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A Framework for Macroprudential Stress Testing

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Abstract

This paper overviews our Macroprudential Stress Testing model built for the Irish banking sector. The model contains a loan level stress testing element for Irish retail banks and an additional structural element describing interactions between the financial sector and the broader economy. It has been developed as a tool to assess banking system resilience from a macroprudential perspective and, in addition, for use as an analytical tool for informing macroprudential policy decisions. In the model, banks respond to solvency concerns by adjusting the size and composition of their balance sheets. These responses feed back to the macroeconomic environment with implications for the real economy. The model facilitates applications to the setting of cyclical capital buffers by providing an analytical framework for considering the trade-off between banks' deleveraging responses to a capital shock and the broader implications of those responses for the real economy.

KEYWORDS: macroprudential stress testing, capital buffers, scenario analysis

JEL Classification: E37, E58, G21.

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Non-Technical Summary

This paper overviews our semi-structural Macroprudential Stress Testing model which can be used for multiple purposes. First, it can be used for general resilience testing of the financial system, improving the realism of traditional stress testing approaches by incorporating feedback from the financial sector to the input scenario. Second, it can be used as an empirical tool to help inform the appropriate level of the counter-cyclical capital buffer (CCyB). The model has recently been used to assess bank solvency and financial feedback in the context of setting the Irish system-wide cyclical capital buffer.[1] The model features an endogenous dynamic balance sheet, with loan level amortisation and new lending, the latter estimated through the use of macroeconomic time series models.

The key difference between macroprudential and microprudential stress testing is that macroprudential approaches are concerned with the banking sector as a whole, whereas microprudential approaches are used specifically for individual institutions. The role of the banking sector, and its interaction with the wider economy, can be incorporated into this class of model. Typical responses by the banking sector during financial crises, such as large-scale deleveraging, pose negative externalities to society through the tightening of credit standards. Our model aims to incorporate responses such as these by combining loan-level stress testing models with macroeconomic models. In this way, our model captures both the dynamic adjustment of banks to macro-financial developments and the interaction between banks and the real economy.

We find the role of deleveraging to be an important channel through which banks aim to improve their capital positions. The inclusion of deleveraging, via reductions in credit supply and an increase in lending rates, mitigates the decline in bank capital over the adverse scenario. This mechanism, however, leads to a further macroeconomic decline as tighter credit conditions dampens consumption and investment. We also find that, following an adverse shock, banks appear to reduce lending to non-financial corporates more than lending to households, somewhat reflecting the relative riskiness of corporate lending and associated capital costs of holding higher risk weighted assets.

In the final section of the paper, we include a hypothetical application using the model where we assume a 150bps reduction in capital requirements following the realisation of an adverse scenario (comparable to the full release of a CCyB of 1.5 per cent). We find this release of capital results in a sizeable reduction in the scale of deleveraging by banks with positive implications for the real economy. Specifically, the presence of releasable capital in an economic downturn minimises the gap between the level of credit banks are willing to supply, and the level of credit the economy demands.

The model presented in this paper is the first iteration of the Central Bank's Macroprudential Stress Testing framework, with future enhancements subsequently planned. In particular, we aim to; (i) include a feedback channel between solvency and funding conditions, (ii) expand the sample of financial institutions to capture more of the Irish financial sector, including non-banks and (iii) further refine the macroeconomic models used.

[1] See Box F in FSR 2022:1 https://www.centralbank.ie/docs/default-source/publications/financial-stability-review/financial-stability/financial-stability-review-2022-i.pdf?sfvrsn=3e74961d_5

1. Introduction

Since the global financial crisis (GFC), stress testing has become a well-established regulatory tool to assess the resilience of the banking sector (Baudino et al. 2018, de Guindos 2019a). Stress tests can provide quantitative, forward-looking assessments of the health and solvency of the banking system under different plausible scenarios and can take a microprudential or macroprudential policy focus. Microprudential stress tests are concerned with assessing the capital position of an individual institution relative to its regulatory requirements over a hypothetical scenario. Authorities can use this information to inform potential supervisory actions, such as setting appropriate levels for regulatory capital buffers. The EBA biennial stress test is a prominent example of this approach.

Macroprudential stress tests, instead, focus on assessing system-wide resilience and the ability of the aggregate banking sector to withstand adverse shocks. The systemic nature of the GFC emphasized the importance of monitoring the resilience of the banking system in addition to the idiosyncratic risk of individual institutions. As a result, macroprudential stress testing models are increasingly being used by national authorities to identify systemic risks (such as those arising from fire sales, contagion or from inter-connections between banks) and inform policy (Demekas, 2015; Anderson, 2018). Recent financial crises show how shocks can be endogenously amplified in the financial system, magnifying losses through feedback effects and spill-overs, so called “second-round” effects (Danielsson et al, 2012; Brunnermeier, 2009). Following the initial shock to the banking sector, such second-round effects occur due to the reactions of banks restricting credit and raising lending spreads to preserve capital, which lead to a further deterioration in economic activity. Accordingly, an important aim of macroprudential stress testing is to capture both the direct impact on system-wide capital of an adverse macroeconomic shock and any second-round effects that may occur. The results of macroprudential stress tests help to inform policy makers on the sector’s ability to withstand adverse shock episodes while continuing to supply credit to households and businesses. Despite adding to modelling complexity, the importance of modelling effects such as contagion and feedback loops in stress testing is widely accepted (Haldane, 2009; Anderson et al, 2022; Bassett & Rappoport, 2022).

In this paper, we present our macroprudential stress testing model. It builds upon an existing bank-level stress testing model, which was used to inform the forward-looking assessment of the financial resilience of the Irish retail banking system (Central Bank of Ireland, 2020). In the previous modelling approach, the relationship between the real economy and banking sector was unidirectional when aggregating the hypothetical cost of an adverse shock to the economy. By contrast, the newly developed macroprudential model accounts for shock amplification mechanisms (such as deleveraging and credit crunches), and links the evolution of the balance sheet to both the input scenario and the capital position of the banks.

We extend our existing modelling approach along two dimensions:

I. Firstly, the assumption of a static balance sheet is relaxed, such that the behavioural reactions of banks (through new lending) to the macroeconomic environment are explicitly modelled. This dynamic approach allows banks to adjust their assets, liabilities and prices accordingly.

II. Secondly, using a Structural Vector Autoregression (SVAR) approach, interactions between the macroeconomy and banking sector are formally modelled through a financial sector amplification channel. Catalan & Hoffmaister (2022) show that accounting for macro-financial feedback loops can significantly affect macroeconomic outcomes and bank-specific stress test results. Despite this, the macro-financial feedback channel is a key element that is often overlooked in macroprudential stress tests (Demekas, 2015; Krznar & Matheson, 2017). Including this channel in our framework allows us to better understand both the impact of macroeconomic shocks on the solvency of the banking sector and the ability of the banking sector to continue to supply credit to the economy without disruption.

The inclusion of a dynamic balance sheet and feedback loop between the financial sector and the real economy provides an effective backdrop for considering the implications of various macroprudential policy decisions relating to capital buffers, particularly the Counter-Cyclical Capital Buffer (CCyB). As a result, many national authorities have started to consider how macroprudential stress testing can be used to inform macroprudential instrument calibration. Naturally, macroprudential stress testing can also be used for wider policy assessment including systemic risk identification, resilience assessment and for communication of financial stability issues.[2] As an illustrative example of how our framework can be used to inform policy, we demonstrate in Section 6 how the model can be used for CCyB related applications.

The remainder of this paper is organised as follows. In Section 2, we provide a high-level overview of the model's structure, in addition to a description of the various elements involved in each iteration of running the model. Section 3 presents detail on the bank-level block, while Sections 4 and 5 present details on the macroeconomic elements of the framework. Section 6 presents an illustrative example of the model, in which we present the impact of a hypothetical release of the CCyB on bank capitalisation and the real economy. We conclude in section 7.

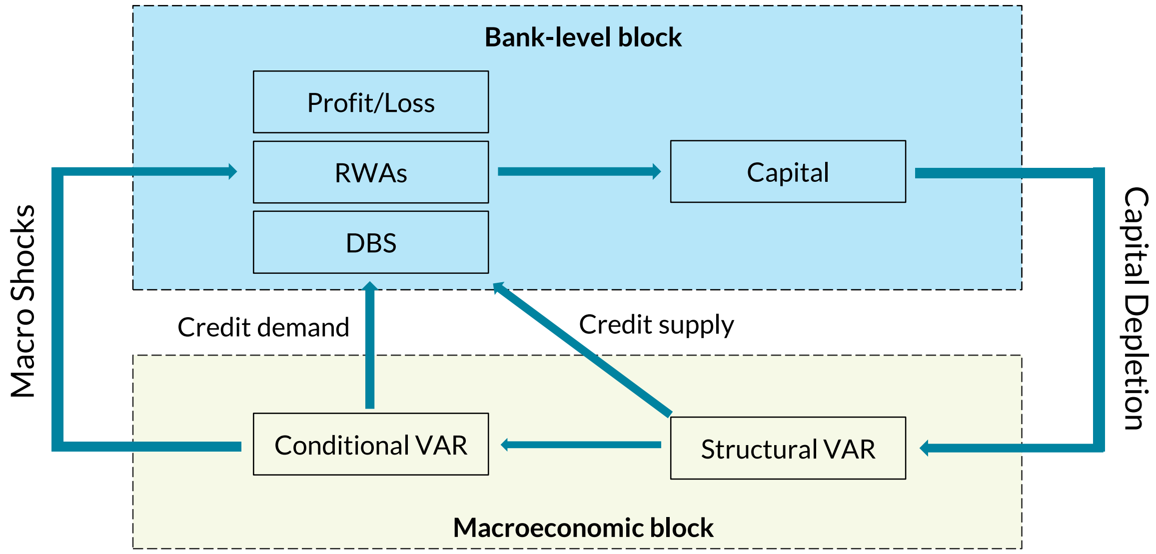
2. Model Overview

In this section, we provide an overview of our macroprudential stress testing model, paying particular attention to the model's structure and how financial sector feedback is incorporated. At a high-level, the framework consists of a bank-level block and a macroeconomic block (Figure 1).

