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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.

Keywords: Financial Vulnerability, Macroprudential Policy, Non-linear Models, Macroprudential Space, Debt.

JEL classification: C32; E51; E58; G51

Model scenarios -depends of the level of cyclical risk

Bank's Stress test model

Structural buffer derived from the expected capital losses

Cyclical buffer derived from the additional losses in current-risk scenario

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CET1 = Common Equity Tier 1 = capital / risk-weighted assets

All Eurozone banks should meet the minimum required CET1 ratio of 15.1% of risk-weighted assets in 2022.

A low CET1 ratio implies an insufficient level of Tier 1 capital.

NON-TECHNICAL SUMMARY

Since the global financial crisis, prudential authorities have substantially reformed banks capital regulation framework. A new set of rules, labelled Basel III, entered into force to strengthen banks resilience in case of materialization of different types of risks. With respect to previous regulation, one of the novelties of Basel III consisted in introducing a distinction between: i) buffers that evolve with the financial cycle and ensure banks resilience against risks related to the evolution of financial conditions (cyclical buffers), ii) buffers which remain constant through the cycle and cover risks related to the structure of the banking system (structural buffers).

In practice, cyclical and structural buffers are often calibrated through 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). 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 resilient.

Big enough buffers to endure adverse events.

Simultaneously calibrated buffers less robust? Vs. profit requirement of the banks.

A formal framework to map projected capital losses into cyclical and structural buffers is still missing. Moreover, when cyclical and structural buffers are calibrated using different parallel Stress test exercises 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.

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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.

Non-linear macroeconomic model generates "reference-" and "cyclical"-risk scenarios.

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, so to obtain a "reference"-risk scenario and a cyclical risk-scenario. In order to show how the Cyclical Amplifier works, we use it in an application on the Euro Area. We generate multiple adverse scenarios in which a fixed set of shocks hits the economy under different risk levels. Typically, a first scenario is produced at a reference risk level (e.g. historical median) to capture dynamics under a reference risk environment, and a second scenario is produced at the current risk level to capture the amplification role played by the current cyclical risk.

"Reference" = historical median.

2

Stylized Stress test model generates CET1 ratio projections.

"Cyclical" = current risk level.

In a second step, the different scenarios are used as inputs in a stylised Stress test model to obtain corresponding CET1 ratio projections. Higher risk scenarios are associated with larger capital losses: under high risk the aggregate reduction of CET1 for European banks will be more than doubled with respect to the case of low risk, whereas under medium risk, the CET1 ratio depletion will be in between.

Following the Risk-to-Buffer approach, we set the structural buffer based on the losses obtained under the reference-risk scenario whereas the cyclical buffer is set based on the extra losses projected under the current-risk scenario. As such, this latter will evolve 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 buffer), the cyclical buffer would be set at zero. In this way, the sum of both buffers would not fall below the structural buffer, which acts as backstop on capital requirements.

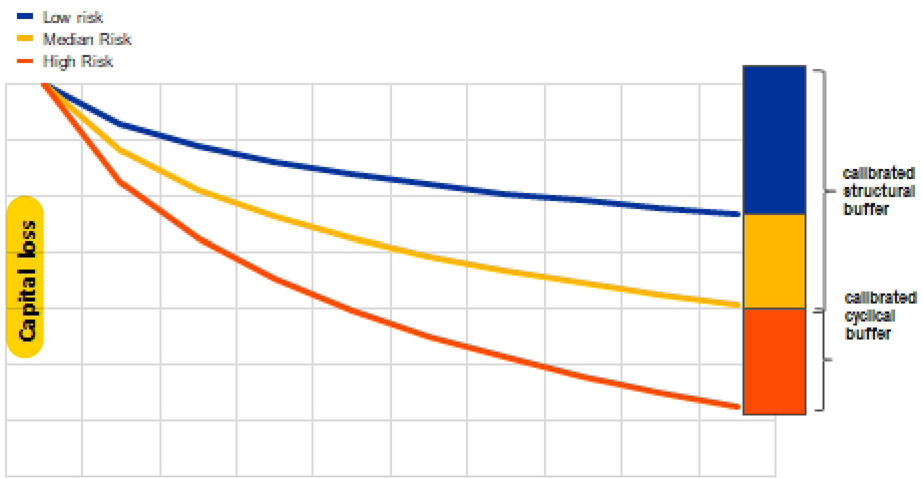
In this way, first, structural and cyclical buffers cover different expected losses, tackling the risk of overlap. Second, the level of cyclical buffer is mechanically linked to the evolution of cyclical risk.

In an alternative calibration strategy, structural buffer would be equal to the loss obtained when the risk is at its historical minimum. This alternative calibration would imply a a positive cyclical buffer when risk is at its median, implying a positive "neutral level" for the cyclical buffer. The second calibration approach increases the relative importance of cyclical buffers, providing releasable buffers as soon as the current risk is higher than the historical minimum.

Cyclical risk could cover 50-66.6% of the total CET1 depletion. → Implies stronger cyclical buffers might be required.

According to the calibration approach, the amplification of losses explained by the cyclical risk could cover form half to two thirds of the total CET1 depletion. A possible policy implication of this result goes in the direction to increase the space allocated to the cyclical buffer with respect to the current regulation.
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.

Illustration of the Risk-to-Buffer framework



Note: Through the use of the Cyclical Amplifier, multiple scenarios are generated using the same set of shocks under different states of the economy: e.g. low risk (blue), median risk (yellow) and high risk (red) scenarios. Those scenarios are used in Banks Stress test. The CET1 losses coming from the reference risk scenario can be used to set the structural buffer. The additional loss obtained under the current risk scenarios can be covered by the cyclical buffer.

