the scenario. Since the GaR is a univariate model, a unique variable (i.e. the output loss) is produced in the first step, whereas an auxiliary model produces the rest of the variables conditional on the target loss of output. In the Cyclical Amplifier, the endogenous variables needed in the Stress test

[25] This methodology consists in: (i) running a set of quantile regressions of GDP growth, typically dependent on lagged economic and financial variables, e.g. the one quarter ahead GDP growth at the 5th percentile (ii) using the estimated coefficients to estimate expected quantiles of output growth. Thanks to the quantile setting, this method aims at capturing the skewness of the distribution of GDP forecast, in particular when the accumulation of financial risks does not affect the mean forecast but creates a heavy left tail, which captures the recession that would occur should the risk materialise. Thanks to this structure, the GaR captures the risk surrounding the central forecast, hence the name of *Growth at risk*.

[26] In a stress test environment, the adverse economic scenario can be designed to target the GDP growth forecast, for some exogenous low threshold (e.g. 5%), which coming out of the Growth at Risk. To complete the scenario, a multivariate auxiliary macroeconomic model is used to generate the path for macroeconomic and financial variables, matching the target loss defined by the GaR. The evolution of the rest of macroeconomic and financial variables would hence depend on the output loss targeted.

[27] In Stress test exercises, the narrative and the shocks chosen to generate scenario might change over time according to the type of vulnerability highlighted in risk analysis.

model can be jointly produced by the multivariate model, allowing to take into account the specific state effects found for each endogenous variables. As shown in Section 4, the importance of state effects dramatically changes across endogenous variables and across shocks.

To sum up, in the GaR, the level of risk coincides with the scenario severity for output: the amplifications for the other variables are automatically determined by the auxiliary model used to generate the complete scenario. In the Cyclical Amplifier, the level of risk *amplifies* the macroeconomic dynamics taking into account: i) the specific combination of shocks chosen for the scenario and ii) the heterogeneous effects that each shock has on the different macroeconomic and financial variables. To this extent, with respect to the GaR, the Cyclical Amplifier can be better suit to conduct studies concerning the non-linear propagation of a wider set of economic and financial shocks on a larger set of macroeconomic and financial variables.

7 Conclusion

In this work, we provide a conceptual framework to jointly calibrate cyclical and structural buffers with stress test models. Moreover we show how the calibration of the cyclical buffer can be automatically related to the evolution cyclical risk level, thanks to the use of risk-dependent scenarios in our Stress test model. The approach allows also detecting an interaction between borrower's based measures (e.g. DSTI and LTV caps) and capital measures. To this extent we quantify the link between indebtedness and cyclical buffer.

In terms of macroprudential space, our approach suggests that a larger fraction of the total buffer space could be covered by cyclical risks with respect to the existing use of the regulation.

With respect to other approaches used to calibrate severity (e.g. Growth at Risk), our approach, based on the Cyclical Amplifier, enables us to obtain scenarios whose severity depends on scenario narrative, taking into account the different types of amplification at play between macroeconomic and financial variables.

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