The bank-level block encompasses several satellite modules which estimate the impact on retained earnings and risk weighted assets (RWAs) for a given macroeconomic scenario. Additionally, the bank-level block also models the evolution of bank balance sheets via the dynamic balance sheet module (DBS). The outputs of the various satellite modules are subsequently aggregated to derive the impact on bank capital.

[2] For examples see the Bank of England (Bank of England, 2016 and Dent et al, 2016), Czech National Bank (CNB, 2020), Norges Bank (Andersen et al, 2019) and Banque de France (Bennani et al (2017)) who have all linked the use of their macroprudential stress test to assist in the calibration of their CCyB. The ECB regularly use their model to assess resilience of the banking system and the reaction of the banking system towards alternative macroprudential policies, such as in Dees et al, 2017; Budnik et al, 2019; Borsuk et al, 2020 and Budnik et al 2021. The use of macroprudential stress testing can also be used to inform issues around crisis management an example of which can be found in Goodhart & Basurto, 2015.

Figure 1: A Stylised Representation of the Central Bank of Ireland's Macroprudential Stress Test Model



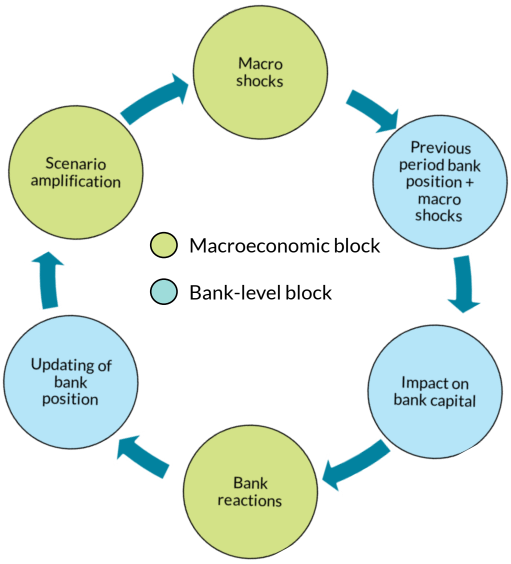
Source: Authors' own calculations.
Notes: Within the bank-level block, various satellite modules translate a series of macro shocks into the impact on the banking sector's profit/loss account, the stock of risk weighted assets and changes in its balance sheet (DBS). These impacts are subsequently aggregated to estimate the impact on capital. The macroeconomic block houses two key macroeconomic models that are pivotal in driving shock amplification in our model. See Section 3 for more detail.

The macroeconomic block maps changes in bank capital (derived from the bank-level block) into changes in key macroeconomic variables that in turn update the initial macro shocks. The updated macroeconomic scenario subsequently affects the satellite modules in the bank-level block. As such, the two blocks are therefore linked via the endogenous response of banks reacting to macroeconomic developments through adjusting their loan volumes and lending rates. For example, in a deteriorating macroeconomy, financial sector feedback arises as the resulting depletion in bank capital amplifies the initial scenario as banks further constrain economic activity through restricting credit and raising lending rates to preserve capital.

The model is run iteratively at an annual frequency, where each iteration is composed of several steps (Figure 2). Each iteration is initiated by an array of shocks that influence the state of the macroeconomy (*Macro shocks*).[3] In turn, the updated macroeconomic environment interacts with the banking sector, ultimately impacting the sector's capital position. In response to changes in its capital adequacy, the banking system reacts by adjusting its balance sheet through changes in lending volumes and lending rates. Changes in credit conditions are mapped back into the underlying economic conditions (financial sector feedback) which will form a new series of macro shocks that will initiate the subsequent iteration. In the following sections we provide more details on the bank-level and macroeconomic blocks.

[3] While details on how macroeconomic scenario is constructed beyond the purview of this paper, the underlying macroeconomic shocks will be calibrated to be consistent with the prevailing risk narrative.

Figure 2: A Stylised Representation of the Amplification Mechanism of the Central Bank of Ireland's Macroprudential Stress Test Model



Source: Authors' own inputs.
Note: The chart shows the various steps involved in one iteration of our model

3. Bank-level Block

The bank level model comprises three main satellite models: the credit risk module, profitability module, and risk-weighted assets module (RWA). The credit risk module and the profitability module impact the profit and loss account through impairments and net interest income, respectively, and ultimately capital through retained earnings in the capital account. Bank capital ratios are expressed in terms of risk weight based capital requirements which are estimated in the RWA module.

The Central Bank of Ireland's loan loss forecasting framework (LLF) forms the basis of the credit risk module (Gaffney et al. 2014). Credit risk losses are estimated for the residential mortgage, non-financial corporate and household consumer lending books. Residential mortgage exposures are split across geographies, and non-financial exposures by geography and sector. The model covers all Irish retail banks, covering 95 percent of the total domestic exposure held by banks operating in Ireland. We project credit risk parameters at a loan-level for the probability of default (PD), loss given default (LGD) and exposure at default (EAD). The product of these components is used to obtain estimates for expected credit losses over the scenario horizon (Gaffney et al, 2014), which affects a bank's capital position through impairment. Additionally, following Gaffney & McCann (2019) the modelling approach reflects the latest accounting framework for expected losses, namely the IFRS 9 expected credit loss (ECL) framework[4].

Each PD model is determined by a unique set of covariates[5]. For example, in the residential Irish PD model, besides loan and borrower specific characteristics, the probability of default is determined by regional unemployment[6], loan-to-value and the change in loan instalment amount. Should macroeconomic projections for unemployment and house prices deteriorate and interest rates increase, this will increase the probability of borrower default through increased repayment burdens, higher loan to value ratios, and greater unemployment

The path of risk-weighted assets over the stress test horizon is estimated in the RWA module. The change in risk weights is endogenously determined, given the stressed credit risk parameters estimated in the credit risk module. To estimate risk weights on Internal Ratings Based (IRB) loans, we follow the Basel treatment of IRB loans and apply the formulas provided in article 153-154 of the Capital Requirements Regulation (CRR). To ensure a common starting point for the IRB risk exposure calculation we use loan-level IRB parameters and exposure values reported to the Central Bank of Ireland in the loan-level data return (LLD). To stress these parameters we use the stressed parameters output from the LLF. The change in LLF modelled parameters is calculated for each scenario-year and this change is used to "stress" the bank submitted IRB parameters. The stressed bank submitted IRB parameters are then used as inputs in the IRB Basel formulas to calculate the stressed risk weighted assets. The risk exposure amount for loans that follow the standardised approach remain steady at their starting point values.

For Irish retail banks, the predominant source of income is net interest income. The profitability module translates projections on interest rates and assumptions on balance sheet growth into interest income and expense.[7] Similar to the credit risk module, we estimate interest income at a loan-level. Interest expense is estimated at the portfolio level, as deposit information is not available at deposit account level. Based on starting balances and interest rates on loans and deposits, the module calculates interest income and interest expenses dependent on the macro scenario projections.[8]

Lastly, bank level capital depletion is aggregated to estimate the impact on the system-wide capital position for a given macroeconomic projection. The capital position, under a risk-based perspective, is

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[4] In 2014, the International Accounting Standards Board (IASB) issued the International Financial Reporting Standard (IFRS 9). A key development within the IFRS 9 accounting reforms is the inclusion of the expected credit loss (ECL) model. The ECL model replaced the "incurred loss" approach in impairment models and is designed to take into account more forward-looking information.

[5] The PD models follow a transition matrix approach of Jackson (2011) and provide estimates of the probability of transition into and out of loan default. The IE and UK residential models are detailed in Kelly & O'Malley (2016) and McCann et al (2014), respectively. Separate sector level corporate PD models are estimated for small and medium enterprises (SMEs), commercial real estate (CRE) and non-financial corporates (NFC).

[6] We add a layer of granularity in our PD model by introducing variation in regional unemployment rates. Changes in regional unemployment rates are pinned down by changes in the national rate.

[7] Other income sources are less material for the Irish retail banking sector. Haircuts are assumed under the adverse for NFCI, dividend income and market risk items. Profits are taxed at the rate paid at the respective reporting date and dividend distributions are capped at 30% where a bank is profit making. See appendix A for a stylized illustration of the profit and loss account.

[8] See Table A1 in Appendix A for further details on interest rate pass-through coefficients used in the profitability module.

reflected through both the common equity tier 1 (CET1) and total capital ratios. Consequently, the capital position may change due to changes in the level of capital (numerator) but also through changes in the stock of risk-weighted assets (denominator). Both of these channels operate through the capital account.

4. Macroeconomic Block

The macroeconomic block comprises two macroeconomic models that interact with the bank-level block in a number of ways. The model run process is described below, focusing on the role of the macroeconomic block. These steps describe the process for using the macroeconomic models to generate scenario amplification in addition to credit supply inputs to the dynamic balance sheet.