Risk-to-Buffer : un calibrage conjoint des coussins cycliques et structurels par le biais des Stress test bancaires

RÉSUMÉ

Dans ce papier nous présentons le Risk-to-Buffer: une nouvelle approche qui permet de calibrer à la fois les coussins cycliques et structurels. Cette approche s'appuie sur l'intégration d'un modèle macroéconomique non-linéaire avec un modèle de Stress test. Le modèle macroéconomique produit des scenarii dont la sévérité dépend du niveau de risqué cyclique. Les scénarii sont ensuite utilisées dans le modèle de Stress test pour projeter les pertes en capital: les pertes obtenues sous le risque de référence sont utilisées pour calibrer le coussin structurel. Les pertes additionnelles associées au risque courant sont utilisées pour calibrer le coussin cyclique.

Mots-clés : vulnerabilité financière, politique macroprudentielle, modèles non-linéaires, espace macroprudentiel, dette.

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1 Introduction

Since the global financial crisis, prudential authorities have substantially reformed banks capital regulation framework.[1] A new set of rules, labelled Basel III, entered into force to strengthen banks resilience in case of materialization of different types of risks. With respect to previous regulation, one of the novelties of Basel III consisted in introducing a distinction between: i) buffers that evolve with the financial cycle and ensure banks resilience against risks related to the evolution of financial conditions (cyclical buffers), ii) buffers which remain constant through the cycle and cover risks related to the structure of the banking system (structural buffers).[2]

In economic literature, structural general equilibrium models integrating a banking sector and a macroprudential authority highlighted the benefits deriving from the introduction of the cyclical component in capital requirements. If structurally higher capital requirements overall stabilise the banking system and reduce the fluctuations of the economy in response to exogenous shocks (Clerc et al. (2015)), the presence of a cyclical component in setting capital buffers allows banks to build up resilience during good times and better absorb losses during times of financial distress, reducing output fluctuations and improving welfare (Angelini et al. (2014); Angeloni and Faia (2013); Paries et al. (2018)).

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

[2]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.

In practice, cyclical and structural buffers are often calibrated through 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).[3] 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 resilient.

A formal framework to map projected capital losses into cyclical and structural buffers is still missing. Moreover, when cyclical and structural buffers are calibrated using different parallel Stress test exercises 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.[4][5]

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. We use a non-linear macroeconomic model -which we call the Cyclical Amplifier- to generate adverse scenarios whose severity depends on the risk level, so to obtain a "reference"-risk scenario and a cyclical risk-scenario. A Stress test model then projects banks' losses according to each risk level. According to our conceptual framework, we set the structural buffer based on the losses obtained under the reference-risk scenario whereas the cyclical buffer is set based on the extra losses projected under the current-risk

[3] 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.

[4] 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.

[5] 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.

scenario. In this way, first, structural and cyclical buffers cover different expected losses, tackling the risk of overlap. Second, the level of cyclical buffer is mechanically linked to the evolution of cyclical risk.

The first key element of our approach consists in generating macroeconomic scenarios whose dynamics depend on the level of cyclical risk. We do that by using the Cyclical Amplifier, i.e. a Multivariate Smooth Transition regime switching model (Auerbach and Gorodnichenko (2013); Tenreyro and Thwaites (2016)) estimated through Local projections (Jordà (2005)). In order to show how the Cyclical Amplifier works, we use it in an application on the Euro Area. The model is estimated on quarterly macroeconomic and financial variables.[6] Thanks to its multivariate structure and through Choleski decomposition, we identify a set of structural economic and financial shocks. The non-linear structure provides impulse responses that depend on the level of risk measure, i.e. the Credit to GDP ratio expressed in 3 years difference, measuring the degree of financially vulnerability of private agents.[7] In line with theoretical and empirical works (Jordà et al. (2013); Kiyotaki and Moore (1997)), higher risk amplifies financial shocks as such as housing and spread shocks.

What about Non-fundamental shocks?

We exploit this non-linear feature 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 substantial recessionary shocks hit the European economy at the beginning of our projection (housing shock, spread shock) causing a deceleration a substantial drop in housing prices (-1.8%) and a increase in spread by 100 basis points. Typically, a first scenario is produced

[6] Observations include output, inflation, unemployment, the yield curve,Spread between 10 years interest rate and short term rate and housing prices for the Euro Area aggregate data. 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 illustrative 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 Debt Service Ratio (Drehmann et al. (2015)), the Credit-to-GDP gap (Borio et al. (2002)) or credit growth. In a robustness appendix we show that the amplification found with the Credit to GDP difference is robust to alternative risk measures. In a real life application, different scenarios could be generated by using several cyclical risk measures to provide wider information to policymakers.

at a reference risk level (e.g. historical median) to capture dynamics under a reference risk environment, and a second scenario is produced at the current risk level to capture the amplification role played by the current 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 used as inputs in a Stress test model to obtain corresponding CET1 ratio projections. In our application, based on the results of the EBA 2018 Banks Stress test exercise, we empirically quantify the elasticity of banks' CET1 results with respect to the evolution of output (i.e. GDP) provided in the EBA macroeconomic scenarios. Higher risk scenarios are associated with larger capital losses: under high risk the aggregate reduction of CET1 for European banks will be more than doubled with respect to the case of low risk (respectively 5.7pp and 1.7pp with respect to the starting point), whereas under medium risk, the CET1 ratio depletion will be in between, i.e. 3.7 pp lower than the value observed at the starting point.

Third, the projected losses are used to calibrate regulatory buffers. The loss of the *reference risk* scenario provides the level to set the structural buffer, whereas the additional loss triggered by the current cyclical risk scenario sets the cyclical buffer. As such, this latter will evolve 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 buffer), the cyclical buffer would be set at zero. In this way, the sum of both buffers would not fall below the structural buffer, which acts as backstop on capital requirements. In our application, the structural buffer would be equal to 3.7pp, corresponding to the average loss that we obtain using the median risk scenario. If we assume that the current risk is at its historical maximum, the cyclical buffer will be set equal to 2pp, i.e. the additional loss deriving from the use of the maximum risk scenario. In an alternative calibration strategy, structural buffer would be equal to the loss obtained when the risk is at its historical minimum. Under this alternative, the structural buffer would be at 1.7pp and, if the current risk is at maximum level, the cyclical buffer would be set at 4pp. This alternative calibration would imply a a positive cyclical buffer of 2pp when risk is at its median, implying a positive "neutral level" for the cyclical buffer. The second calibration approach increases the relative importance of cyclical buffers, providing releasable buffers as soon as the current risk is higher than the historical minimum.

According to the calibration approach, the amplification of losses explained by the cyclical risk could cover form half to two thirds of the total CET1 depletion. A possible policy implication of this result goes in the direction to increase the space allocated to the cyclical buffer with respect to the current regulation.[8]

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 can be a valid alternative to the Growth-at-Risk model (henceforth GaR) that has become an influential tools for cyclical risk analysis over the past few years. While in the GaR the systemic risk is captured by a unique GDP (quantile) forecast, our Cyclical Amplifier links the evolution of risk to a state variable. Besides, thanks to its multivariate structure, the Cyclical Amplifier assesses the heterogeneous amplification mechanisms of a larger set of macroeconomic variables with respect to the different shocks policymakers may be interested in. As such, this model allows for directly designing scenarios related to specific narratives (i.e. set of

[8] In this work we adopt a macroprudential perspective, focusing on the systemic dimension, i.e. setting capital buffers homogeneous across banks. In doing so we set capital buffers 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. A possible top-up in this sense would be the use of more sophisticated Stress test models considering the role of idiosyncratic characteristics of banks (i.e. size, business models) in affecting their dynamics. This additional microprudential application could provide additional indication to set individual capital buffers tackling idiosyncratic vulnerabilities, in the spirit of what is done for the Pillar-to-Guidance (P2G) buffer at European level.

incoming shocks), an attractive feature for Stress tests.[9] 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 6 houses the application of the Risk-to-Buffer framework to the Euro Area banks. Section 7 presents a comparison between our method and the Growth-at-Risk. Section 8 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.

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 lit-

[9]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).

erature, 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 Risk-to-Buffer allows the policymaker to design the shock of interest, which then translates into economic scenarios through the Cyclical Amplifier. 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 generated through an economic model $g()$ producing the macroeconomic and financial trajectories conditional on the assumed sequence of economic shocks ($Shocks_t$) specified by the econometrician[10]:

$$Macro_t = g(Shocks_t). \quad (2)$$

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:

$$Buffers_{i,t} = h(CET1_{i,t}). \quad (3)$$

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 (3) can be rewritten as:

$$Buffers_t = h \circ g \circ f(Shocks_t) \quad (4)$$

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.[11][12]

[10]In practice, policy makers are willing to test banks' resilience with respect to adverse macroeconomic scenarios. Those scenarios usually mimic strong downturns, e.g. the Global Financial Crisis or the Euro-Area Sovereign debt crisis.

[11]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.

[12]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.

3.2 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 3 years change in credit to GDP ratio in our application). We generate multiple adverse scenarios across different levels of risk (e.g. low risk, medium risk, high risk, current risk):

$$Macro_t^{Risk} = f(Shocks_t, Cyc_t^{Risk}) \tag{5}$$

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.[13] Thanks to the non-linear features of the model, the severity of the scenario varies with respect to the cyclical risk. If the state variable is a good measure of cyclical risk, higher risk scenarios will be associated to more severe output loss, e.g. featuring stronger amplification of economic and financial shocks (Carriero et al. (2018); Jordà et al. (2013)).

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. A second adverse scenario is produced based on the current (or expected) 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.[14] By the same token, the cyclical buffer covers the expected losses due to the amplification role played by the financial accelerator according to the position of the economy in the financial cycle.

Figure 1 provides an illustration of the Risk-to-Buffer. In our baseline framework, we assume that the policymaker sets the structural buffer using the

[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.

[14] 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.

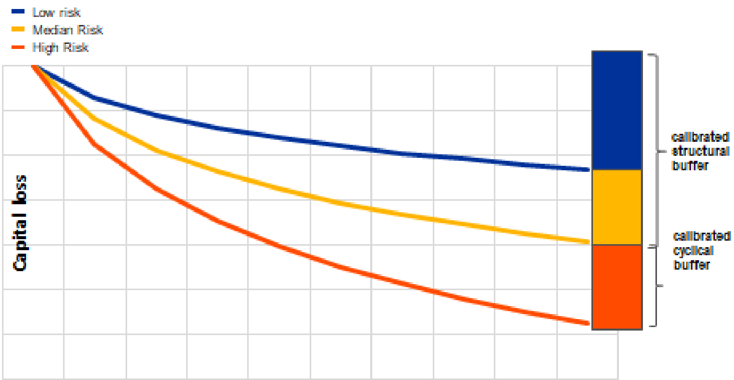

Figure 1: Illustration of the Risk-to-Buffer. Note. The methodology proposes the use of multiple scenarios generated with the same set of shocks under different states of the economy. Dynamics are state dependent: the low risk (blue), the median risk (yellow) and the high risk (red) scenarios have different severity. The stronger severity will cause larger CET1 losses. The loss coming from the reference risk scenario can be used to set the structural buffer. The additional loss obtained under the current risk scenarios can be covered by the cyclical buffer.

median historical risk level as the reference level:

$$Buffers_t^{StructuralRisk} = h \circ g \circ f(Shocks_t, Medium\,Risk) \tag{6}$$

corresponding to the sum of the blue and yellow bar of Figure 1. Instead the cyclical risk is the level of additional loss related to the current level of risk:

$$\begin{aligned} Buffers_t^{CyclicalRisk} = max\Big(& h \circ g \circ f(Shocks_t, Current\,Risk) \\ & - h \circ g \circ f(Shocks_t, Medium\,Risk),\, 0\Big) \end{aligned} \tag{7}$$

This framework is flexible enough to adapt to different policy maker's preferences. If the policy makers wants to cover all the losses deriving from the amplification generated by cyclical risks through cyclical buffers, she can choose a the historical minimum level as the reference level to set the structural buffer. In this case, in Figure 1, the structural buffer is equal to the loss under the low risk scenario (blue bar only), whereas the cyclical buffer is set at a positive value as soon as the cyclical risk is above the minimum level. In other words, under medium risk (i.e. when the financial cycle is at its steady-state level), the "neutral" cyclical buffer is positive (in Figure

1 equal to the yellow brick).[15] Under this option, the cyclical component of the total buffer space would be larger, increasing the room that authorities would have to counter-act negative economic fluctuations by releasing capital requirements.