1. To begin with, macroeconomic scenarios for unemployment, house prices, CRE prices, inflation and monetary policy are generated exogenously using the Bank's large-scale macroeconomic model (COSMO) and growth-at-risk models. These scenarios are input as conditional assumption paths into a reduced-form conditional forecasting module (bottom left of Figure 1). This conditional forecasting module is used to forecast credit demand paths for household and non-financial corporate lending.
2. These scenarios interact with the loan-level models within the Bank level block, influencing the balance sheet and profit and loss accounts across individual banks. This process generates paths for CET1 capital resulting from the realisation of the input macroeconomic scenarios for first year of the model run.
3. The derived path for CET1 capital from the Bank-level block is used to calibrate a capital deleveraging shock in a Structural Vector Autoregression (SVAR) model (bottom right of Figure 1). This calibration is sensitive to both the scale of capital depletion, and banks' initial level of capital headroom, as explained below in Section 4.1.[9] The SVAR generates impulse responses for unemployment, credit supply (for households and non-financial corporations) and lending rates, in addition to other control variables in line with the scale of capital depletion emanating from the Bank-level block.
4. Impulse responses for unemployment and credit supply are used to update the assumption paths in the conditional forecasting module. The conditional forecasting module is re-run and generates updated paths for house prices and commercial real estate prices for the macroeconomic scenario in year two. This step describes the scenario amplification channel within the model.
5. Along with the demand forecast (generated in step 1), the impulse response function for credit supply is also used as an input into the dynamic balance sheet to drive new lending volumes.
6. Steps 2-5 above are repeated for each of the three annual model iterations.

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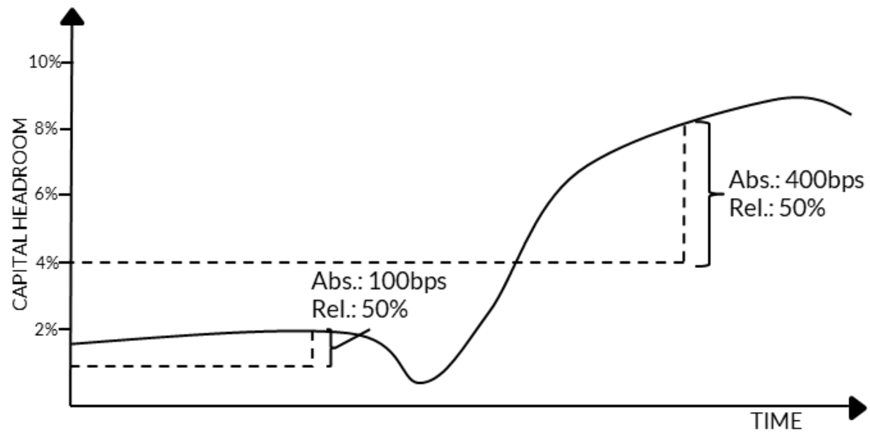
[9] Capital headroom in our framework is defines as the quantity of CET1 capital held in excess of regulatory requirements.

4.1 Capital Headroom and Credit Supply – Non-linearity

A key finding in the bank-capital-bank-lending literature is the non-linearity in the supply of bank credit given changes in bank capital (Berrospide et al. 2010; Carlson et al. 2013; Catalan et al. 2017). Specifically, banks with relatively low levels of initial capital[10], tend to adjust credit standards more aggressively when experiencing a decline in capital in comparison to banks with relatively high capital ratios (where minimum regulatory capital ratios are less binding). Within the Irish banking system, while all retail banks operate with a buffer of capital above minimum requirements, there is heterogeneity in the scale of this buffer across banks. A bank with larger capital headroom may be under less pressure to deleverage to protect their capital position for a given depletion in capital. To account for this in our model, we use a relative scaling approach (rather than absolute depletion), where the size of the capital shock that is fed into the SVAR is linked to the size of banks' initial capital ratio. Using a relative, rather than absolute, approach also reflects the fact that during the first half of the dataset used for empirical estimation (2003-2011) banks were more responsive to fluctuations in capital headroom due to the fact that capital headroom was lower than during the post-crisis period (2011-2021). Figure 3 below illustrates the difference between the two types of approach.

Figure 3: Illustration of absolute and relative approach to scale capital depletion in the model



Notes: The solid line shows a hypothetical path for capital headroom over time. Where banks have low levels of capital headroom, a comparable solvency shock in absolute values is likely to translate into a larger deleveraging response than when banks have larger levels of capital headroom. In the example above, where capital headroom is 2%, a 100bps absolute (Abs.) depletion equates to a 50% relative (Rel.) depletion. On the other hand, where headroom is 8%, a 400bps absolute (Abs.) depletion also equates to a 50% relative (Rel.) depletion.

As shown in Figure 3, a 100bps depletion in CET1 from the bank-level block would translate into a 50% relative shock to the capital headroom SVAR series where starting headroom is 2 percentage points. On the other hand, it would take a larger 400bps depletion from the bank-level block to translate into a 50% relative shock to capital where starting headroom is 8 percentage points (closer

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[10] Where the regulatory minimum capital ratios are closer to binding i.e. banks have less capital headroom, defined as the difference between the actual capital ratio and minimum regulatory required ratio.

to what it is for Irish banks in the post-crisis period). In this way, a bank with lower initial capital headroom would tend to deleverage more aggressively in response to an adverse shock.

4.2 Dynamic Balance Sheet

The assumption of a dynamic balance sheet marks a key departure from microprudential stress testing, explicitly modelling the way in which banks may react when put under stress. In our framework, the dynamic balance sheet module (DBS) captures two channels which impact the size of banks' balance sheets over a stress test scenario. First, the DBS calculates the amortisation schedule at a loan-level. This is largely deterministic in that the rate of amortisation is dictated by pre-determined variables known at the start of each period such as term, $Term_t$, interest rate, Int_t, and product type, $Type_t$. There is a stochastic element in the amortisation function since we assume that defaulted loans do not amortise.[11] Formally, the rate of amortisation between two periods is given by:

$$Amort_{t,t+1} = F(Term_t, Int_t, Type_t, \mathbb{E}_t[Perf_t]) \tag{1}$$

Secondly, the DBS maps changes in macroeconomic conditions into changes in new lending at a bank-level. Specifically, the DBS takes, as inputs, the joint forecasts for credit demand and credit supply to inform new lending paths over the scenario horizon. Here we assume credit disequilibrium, whereby movements in the interest rate do not guarantee market clearing between demand and supply due to the presence of non-interest credit standards (in line with Couaillier et al. 2019). Credit demand and supply are estimated separately and new lending is determined by the minimum of the credit demand and credit supply forecast. An excess of demand implies that banks are the binding constraint on lending due to non-interest rate credit standards pushing them to reject a portion of credit demand. An excess of supply means that these lending standards are sufficiently loose to cover all demand in the economy.

$$NLend_{t,t+1} = min(Demand_t, Supply_t) \tag{2}$$

Intuitively, the minimum function imposes a constraint that either: (i) banks cannot supply more credit than that demanded by the real economy and (ii) the real economy cannot receive more credit than the level willing to be supplied by the banking system. Once the quantity of new lending is determined, the module creates new artificial loans that, in aggregate, sum to the quantity of new lending determined in (2).[12] These new loans are drawn at random from the latest year of actual loan origination across the banks. We restrict these new loans to be IFRS9 stage one at origination, although these loans may deteriorate across scenario years under an adverse economic scenario.

[11] A loan's default status can vary over the scenario horizon in line with the severity of macro shocks

[12] In our framework, new lending takes the form of mortgages and commercial lending since these account for a large share of total assets in the Irish banking system. Furthermore, we assume that banks do not offset changes in capital by increasing debt, such that the adjustment occurs through changes in the size of their loan portfolios.

In addition to amortisation and new lending, we make the assumption that corporate borrowers will utilise existing approved lines of credit on a greater scale under an adverse scenario, which will have a positive effect on the banks' on-balance sheet exposures. The aggregate net effect on bank's balance sheet size therefore, will be determined by the relative magnitudes of the amortisation function (which reduces total on-balance sheet assets) and the new lending and undrawn assumptions (which both expand total on-balance sheet assets). If the macroeconomic scenario is sufficiently adverse, the collapse in bank lending may lead to a contraction in balance sheet size as banks seek to preserve capital by reducing risk weighted assets.

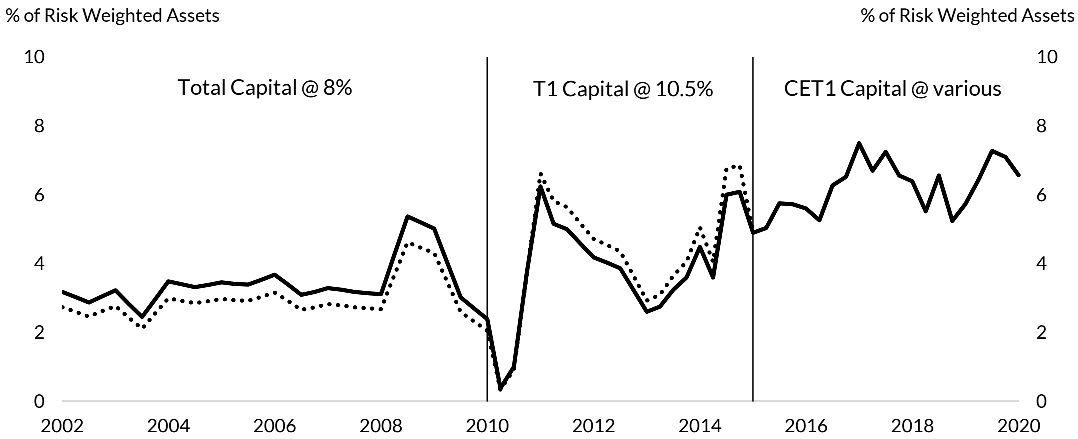
4.3 Data Inputs

The key data input in the bank-level model is a unique loan level dataset collected by the Central Bank of Ireland. Loan Level Data (LLD) are used as primary model inputs in the residential and commercial Loan Loss Forecasting (LLF) credit risk models. The LLD were initially collected as part of the Financial Measures Program (FMP), March 2011 and have been collected every 6 months since. The LLD includes data submissions from the five main retail banks (AIB, BOI, PTSB, KBC and UBIDAC). Each biannual data submission involves a full snapshot of all loans outstanding on each of the bank's loan books. To model the impact on bank profitability and solvency, detailed bank level information on the income statement and capital account is required. For this, we use the EU regulatory reporting datasets FINREP and COREP which provide full income and capital account information for each bank. We use these data as starting points for both accounts.

Our chosen measure of capital in the analysis is the management buffer (or headroom), defined as the gap between the actual capital ratio and the regulatory requirement. We aim to capture time variation in capital requirements in order to capture the key headline capital target for Irish banks over time. This includes a total capital requirement of 8% from 2003-2011, a Tier 1 capital requirement following PCAR Stress tests of 10.5% from 2011-2016, and finally a CET1 target which varies by institution thereafter. Given the structural breaks in the definition of required capital, we rescaled the series via backward extrapolation. Data for the earlier series (pre 2014) is sourced from Bloomberg with the latter half of the series (2014-2021) sourced from COREP regulatory returns (Figure 4). Appendix C provides further information on data sets and sources used in the model.

It is important to caveat some limitations in the capital headroom series shown in Figure 4, largely as a result of the changes in capital regulation over time. First, as a result of these regulations, a level of CET1 capital headroom of 6 per cent in 2016 does not mean the same thing as a level of total capital headroom of 6 per cent in 2002. The former definition is made up entirely of the highest quality of capital, which has better loss absorbing properties than the broader definition. Furthermore, by focussing on capital headroom, we are not fully capturing the full extent of capitalisation in the banking system (we are missing the capital requirement element, which is also increasing over time). Second, there was a sizeable bank bail-out during the financial crisis period in Ireland. During this time, equity injections from the government are likely to have had atypical implications for banks' lending decisions notwithstanding the economic situation at the time.

Figure 4: Construction of the Capital Headroom Series



Source: Bloomberg and banks' regulatory returns (COREP)
Notes: The dashed lines represent the former (unscaled) capital headroom series, while the solid continuous line represents the final (scaled) version of the capital headroom series used in the model. Scaling is necessary to account for the changing base definition of target capital over the time series. The three periods separated by the vertical lines indicate the changing regimes relating to Basel implementation or the response of the central bank to the crisis. Post 2015, the CET1 capital requirements have varied by institution.

5. Macroeconomic Effects

In this section we provide detail on the macroeconomic models used within the MaPST model. The central component of the macroeconomic block is the Structural Vector Autoregression (SVAR) model. This model estimates the macroeconomic implications of the solvency shock obtained from the Bank-level model. These macroeconomic effects are assumed to stem from a deleveraging response by the financial sector via a reduction in the supply of credit into the economy, and an increase in lending rates. The Impulse Response Functions (IRFs) obtained from the SVAR determine the scale of the scenario amplification for the following year of the model run, via the conditional forecast model. The output of the SVAR also drives the credit supply channel within the dynamic balance sheet.

5.1 SVAR Model

The Structural VAR model begins with estimation of the reduced-form VAR model. This requires regressing the vector of dependent variables across time on their own lags, and lags of the independent variables. The reduced form notation is below:

$$y_t = C_a + \sum_{j=1}^{m} A_j y_{t-j} + U_t \qquad 3$$

where y_t is a vector containing the model's endogenous variables, C_a are constant terms, A_j for j=1,...,p describes the coefficient matrices, and U_t are the residuals with $N(0, \sum)$ where $\sum$ denotes the residual variance-covariance matrix. The number of lags is given by m.The issue with using the reduced-form version of the model for our purposes is that there is correlation across the error terms in U_t, and therefore it is incorrect to apply economic intuition to identify singular innovations (in our case a "capital deleveraging shock" is not identifiable using a reduced-form specification). However, the residual terms can be expressed as a linear combination of structural innovations, $U_t = B_0^{-1}\epsilon_t$, where B_0 is a non-singular parameter matrix and $\epsilon \sim N(0, I_n)$ where I_n is an identity matrix. The model in structural form is as follows:

$$B_0 y_t = C_b + \sum_{j=1}^{m} B_j y_{t-j} + \epsilon_t \quad (4)$$

In order to derive B_0 and identify the SVAR, $n(n-1)/2$ restrictions are needed. Given that identification via recursive ordering involves some rigid assumptions about the directional co-movement among variables, we use a more robust and theoretically founded approach - imposing sign and zero restrictions on the impulse responses. Using sign restrictions we are able to restrict $B_0$to a range from which we can gather informative estimates. The data and estimation process, including the matrix of imposed restrictions are summarised in the following section.[13]

5.2 Data and Estimation Approach

The specification used for the model includes demand, supply, monetary and capital deleveraging shocks. The key shock of interest is the capital deleveraging shock, while the additional shocks are used to help identify this shock, in line with Paustian (2007). The quarterly sample of data we use for the estimation spans from January 2003 to December 2020. A challenge for our analysis is that this relatively short time period contains extended periods of macro-financial volatility and subsequent changes in the regulatory landscape. While we leave it to future iterations of this model to capture a wider array of shocks via our identification scheme (which is discussed below), we partly address changes in the regulatory landscape via the changes to capital requirements (in both target and size) incorporated into our measure of capital headroom (shown in Figure 4). Furthermore, given that the *Bank-Level Block* within our model is loan-level, other regulatory changes occurring during the time series (such as the Central Bank of Ireland's Mortgage Measures, introduced in 2015) will be reflected via individual borrower credit metrics, which are a key determinant of capital depletion.

[13] For more information on the estimation procedure we follow when implementing zero and sign restrictions see Arias et al (2019).

The variables we include as endogenous are unemployment, HICP, Euribor, lending rates, new lending for mortgages, new lending for NFCs, equity prices and our measure of capital headroom.[14] As a measure investor risk appetite, Irish equity prices are included as an additional proxy for real economic performance in the absence of Gross Domestic Product (GDP). All variables enter the VAR in log differences, except for unemployment, the lending rate and Euribor, which enter in differences. The equations include three lags and a constant term. We use Bayesian estimation techniques to estimate the reduced-form, with Bayesian shrinkage on the priors. Our approach uses Minnesota priors and, in line with Banbura et al. (2010), the degree of shrinkage is set in relation to the cross-sectional dimension of the VAR.[15]

Table 2 – Identification via Sign Restrictions

Variable/shock	Aggregate Demand	Aggregate Supply	Monetary Policy	Capital (Deleveraging)
Unemployment	+	+	+	0
HICP	-	+	-	NA
Euribor	-	NA	+	NA
Lending Rates	-	NA	NA	+
New Lending MTG	-	NA	NA	-
New Lending NFC	-	NA	NA	-
Equity Prices	NA	-	NA	-
Capital Headroom	NA	NA	NA	-

Source: Authors' own calculations.
Notes: "+" and "-"denotes a positive and negative sign restriction on a respective variable's impulse response to a given shock respectively. "NA" indicates no sign restriction is imposed.

Table 2 provides an overview of the sign restrictions imposed on the impulse response functions of the model, and the impulse responses for each specified shock are included in Appendix B. [16] All sign restrictions are imposed on impact. We follow the well-established signs for aggregate demand and supply shocks, whereby negative shocks lead to an increase in unemployment with a decrease in the level of inflation for demand shocks, while supply shocks have the opposite effect on inflation. For aggregate demand shocks we also assume a negative sign on the Euribor, lending rates and new lending. For the contractionary monetary policy shock we assume a positive sign on Euribor, an increase in unemployment and a decrease in inflation. The majority of papers in the literature choose to identify a loan supply shock (rather than a capital shock). However, including the capital series is necessary for calibration purposes in our model, and inclusion of a capital shock is consistent with our underlying assumption that banks respond to solvency concerns via deleveraging. In line with Budnik et al (2019) we apply a zero restriction on unemployment to further distinguish the shock from aggregate demand

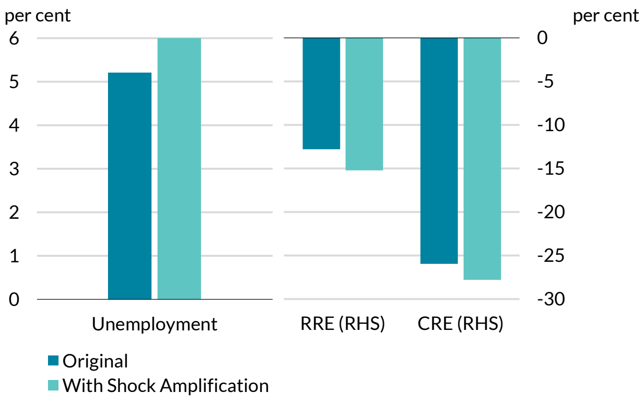
[14] Since Irish macroeconomic variables are unlikely to cause a response in the Euribor rate, we will alter the assumption that Euribor is an endogenous variable in future iterations of this model. However, since Ireland is a small open economy Irish economic performance is likely to be correlated to economic performance elsewhere in the euro area, and therefore we might expect to see a response in Euribor within the identified aggregate demand shock.
[15] For full detail on the estimation of priors in our model, see Banbura et al (2010).
[16] We achieve only partial set identification with the inclusion of four shocks in our structural identification, for future iterations of this model we strive to incorporate additional shocks in attempt to capture a broader range of innovations that may have occurred over our time sample

and supply shocks. For the other variables we assume the same sign on lending, equity prices and capital headroom and the opposite sign for the lending rate, consistent with Gambetti and Musso (2017) where banks attempt to reduce the supply of credit by both increasing the lending rate and reducing lending volumes.