4 The Cyclical Amplifier

In this section we present the Cyclical Amplifier, a 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 Local Projections (thereafter LP) by Jordà (2005).[16]

The non-linear structure allows to estimate impulse responses whose dynamics depend on the regime of the economy (i.e. change in credit to output ratio). 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:

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

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 driven by $F(z_t)$, that is the scalar function governing the transition between the high and the low regime. $F()$ is

[15] 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.

[16] 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.

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 (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[17], v determines the part of the sample spent in either state[18], and σ_z is the standard deviation of the observed state variable. Both θ and v are generally calibrated (Auerbach and Gorodnichenko (2013)). We set v to the historical median of the original state variable, so that the resulting state spends half of the time in both regimes. Our baseline specification uses $\theta = 3$ (Franz (2017); Tenreyro and Thwaites (2016)), but our results are robust to a large range of alternative calibrations.

The use of LP allows extracting impulse responses directly from the estimated model without the need to compute its Wald representation. This facilitates the inclusion of non-linear features. Besides, LP do not accumulate the misspecification error over the projection horizon, differently from the standard VAR-type representation.

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 will be 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.[19]

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

[18]$z_t > v$ 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.

[19]We construct all possible overlapping tuples of m consecutive dates in the matrix Y

5 Application for the Euro Area: estimation of the macroeconomic model

In this section we present an application of our Cyclical Amplifier to the Euro Area case. First, we present the data and the interaction variable used in the benchmark estimation. Second, we show the structural identification strategy. Third, we present the impulse responses produced by the model, focusing on a sub-set of structural shocks (i.e. housing shock and spread shock). In doing that, we highlight the substantial state effects related to level of cyclical risk, in that both shocks are amplified under high cyclical risk. This feature of the model allows producing scenarios, that, given the same set of initial shocks, are more recessionary under high risks.

5.1 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 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)) 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 their income, increasing their financial vulnerability. As such, the same negative economic scenario is expected to have more adverse consequences when the Credit to GDP ratio increased, as more agents are likely to be in a situation of financial distress.

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)).

5.2 Structural identification

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.[20]. We order variables as follows: Output, Inflation and Unemployment rates, Short term interest 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 (spread shocks and housing shocks). This ordering is consistent with financial variables reacting faster than macroeconomic ones. 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 overall standard and is line with Aikman et al. (2016); Cesa-Bianchi (2013); Goodhart and Hofmann (2008). Importantly, the sign of the responses and their state

[20]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))

amplifications are strongly robust to alternative Choleski ordering.

5.3 Results

In this section we present the results of the estimated macroeconomic model. In particular, 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, $F(z) = 1$). Thanks to its structure, the model allows to compute the responses at any intermediate level. Under high vulnerability (red line), 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 (green line), 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 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

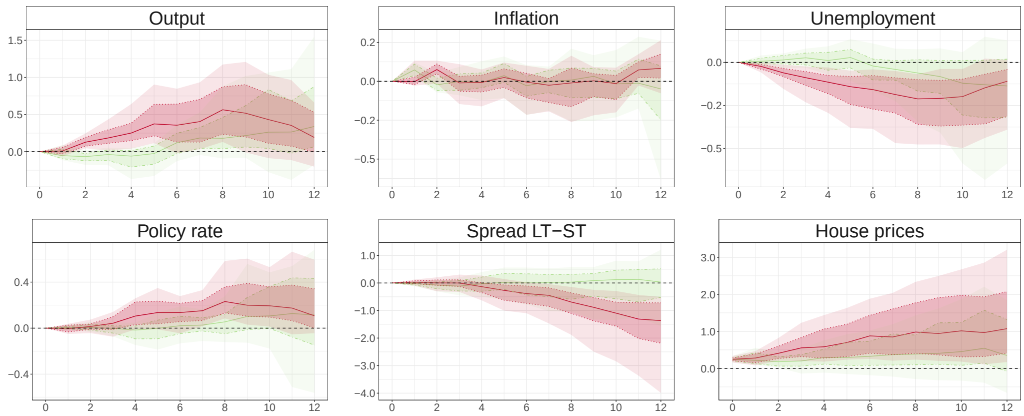

Figure 2: Impulse responses of our endogenous variables to a housing shock.
Note. The responses of output growth, inflation and house prices are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (green) lines are the impulses when leverage is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

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 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 in-

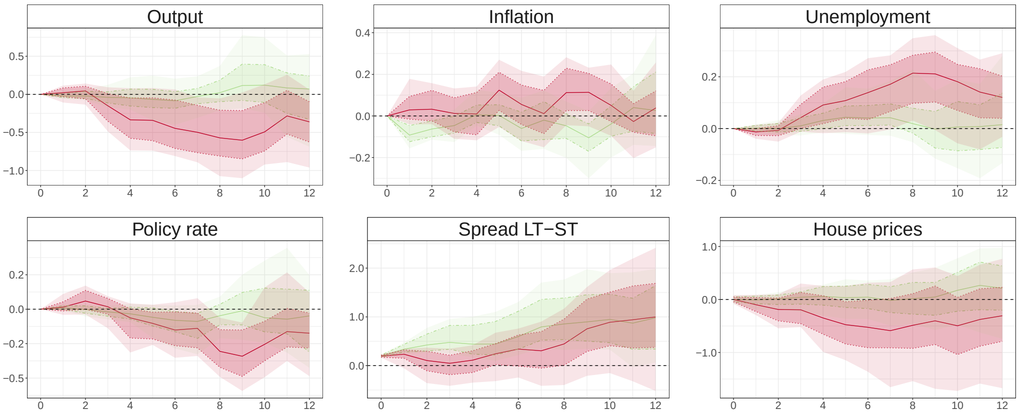

Figure 3: Impulse responses of our endogenous variables to a spread shock.
Note. The responses of output growth, inflation and house prices are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (green) lines are the impulses when leverage is high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

creases 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.