6. Model Application

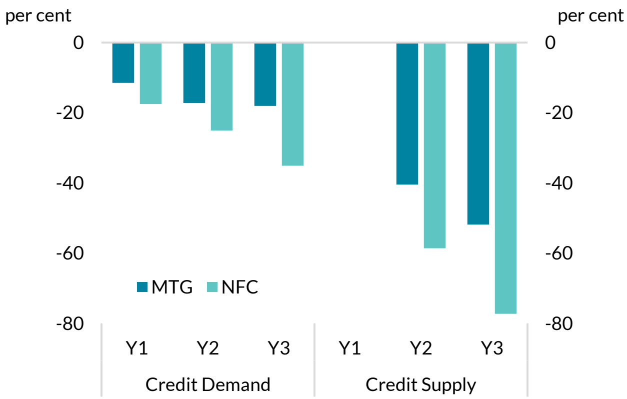
In this section, we illustrate the key model mechanics using as an example the scenario generated by the CBI in FSR 2022:1. This exercise highlights the model's use in assessing the likely extent of amplification under various paths for the CCyB. In particular, we demonstrate the macroeconomic implications of releasing capital following an adverse shock. In demonstrating the use of our model, we consider the recent scenario used to inform the Bank's decisions on the appropriate level of the CCyB.[17] The scenario was estimated using the Banks macroeconomic forecasting models.[18] The scenario was calibrated to reflect both the cyclical position of the Irish economy, and the risk narrative presented in Central Bank of Ireland (2022).

Figure 5(a): Scenario Amplification



Source: Authors' own calculations.
Notes: The chart shows the evolution of key macroeconomic variables over the scenario horizon with and without the impact of banking sector amplification. The unemployment series presented reflects the difference between the starting point of inflation and the max unemployment rate attained over the scenario (left axis). The CRE and RRE series reflect the cumulative growth rates over the scenario (right axis).

Chart 5(b): Credit Supply/Demand



Source: Authors' own calculations.
Note: The chart shows the new lending responses for mortgages (MTG) and non-financial corporations (NFC) over the scenario. Note that there is no credit supply response in Y1 as we assume that banks adjust credit with a lag.

Figure 5(a) reports changes in key macroeconomic variables under the initial scenario, and those that pertain after the impact of banking sector amplification. As can be seen, our MaPST framework

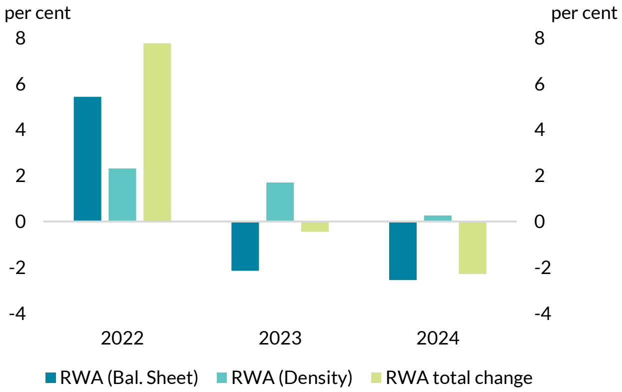
[17] See Box F in Central Bank of Ireland Financial Stability Review 2022:1
https://www.centralbank.ie/docs/default-source/publications/financial-stability-review/financial-stability/financial-stability-review-2022-i.pdf?sfvrsn=3e74961d_5

[18] CBI Growth at Risk models were combined with large macroeconomic models. Of these, NiGEM model was used to generate the global shocks while COSMO was used to estimate the impact of the global shocks on the Irish economy and to incorporate the Irish specific elements of the scenario. NiGEM is a global economic model developed by the National Institute of Economic and Social Research in the UK. COSMO is a model of the Irish economy used by the Central Bank. See Bergin et al (2017) and Conefrey et al (2018) for more details.

endogenously generates systemic risk as shock amplification via the banking system leads to a further deterioration in macroeconomic conditions, reflected in higher unemployment and more severe falls in real estate prices relative to the original macroeconomic scenario.

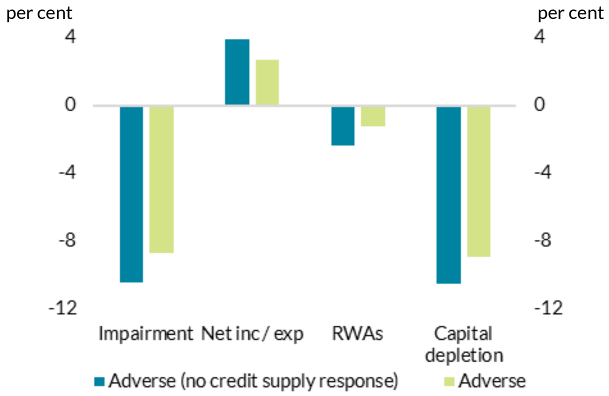
The key mechanism underpinning shock amplification is the contraction in bank credit as banks seek to preserve their capital through shedding risk weighted assets (RWAs). Changes in credit supply and demand over the scenario are reported in Figure 5(b). Intuitively, credit demand contracts over the scenario as the prevailing macroeconomic deterioration constrains the demand for investment and consumption. Additionally, credit supply also declines as banks adjust credit conditions due to the strain on capital resources absorbing an increase in credit risk. At a portfolio level, the bank lending response to NFCs exhibits a much sharper decline relative to the response on mortgage lending. This finding is consistent with a large body of empirical evidence (Bridges et al. 2014; Noss and Toffano 2016; Meeks 2017; Kanngiesser et al. 2020) and appears to be indicative of both supply and demand forces, as banks shift their lending away from exposures that attract relatively high risk weights and corporate credit demand falls faster than household mortgage demand. Taken together, the larger contraction in credit supply relative to demand implies a further weakening of the macroeconomy via credit-crunch type dynamics emanating from the banking sector.

Figure 6(a): RWA Movements



Source: Authors' own calculations.
Notes: The chart shows the competing effects driving RWAs over the scenario. On the one hand, changes in new lending and the drawing down of exposures impact RWAs through changes in total exposures (RWA (Bal. Sheet)), on the other, changes in risk densities also drives RWAs in line with changes in credit risk (RWA (Density)). The net effect of these two competing forces is captured by "RWA total change".

Figure 6(b): Capital Depletion



Source: Authors' own calculations.
Note: The chart shows the respective waterfalls for the main model run (Adverse) and when the bank slowdown in credit supply is shut off (Adverse (no credit supply response)).

As discussed in Section 3.2, the size of bank balance sheets and, by construction, the stock of risk weighted assets (RWAs) will be influenced by both amortisation (which decreases RWAs) and new lending (which increases RWAs). Figure 6(a) plots the net impact of these two competing effects, while Figure A5 in Appendix D shows the individual contribution of the underlying drivers in more detail. In Figure 6(a), for year 1 of the scenario, an expansion of RWAs is observed since the additional exposures owing to new lending and the drawing down of undrawn credit facilities exceed amortisation. Conversely in years 2 and 3, the sharp contraction in new lending does not offset the impact of amortisation resulting in a reduction of RWAs through the balance sheet channel. Additionally, RWAs are a function of the macroeconomic environment as the credit risk parameters used in their calculation (Section 2.2) will vary with the severity of the scenario (RWA density). Intuitively, higher RWA densities increase the stock of RWAs over the scenario in line with the deteriorating macroeconomic environment.

In years 2 and 3 of the scenario, the reduction in total exposures dominates the impact of higher densities such that RWAs decline in these two years. Such deleveraging is a powerful mechanism in which banks can preserve capital when under stress. To further illustrate how large-scale deleveraging can offset declines in bank capital, in Figure 6(b) we include capital depletion waterfalls with both the main model run (*Adverse*) and a run where we impose the restriction that the reduction in bank credit is equal to the credit demand path over the same scenario (*Adverse (no credit supply response)*). In the latter case, new lending follows the path of credit demand and banks lend at greater volumes relative to the case in which they are able to restrict credit supply after the shock. Larger volumes of new lending increase bank profitability through net interest income but also increase risk weighted assets and credit losses.[19] The net effect is that if the credit supply channel is shut off, capital depletion is greater (Figure 6(b)), highlighting the beneficial effects of the credit supply response from the perspective of the banking sector. Despite these beneficial effects, the negative impact of contracting credit supply on the economy increases the probability of default across the lending portfolio through higher unemployment and negative impacts on macroeconomic variables, which is evident from the difference in PDs between the two scenarios (see Appendix E).

Having shown that the mechanisms of our model endogenously determine scenario amplification, and the dynamic balance sheet response, next we use a simple example to illustrate how our framework may be used to consider the role of macroprudential policy. In particular, we focus on the imposition of the countercyclical capital buffer (CCyB)[20]. Recent research suggests that those banks holding relatively more capital at the onset of the recent pandemic reduced their lending to the real economy by less (Berrospide et al. 2022; Couaillier et al. 2022). This finding is indicative of the importance of having releasable capital that facilitates the banking system supporting the economy in a period of stress. To examine the value in having a stock of releasable capital in the system via the CCyB, we simulate the Irish banking sector on the same adverse scenario as described above under two counterfactual runs:

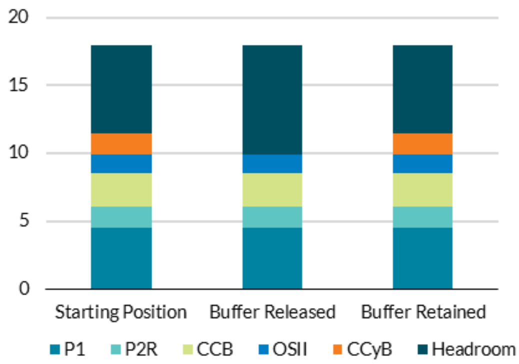
I. An existing CCyB rate of 1.5 percentage points is released, freeing up capital headroom in the event of a downturn ('*Buffer Released*' in Figure 7).

II. An existing CCyB rate of 1.5 percentage points is not released, and capital requirements remain the same in the event of a downturn ('*Buffer Retained*' in Figure 7).

[19] See Appendix F for more details on the evolution of the key credit risk metrics used to calculate impairments over the scenario – probability of default (PD) and loss given default (LGD).