6 An application on European banks: mapping adverse scenarios to buffer calibration

In this section we present an application of the Cyclical Amplifier, estimated in the previous Section, to calibrate structural and cyclical buffers of European banks. First, based on the results of the 2018 EBA stress test exercise, we estimate a reduced form regression capturing the key elasticity of CET1 depletion to macroeconomic variable. Second, we use our Cyclical Amplifier to generate risk-related adverse scenarios for the European economy. Third we use the different adverse scenarios as inputs in our stylised stress test model, to project the evolution of CET1 ratios and compute losses for the banking system. For the sake of clarity we focus on three different risk levels: low risk (minimum Credit to GDP ratio difference), medium risk (median Credit to GDP ratio difference) and high risk (maximum Credit to GDP ratio difference). These scenarios and their related CET1 losses will be our reference points to calibrate structural and cyclical buffers. The results of this exercises provide an intuition on the different role that risks can play in capital depletion and in buffer calibration.[21]

6.1 A simple reduced form stress test model

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 equation as 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.

$$\Delta CET1\_ratio_t^{i,j} = \alpha + \beta_{GDP} \Delta GDP_t^j, \tag{10}$$

where $\Delta CET1\_ratio_t$ is the vector of year-on-year change in CET1 ratios for each bank, ΔGDP_t is the vector of output yearly growth variations. In other words, we simply estimate the elasticity of CET1 to output growth in the EBA 2018 stress test, mimicking a back-of-the-envelop simplified stress

[21] This example has a purely illustrative purpose and a proper calibration exercise would require the use of a fully fledged stress test exercise. Besides, a wider set of shocks could be considered (i.e. demand shocks, supply shocks, external shocks) as done in the real life Stress test exercises.

test exercise.[22][23][24]. Both bank CET1 ratios and macroeconomic scenarios are public. The banks dataset covers the biggest 49 European banks observed CET1 ratios at the moment of the exercise and the CET1 ratios for three years of projections, considering two scenarios, each one spanning for three years. First, the central scenario is in line with the official European projection for macroeconomic variables. Second, the adverse scenario features an important drop in asset prices and house prices, triggering a strong recession, reaching its maximum amplitude in the second year.
We obtain the following estimated equation:

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

The regression R^2 equals 0.33, whereas the coefficients for the elasticity to GDP is statistically significant ($p < 0.01$). In order to test robustness of our result, first, we try different specifications, including a larger number of macroeconomic variables which are included in the EBA scenarios, as such as inflation, residential real estate variations, short term rate, spread between long term and short term rate, stock prices. Second, we estimated Equation (10) using only projections coming from the adverse scenarios. Third, we estimated this equation by using alternative measure of CET1 variation, considering only the difference between the final projected CET1 ratio in the third year and the initial observed CET1 ratio. In this case, this variable is

[22] 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.

[23] 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.

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

regressed on the cumulated output growth over the scenario horizon. Results are overall quantitatively significant across all these specifications. In all our estimations, β_{GDP} ranges between 0.3 and 0.6.[25]

6.2 Scenario Design

In this subsection we prepare the macroeconomic 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, as central scenario we use a fictitious scenario where Euro Area output constantly grows with an annual variation of 2% per year. Second, the adverse scenario features the evolution of macroeconomic and financial variables going through an economic downturn.[26]

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 (8)). Different initial Credit to GDP ratio differences are considered, and associated to different transition variables $F(z_t)$ thanks to the transition function (Equation (9)): we run four scenarios with $F(z_t)$ equal to 0, 0.5, 0.75 and 1.[27]

In Figure 4, we report the impulse responses of the endogenous macroeco-

[25] As a general result, when including stock prices among the regressors, the elasticity to output tends to decrease, since in the 2018 EBA Stress test an initial strong drop in asset prices substantially decreases net interest income and CET1 ratios since the first year of the projection, whereas the biggest output drop occurs in the second year.

[26] 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.

[27] 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%.

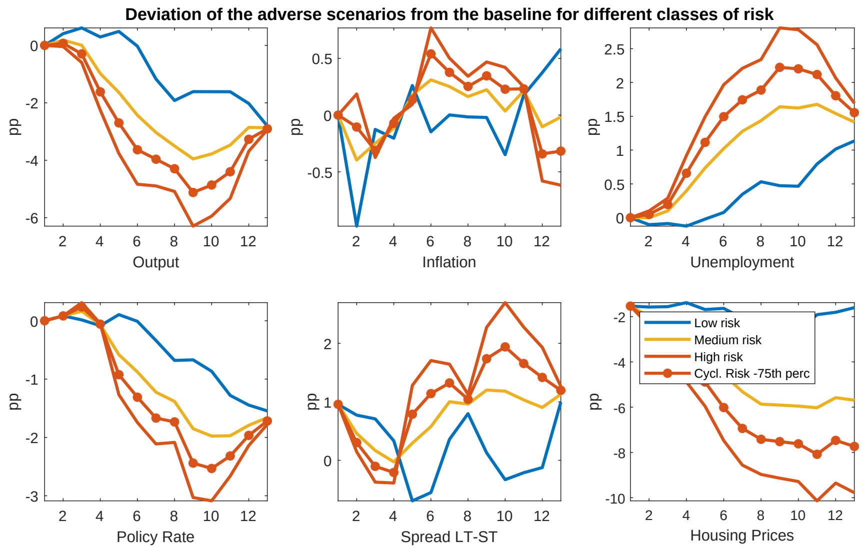

Figure 4: Deviation of the adverse scenarios from the baseline scenario. Note. The deviation between central and adverse scenario corresponds to the sum of the impulse responses of the macroeconomic variables to the set of housing shock (-4 standard deviation), spread shock (4 standard deviation shock). 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.

nomic 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 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 terms of severity, the medium risk and the 75th percentile scenarios lie in between the Low and the High risk