[20] It is important to note that the CCyB is one of several capital buffers that banks hold to absorb losses associated with unexpected shocks. The CCyB, however, is fully releasable in the event of a downturn unlike other buffers that make up a bank's capital requirements.

Figure 7: Counterfactual Analysis



Source: COREP
Note: The chart reports the capital stack on aggregated for AIB, BOI and PTSB (weighted by risk weighted assets). "P1" denotes the pillar 1 requirements, "P2R" denotes the pillar 2 requirements, "CCB" denotes the capital conservation buffer, "CCyB" denotes the CCyB rate, "OSII" denotes the capital requirement for other systemically important institutions and "Headroom" denotes the level of CET1 capital held in excess of the preceding requirements. Under "Buffer Released" we assume that the starting CCyB rate of 1.5 per cent is released and becomes usable capital headroom. Under "Buffer Retained" we assume that the starting CCyB rate of 1.5 per cent is not released, thus requirements stay the same.

We present the results of these two exercises in Figures 8(a) – 8(f). Firstly, the impact on capital headroom is reported in Chart 8(a). Under *Buffer Released*, the impact of releasing the CCyB rate frees up additional capital headroom that persists over the entire scenario horizon. Mechanically, this is due to the additional 1.5 percentage points of headroom released in Year 1 that the sector carries forward. Additionally, however, because the banking sector (under *Buffer Released*) has relatively more headroom to absorb additional losses, the extent of shock amplification is attenuated. Consequently, more benign second-round effects owing to banking sector amplification under *Buffer Released* are more supportive of capital.

Figure 8(a): Capital Headroom

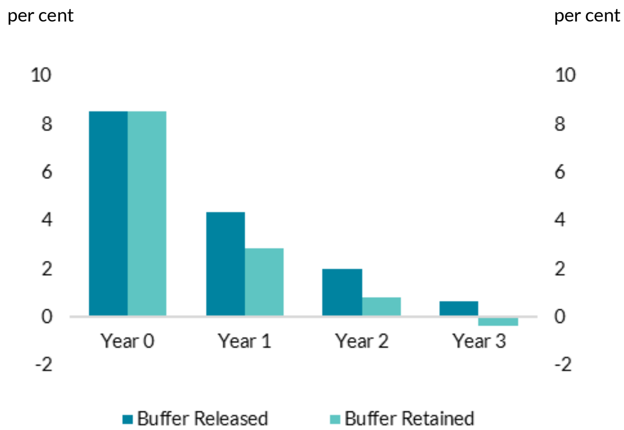


Figure 8(b): New Lending (Mortgages)

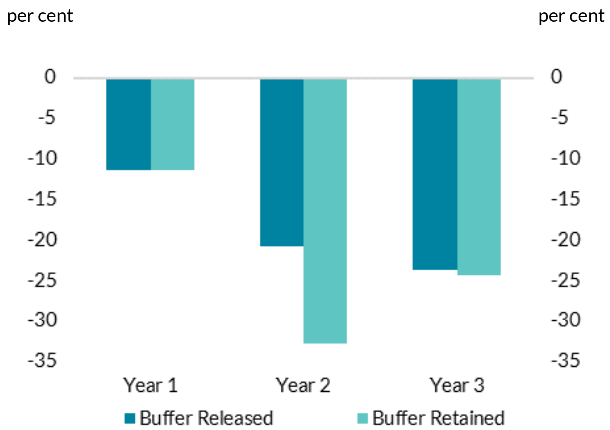


Figure 8(c): New Lending (NFCs)

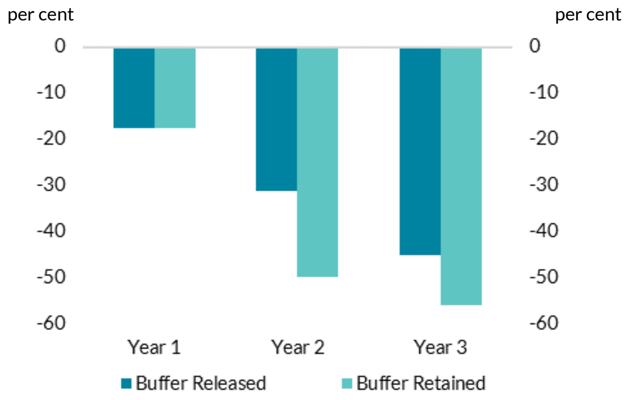


Figure 8(d): Residential Real Estate Prices

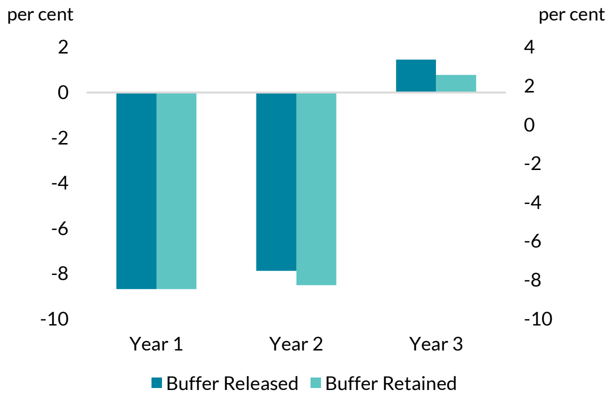


Figure 8(e): Commercial Real Estate Prices

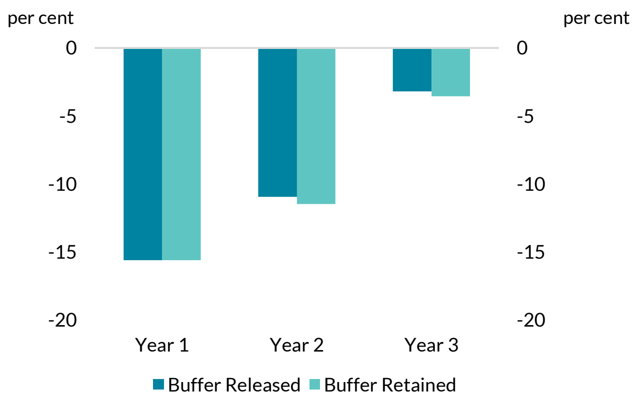
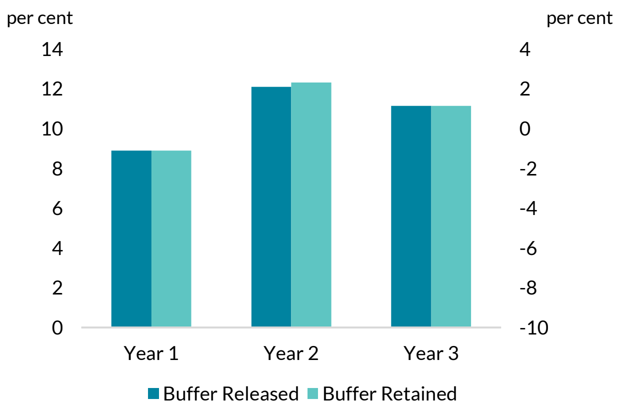


Figure 8(f): Unemployment



Source: Authors' own calculations
Notes: Under *Buffer Released* we impose that the release of the 1.5% CCyB rate occurs during year 1 of the scenario. We assume that the financial sector response (altering the path of credit) occurs in year 2 and 3 (i.e. with a lag). Under *Buffer Retained*, we assume that there is no release of the 1.5% CCyB in place that may be used to support the banking sector.

In terms of new lending volumes, the contraction in both mortgage and NFC lending is significantly lower in the instance that capital is released via the CCyB. As explained above, the release of additional capital bolsters the sector's capacity to absorb losses, subsequently reducing the tendency to deleverage in order to preserve capital. Unsurprisingly, the impact of banking sector amplification on key macroeconomic variables is relatively milder when capital is released under the CCyB (Figures 8(d) – 8(f)). This is explained through the smaller retrenchment in credit causing smaller falls in economic activity as borrowers are not as credit constrained as would be the case in the instance of no releasable capital. Consequently, less amplification is observed in the macroeconomy and is therefore relatively more supportive of capital (Figure 8(a)).

7. Conclusion

In this paper, we introduce our macroprudential stress testing framework. We show how we extend existing stress testing architecture along two dimensions to include important macroprudential elements. First, we relax the common assumption of the static balance sheet, such that the size of banks' balance sheets are estimated using macroeconomic models and in line with macroeconomic conditions. Second, interactions between the financial sector and the real economy are formally modelled through a financial sector amplification channel. Including these channels in our approach allows us to better understand both the impact of macroeconomic shocks on the solvency of the banking sector and the ability of the banking sector to continue to supply credit to the economy without disruption.

Using an illustrative application of the model, we show how we can capture financial feedback endogenously generated via banking sector amplification and how the deleveraging channel can have a significant impact on capital depletion. These modelled inter-linkages between the real economy and banking sector make this framework ideal to inform policy decisions on cyclical buffers such as the CCyB.

This model described in this paper represents the first version of a macroprudential stress testing model for the Irish retail banking system. The model will continue to be refined, and we have identified a number of areas requiring further development. To begin with, we aim to improve on the evolution the balance sheet over the scenario, with more focus given to the sensitivity of liabilities to macroeconomic developments. Second, we would like to incorporate the capital implications of fluctuations in funding conditions, in particular via incorporation of a feedback loop between funding conditions and solvency. Third, we aim to build on the macroeconomic components of the model, by introducing more shocks and constructing a fully-fledged version of structural scenario analysis (as per Antolin-Diaz et al. (2021). Forth, we aim to expand the sample of financial institutions in the model, to include non-bank financial institutions. Finally, at a further point, we envisage using our MaPST framework to incorporate climate risk considerations as well as expanding it to include the interactions of the banking sector with the broader financial sector, thus giving a more complete assessment of systemic risk.

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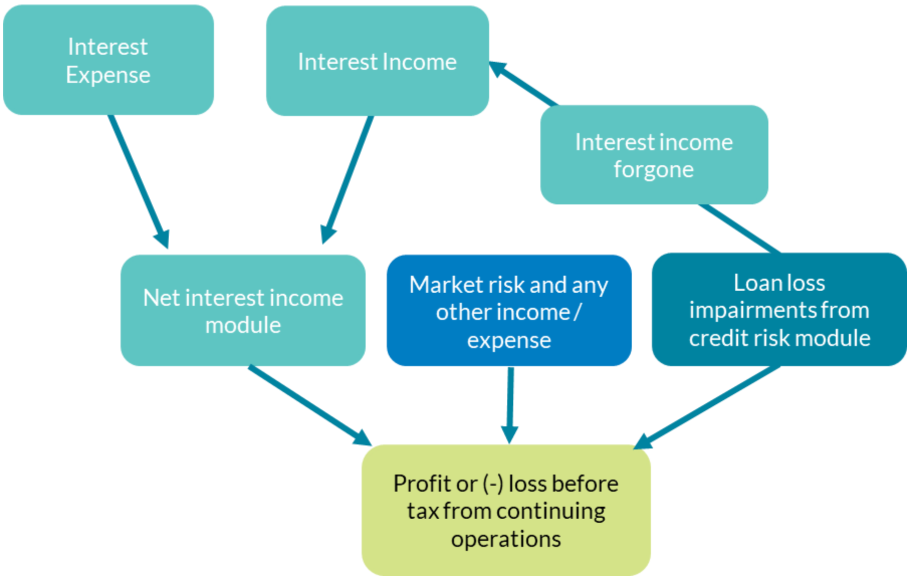
Appendices

Appendix A – Bank-level Profitability

Figure A1: Stylised illustration of the bank profit and loss account



Notes: The figure shows the main elements of the profit and loss account from the bank-level block. The profitability module estimates the net interest income from interest income and expense while also accounting for interest income forgone on assets that flow into default in the stressed scenario. The impact from the credit risk module enters the profit and loss account as loan loss impairments.

Table A1: Interest rate pass-through coefficients

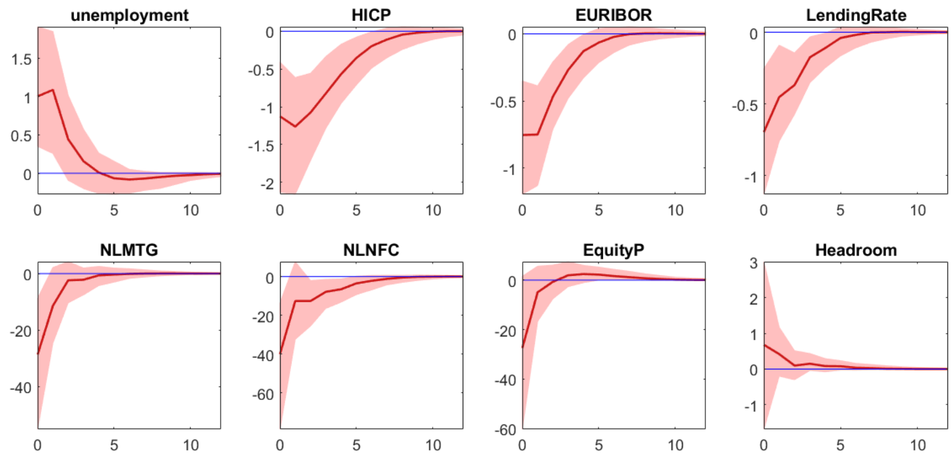
Deposit Portfolio	Pass through coefficient	Loan Portfolio	Pass through coefficient
Household Sight	0.26	Household mortgage	0.35
Household Term	0.83	NFC lending	0.65
NFC Sight	0.18	UK household mortgage	0.35
NFC Term	0.87		

Source: Central Bank of Ireland authors' calculations

Notes: The table shows the interest rate (3 month Euribor) pass-through coefficients to deposit and lending portfolios used in the interest income and interest expense estimations. For interest income, in terms of pass-through, there is a zero pass through applied to fixed rate loans while for tracker mortgages, a 100% pass-through is applied. For standard variable rate mortgages, the pass through is specified according to the pass-through coefficient (above) and varies by asset class (Residential v Commercial) and geography for household loans (IE or UK). For interest expense, the pass-through coefficients (above) are applied to the relevant deposit portfolio. Interest rate pass-through coefficients are estimated using monthly Irish aggregate new business rates from CBI credit and banking statistics 2003-2020 and an ARDL model in the spirit of Pesaran and Shin (1999) and Pesaran et al (2001). Loan rate pass-through coefficients are informed both through empirical estimation and evidence from the literature.

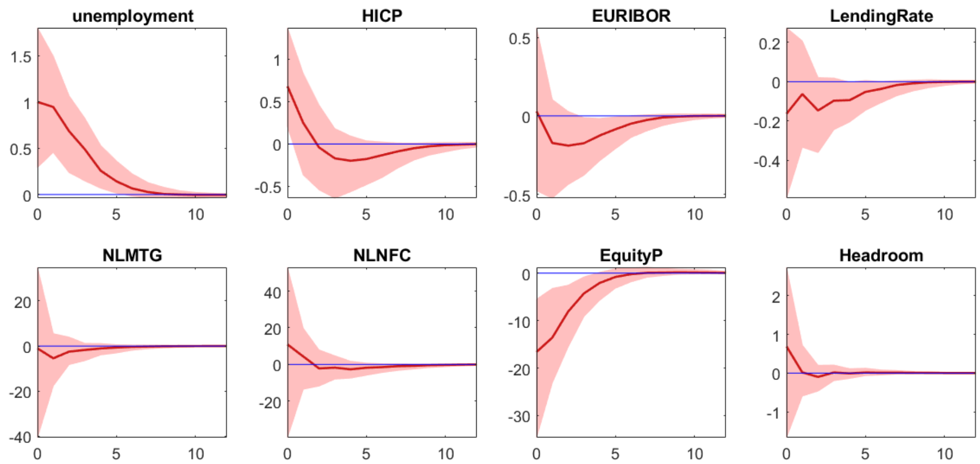
Appendix B – Impulse Response Functions

Figure A2: Negative Aggregate Demand Shock – Impulse Response Functions (non-cumulative)



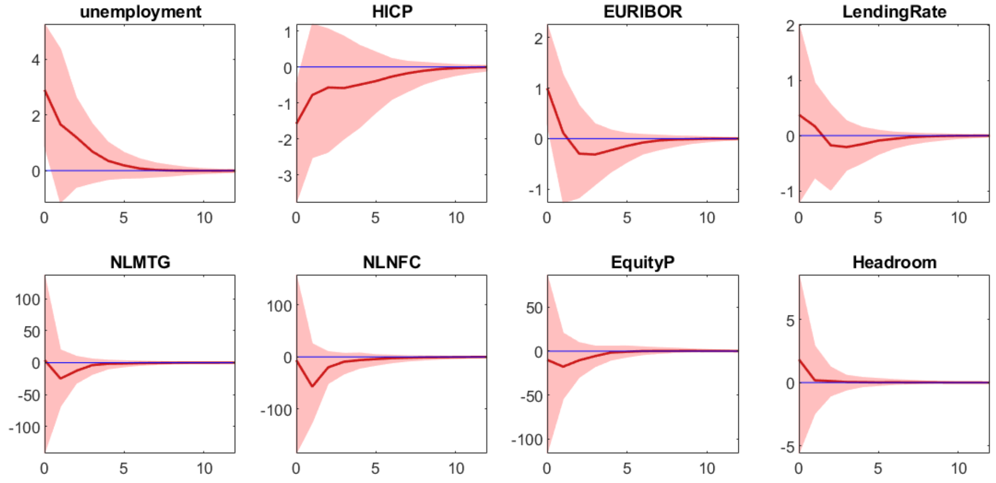
Source: Central Bank of Ireland authors' calculations
Notes: Shown are the impulse response functions for a 1pp. shock on impact to unemployment. The x-axes show the quarterly time horizon over three years. Confidence bands are at the 68% level. The cumulative shock (across all quarters) to unemployment is 2.4 p.p. Unemployment, Euribor and the lending rate should be interpreted by percentage points, while HICP, new lending MTG, new lending NFC, equity prices and capital headroom are in growth rates (%). Unemployment is the headline unemployment rate in first differences. HICP represents the Harmonised Index of Consumer Prices (all items) in log first differences. EURIBOR is the 3-month ECB interest rate in first differences. LendingRate is a weighted average of NFC and mortgage interest rates and is expressed in first differences. NLMTG is the total volume (€) of mortgage lending in log first differences. NLNFC is the total volume (€) of NFC lending in log first differences. EquityP is the quarterly average Irish equity prices (ISEQ) in log first differences. Headroom is the aggregate capital headroom across banks (p.p.) expressed in log first differences.