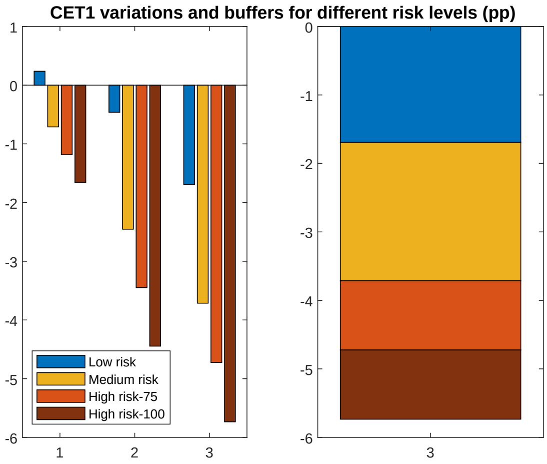

Figure 5: CET1 and Buffers. Note. Aggregate CET1 ratios variation for three years of the projection are reported on the left hand side in % ratios. The buffer corresponding to each losses are reported on the right hand side. Results for the low risk scenario are reported in light blue. Results for for the medium risk scenario are in yellow. Results for the cyclical shortfall when transition variable is at its 75th percentile is in light red whereas the results for the maximum risk scenario are in dark red. On the right hand side for each risk we report the additional contribution the to the CET 1 losses (pp level). 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.

case. In order to compute the adverse scenario, these impulse responses are added to the central scenario[28].

6.3 Banks projections

The four scenarios presented above are used in our stylised Stress test model (Equation (10)), 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

[28]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 internal consistency.

	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.

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, $F(z_t) = 1$)).

6.4 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.[29] 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).[30]
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 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.[31]

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

[30]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.

[31]To this extent, the Bank of England's Financial Policy Committee (FPC) announced

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.

7 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 quantify the tail risks of the economy (typically at the 5th percentile).[32] In Stress test, the model is used to tailor the severity of Stress test adverse

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.

[32]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*.

scenarios according to the current risk flagged in policy analysis.[33]
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.[34]
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 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 de-

[33]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.

[34]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.

termined 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.

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

Cyril Couaillier[*] Valerio Scalone[†]

1 Robustness with respect to the state variable

In this section we present the results of the two main shocks presented in the paper (Housing shock, Spread shock) across different state variables. Our goal is to assess the robustness of the results of macroeconomic model with respect to different measures of financial vulnerability.

Debt Service Ratio. A possible measure of cyclical risk is the Debt Service Ratio. This ratio measures the fraction of annual income that is used to pay back the debt. In line with Drehmann et al. (2015), at aggregate level, the DSR can be computed as:

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

where Y_t is the gross disposable income augmented with gross interest payments,[1] D_t is the stock of households' debt, i_t is the effective lending rate, m

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[1]gross interest payments are added back to income to logically compute the DSR as a share of income pre-interest payment

is the maturity. The effective lending rate i_t is computed as the ratio between the gross interest payment and the financial intermediation services over the stock of debt. With respect to the Credit over GDP ratio, the DSR takes into account the role of the effective interest rate. State effects found for the Housing shock, Spread shock (Figures 1, 2) are qualitatively in line to the ones found in the benchmark specification, where cyclical risk amplifies the effectiveness of housing shocks and spread shocks.

Credit to GDP gap. A popular measure for cyclical risk is the Credit to GDP gap (Borio et al. (2002)). This indicator is obtained as the ratio between Credit over GDP and its long run trend, obtained by using a one sided HP filter with $\lambda = 200,000$, in order to take into account the low frequency evolution of the financial cycle. In this case (Figures 3, 4), we find similar state effects to the ones found for the benchmark case, in that high cyclical risk amplifies housing and spread shocks.

2 Robustness with respect to the set of countries used in the estimation

In this section we show the robustness of our results by using the data of the four biggest European countries in terms of output size (i.e. Germany, France, Italy and Spain). As in the benchmark specification, the interaction variable is the the Credit to GDP ratio in 3 years difference. We find statistically significant state effects in line with what found in the benchmark specification (Figures 5, 6).

3 The shadow short term interest rate

A large part of the sample used in our benchmark estimation features a period of Effective Lower Bound (ELB). In order to assess whether our results are robust also when considering the presence of unconventional monetary policy, we estimate the model by using the shadow short interest rate computed by

Wu and Xia (2016). We find very similar quantitative results (Figures 7 and 8) to the ones found in the benchmark estimation.

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Debt Service Ratio: Housing shock

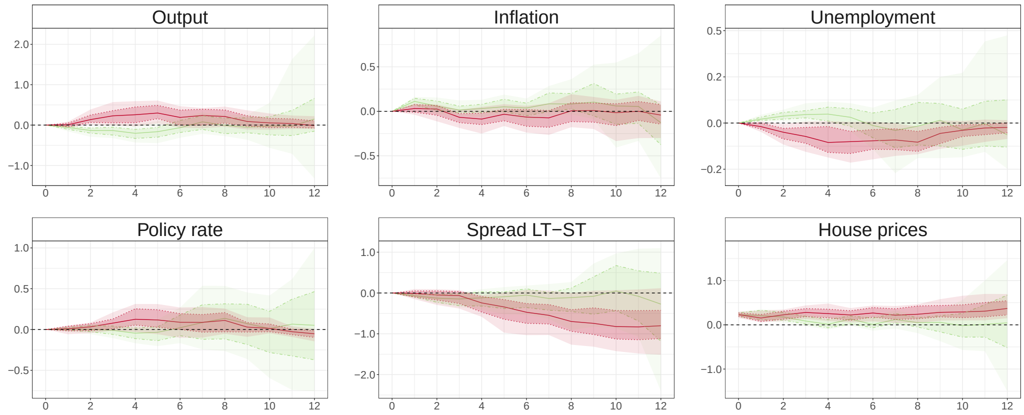

Figure 1: Impulse responses of our endogenous variables to a housing shock.
Note. The responses of output growth, inflation and house prices are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (green) lines are the impulses when leverage is high (low). Shaded areas represent the 67% and 90% confidence intervals.

Debt Service Ratio: Spread shock

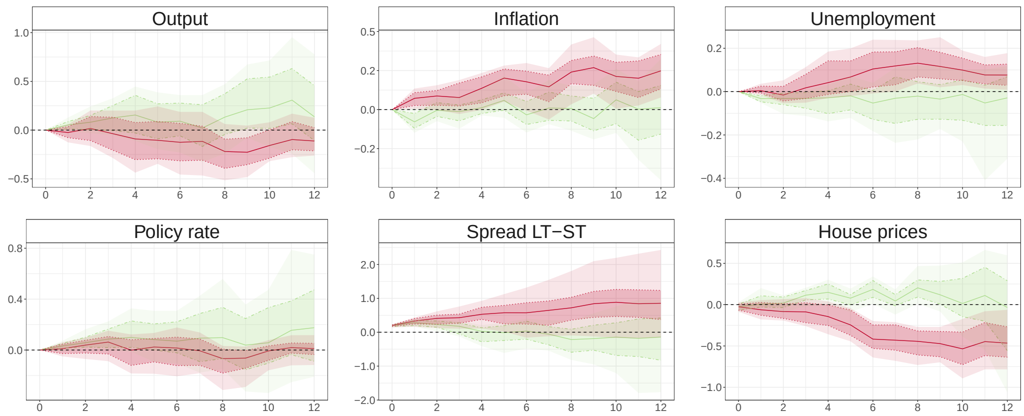

Figure 2: Impulse responses of our endogenous variables to a spread shock.
Note. The responses of output growth, inflation and house prices are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (green) lines are the impulses when leverage is high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

Credit to GDP gap: Housing shock

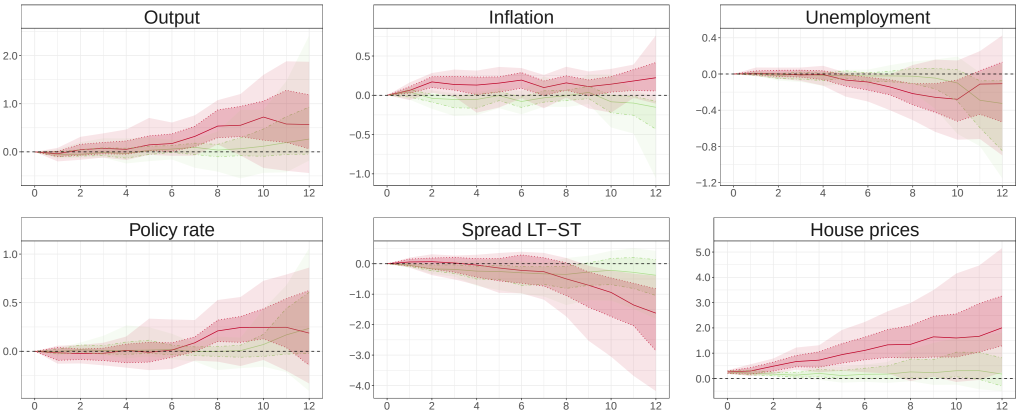

Figure 3: Impulse responses of our endogenous variables to a housing shock.
Note. The responses of output growth, inflation and house prices are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (green) lines are the impulses when leverage is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

Credit to GDP gap: Spread shock

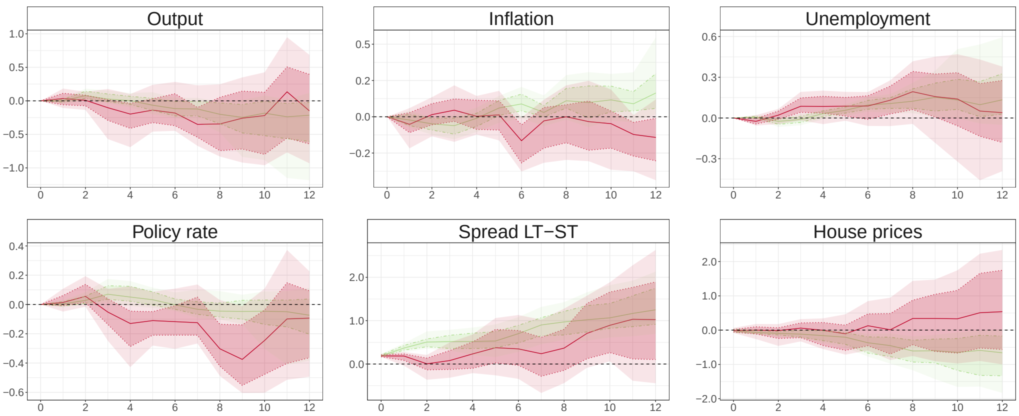

Figure 4: Impulse responses of our endogenous variables to a spread shock.
Note. The responses of output growth, inflation and house prices are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (green) lines are the impulses when leverage is high (low). Shaded areas represent the 67% and 90% confidence intervals.

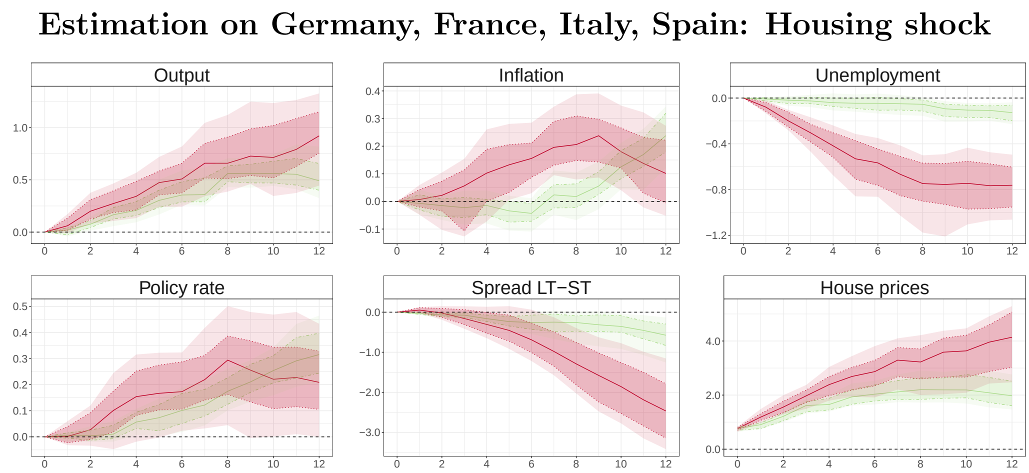

Figure 5: Impulse responses of our endogenous variables to a housing shock.
Note. The responses of output growth, inflation and house prices are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (green) lines are the impulses when leverage is high (low). Shaded areas represent the 67% and 90% confidence intervals.