Figure A3: Negative Aggregate Supply Shock – Impulse Response Functions (non-cumulative)



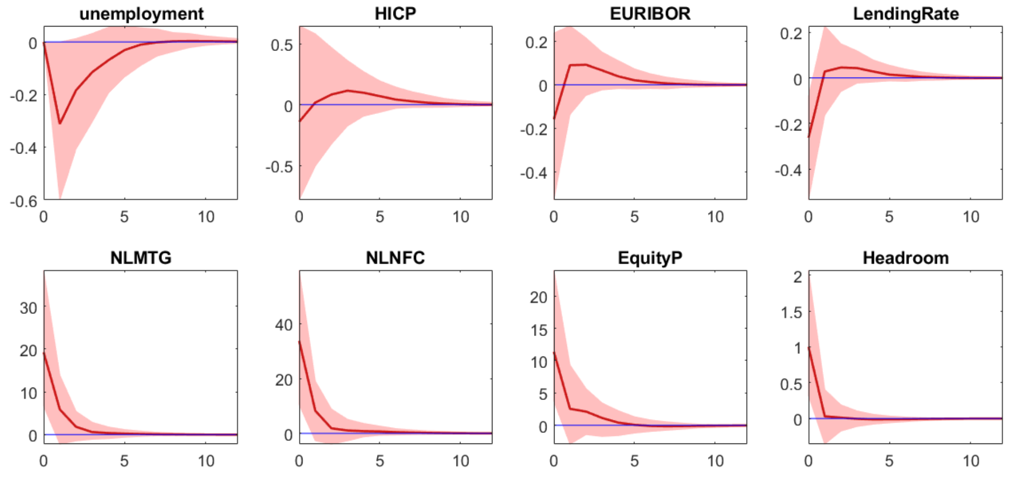
Source: Central Bank of Ireland authors' calculations
Notes: Shown are the impulse response functions for a 1pp. shock on impact to unemployment. The x-axes show the quarterly time horizon over three years. Confidence bands are at the 68% level. The cumulative shock (across all quarters) to unemployment is 3.6 p.p. Otherwise all other relevant details are covered in the note under Figure A1.

Figure A4: Contractionary Monetary Policy Shock – Impulse Response Functions (non-cumulative)



Source: Central Bank of Ireland authors' calculations
Notes: Shown are the impulse response functions for a positive 1pp. shock on impact to the 3-month Euribor. The x-axes show the quarterly time horizon over three years. Confidence bands are at the 68% level. Otherwise all other relevant details are covered in the note under Figure A1.

Figure A5: Negative Capital Headroom Shock – Impulse Response Functions (non-cumulative)



Source: Central Bank of Ireland authors' calculations
Notes: Shown are the impulse response functions for a negative 100% shock on impact to aggregate capital headroom. The x-axes show the quarterly time horizon over three years. Confidence bands are at the 68% level. Otherwise all other relevant details are covered in the note under Figure A1.

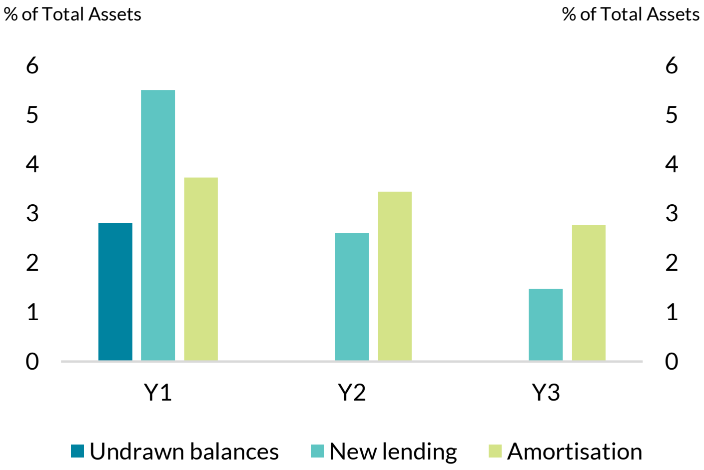
Appendix C – Data Sources

Data Series	Source	Description
Unemployment Rate	Irish Central Statistics Office (CSO)	Seasonally adjusted, 2003Q1 - 2021Q4
Harmonised Index of Consumer Prices (HICP	Irish Central Statistics Office (CSO)	All items, Seasonally adjusted, 2003Q1 - 2021Q4
Residential Real Estate Prices	Irish Central Statistics Office (CSO)	Index, seasonally adjusted, 2003Q1 - 2021Q4
Commercial Real Estate Prices	Morgan Stanley Capital International (MSCI)	Index, seasonally adjusted, 2003Q1 - 2021Q4
Euribor 3 month	ECB Statistical Data Warehouse (SDW)	3 month rate, 2003Q1 - 2021Q4
Lending Rates	Central Bank of Ireland	Balance-weighted average of NFC and mortgage lending rates, 2003Q1 - 2021q4
Bank Equity Prices	Thompson Reuters DataStream	Average equity prices for Irish banks weighted by capitalisation share, 2003Q1 - 2021Q4
10 Year Government Bond	Irish Central Statistics Office (CSO)	2003Q1 - 2021Q4
Capital Headroom	Bloomberg and Central Bank of Ireland Regulatory Returns Data	Authors' calculations using data on capital levels and RWA 2003Q1 - 2021Q4
New Lending Mortgages	ECB EMIR and Central Bank of Ireland	New lending volumes €, EMNIR from 2007 onwards and CBI pre-2007
New Lending Non-Financial Corporations	ECB EMIR and Central Bank of Ireland	New lending volumes €, EMNIR from 2007 onwards and CBI pre-2007

Appendix D – Net Balance Sheet

Figure A6 plots the evolution of undrawn balances, new lending and amortisation over the three year adverse scenario.[21] In year 1 of the scenario, an expansion of the balance sheet is observed since the additional exposures owing to new lending and the drawing down of undrawn credit facilities exceed amortisation. Conversely in years 2 and 3 of the scenario, amortisation exceeds new lending resulting in a reduction of exposures.

Figure A6: Illustration of Amortisation and New Lending in the Dynamic Balance Sheet Component of the Central Banks of Ireland's Macroprudential Stress Testing Model



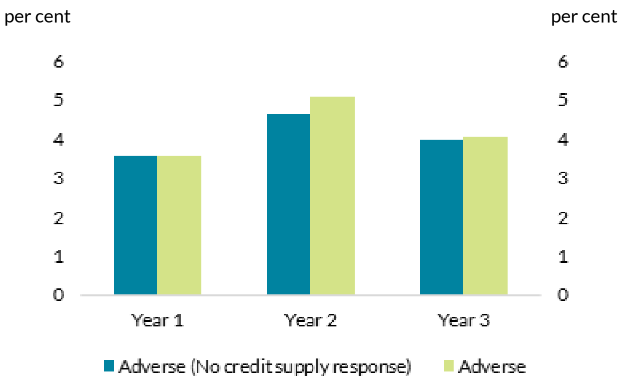
Source: Authors' own calculations.
Notes: The chart shows the competing forces driving the dynamic balance sheet over the scenario. Both undrawn balances and new lending expand the balance sheet, while amortisation leads to a decline.

[21] A standard assumption in our framework is that in year 1 of an adverse scenario, corporates drawdown 80 per cent of their undrawn credit facilities to bolster their liquidity position.

Appendix E – Probability of default amplification effects

Figure A7 plots the probability of default (aggregate household and NFC lending) over three years for two scenarios, adverse and adverse with no credit supply response. In year 1 probability of default are the same across both scenarios. In years 2 and 3 of the adverse scenario, default probabilities are larger due to amplification effects in the adverse scenario.

Figure A7: Probability of default

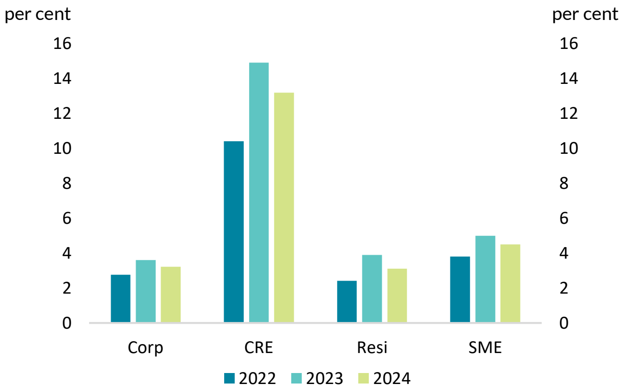


Source: Authors' own calculations.
Notes: The chart shows the probability of default over the scenario at an aggregate level for both household and NFC lending. The probability of default reported is computed by dividing the *t+1* flow of defaulted exposures by the time *t* stock of non-defaulted assets.

Appendix F – Credit Risk Metrics

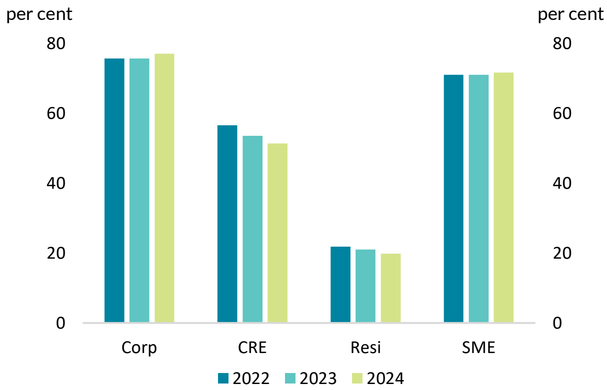
Figures A8 and A9 show the probability of default (PD) and loss given default (LGD) split by portfolio over the three year horizon of the adverse macroeconomic scenario introduced in Section 6. The main macroeconomic variable driving the probability of default on the commercial portfolio asset classes is the increase in unemployment in the adverse scenario. For the residential portfolios, house prices and interest rates (in addition to unemployment) are also important macroeconomic drivers. Under the adverse scenario in this example, commercial lending accounts for over 70% of new provisions while households account for just under 30%.

Chart A8: Probability of Default



Source: Authors' own calculations.
Notes: The chart shows the probability of default over the scenario at a portfolio level. "Corp" denotes lending to large corporates, "CRE" denotes commercial real estate lending", "Resi" denotes residential mortgage lending and "SME" denotes lending to small-medium enterprises. The probability of default reported is computed by dividing the *t+1* flow of defaulted exposures by the time *t* stock of non-defaulted assets.

Chart A9: Loss given Default



Source: Authors' own calculations.
Note: The chart shows the loss given default over the scenario at a portfolio level. "Corp" denotes lending to large corporates, "CRE" denotes commercial real estate lending", "Resi" denotes residential mortgage lending and "SME" denotes lending to small-medium enterprises. The loss given default reported is computed by dividing the expected losses by the flow of defaulted exposures.