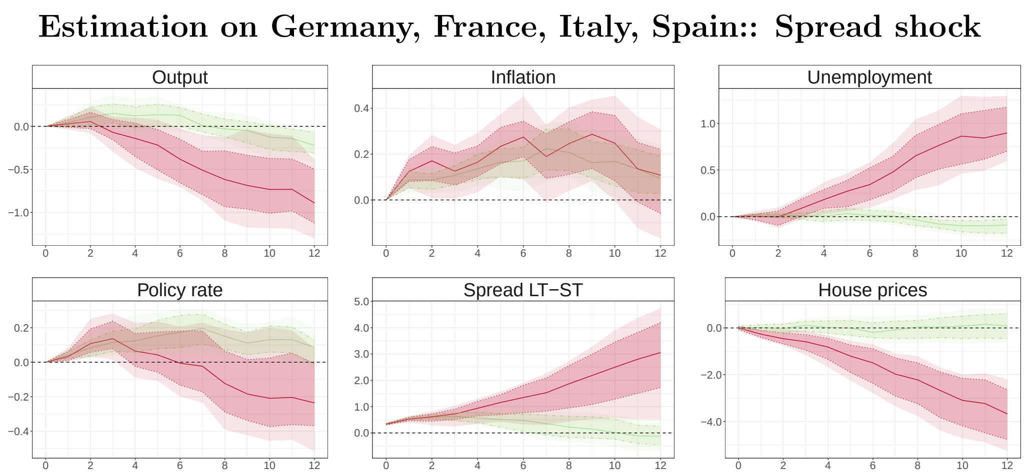

Figure 6: Impulse responses of our endogenous variables to a spread shock.
Note. The responses of output growth, inflation and house prices are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (green) lines are the impulses when leverage is high (low). Shaded areas represent the 67% and 90% confidence intervals.

Shadow short term rate: Housing shock

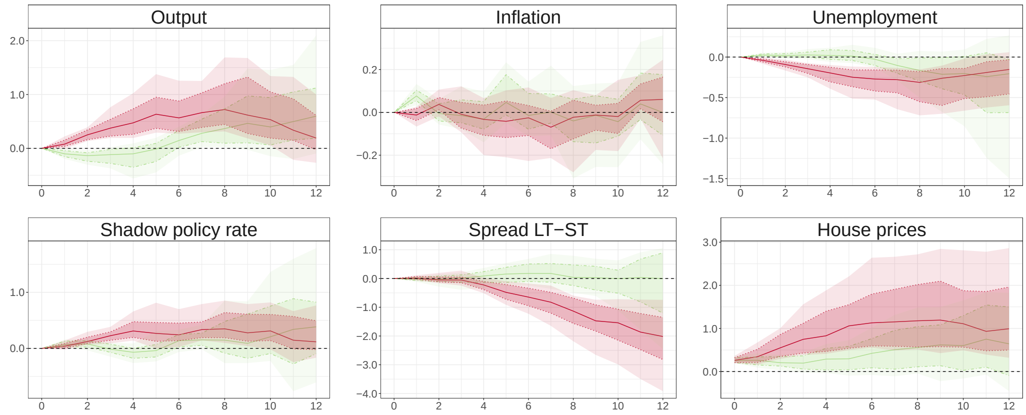

Figure 7: Impulse responses of our endogenous variables to a housing shock.
Note. The responses of output growth, inflation and house prices are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (green) lines are the impulses when leverage is high (low). Shaded areas represent the 67% and 90% confidence intervals.

Shadow short term rate: Spread shock

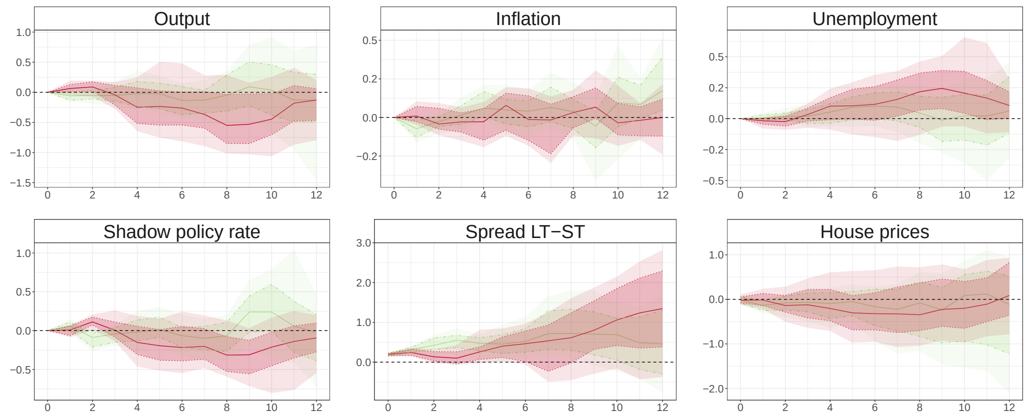

Figure 8: Impulse responses of our endogenous variables to a spread shock.
Note. The responses of output growth, inflation and house prices are cumulated, while the responses for the interest rates, spread and unemployment rates are in levels. The red (green) lines are the impulses when leverage is high (low). Shaded areas represent the 67% and 90% confidence intervals.