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Abstract

We develop a Quick Stress Testing (QST) methodology to provide high-frequency assessments of the resilience of the Irish banking system under different adverse macro-financial outlooks. The framework accommodates both internally generated scenarios—whose severity depends on the credit cycle—and externally provided ones. We estimate the capital depletion banks would face under such scenarios by interacting them with bank balance-sheet sensitivities to macroeconomic outcomes, derived from European Banking Authority (EBA) data. Through Monte Carlo simulations, we then ensure we are considering severe enough yet plausible scenarios. A key advantage of our streamlined methodology is that it can be applied more frequently than conventional stress-testing exercises.

JEL classification: E58, G01, E32, G21.

Keywords: Stress Test, State-Dependent Local Projections, Macroprudential Policy, Credit Cycle, Bank Resilience.

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Non-Technical Summary

This paper presents the Quick Stress Testing (QST) methodology we developed to support timely and data-driven assessments of the Irish banking system resilience with regard to changing macro-financial conditions. Unlike macroprudential stress tests models, often resource intensive, the QST is designed for frequent use and allows for the evaluation of how adverse economic developments might affect bank capital levels.

The QST consists of three modules. The first module generates model-based scenarios whose severity depends on the level of cyclical risks. In particular, we assess how the credit cycle can amplify or dampen the transmission of unexpected monetary policy shocks to the Irish economy. We consider output growth, the unemployment rate, and residential house prices as our main macroeconomic outcomes. Considering that banks' capital resilience is also subject to a wider set of macroeconomic shocks, such as geopolitical or supply-side shocks, our methodology allows for the use of external scenarios—generated either by other models or by expert judgment. By incorporating such a wide range of scenarios, in the second module we estimate the resilience of banks to these events. Using EBA stress-test data, we assess how the final Common Equity Tier 1 (CET1) capital reacts to different macro-financial outlooks. Our estimates of capital depletion associated with each scenario support informed discussions on the stability of the Irish banking system across diverse macro-financial conditions. The third module proposes an approach to evaluate a wider range of scenarios along two key dimensions—severity and plausibility. In doing so, it aims to identify the macro-financial risk factors of particular relevance for the Irish banking system.

The QST methodology complements the Central Bank of Ireland Framework for Macroprudential Capital,[1] which incorporates the Macroprudential Stress Test (MPST) introduced in Morell et al. (2022)—alongside other qualitative and quantitative tools—to inform decisions on the calibration of the Countercyclical Capital Buffer (CCyB). The MPST provides a comprehensive assessment of the entire balance-sheet structure of Irish banks, estimating the potential capital depletion under both baseline and adverse scenarios. By making use of highly granular data, this approach allows for an in-depth understanding of the resilience of the banking system, although, like many bottom up stress tests, it is resource-intensive. In contrast, major benefits of the QST methodology is that it can be conducted at greater frequencies and it can incorporate easily multiple scenarios, making it ideally suited to perform quarterly evaluations of the resilience of Irish banks.

[1] "The Central Bank's Framework for Macroprudential Capital", June 2022.

1 Introduction

The Global Financial Crisis demonstrated the destructive feedback loops that can emerge when an economic downturn follows excessive credit growth. In such scenarios, significant banking sector losses trigger a vicious cycle: credit institutions restrict lending to strengthen their balance sheets, further deepening the downturn and exacerbating vulnerabilities. As a result, recent advances in stress-testing frameworks, such as the Central Bank of Ireland Macroprudential Stress Test (MPST, Morell et al., 2022) and others (Budnik et al., 2023; Anderson et al., 2022), have incorporated second-round effects, where deteriorating credit conditions amplify initial shocks. Yet, the complexity of these models and their reliance on loan-level data constrain their feasibility for high-frequency implementation (Hirtle et al., 2016). Moreover, their design typically limits the analysis to a narrow set of extremely severe, yet less plausible scenarios, reducing the scope to compare capital impacts across alternative macro-financial paths.

In this paper, we present the Quick Stress Testing (QST) methodology we developed to overcome these shortcomings and allow for rapid assessments of the resilience of the Irish banking system. The QST methodology contributes to the Central Bank analytical toolkit in two innovative ways. First, we generate macroeconomic scenarios whose severity depends on the level of cyclical risks. In particular, we explore how monetary policy shocks are transmitted to the Irish economy contingent on the Irish credit cycle. Second, the flexibility and simplicity of the framework allow for the comparison of a wide range of such scenarios in terms of their severity—defined as the cumulative capital depletion of Irish banks—and their plausibility, relative to the specific macro-financial dynamics of the Irish economy, to monitor financial stability risks and support macroprudential policy decisions.

Cyclical risks, often linked to excessive private-sector indebtedness or inflated asset prices, can magnify financial instability during downturns (Lang and Welz, 2018). However, while the early-warning properties of cyclical indicators are well-documented, their role in amplifying monetary policy shocks remains underexplored in the stress-testing literature. This gap underlines the need for models that integrate the credit cycle into scenario design, capturing its influence on capital adequacy during periods of heightened risk. The QST methodology addresses this challenge by proposing a streamlined approach that links macroeconomic scenarios to their plausibility with regard to historical data, and to the capital depletion they would cause for Irish banks, as a measure of severity. This facilitates the comparison of scenarios that are both relevant and realistic. To achieve this, the QST methodology is structured into three modules.

The first module assesses how exogenous monetary policy shocks impact the economy and generate recessionary macro-financial scenarios. Employing a smooth-transition local-projection (STLP) model with state dependence linked to the credit cycle, we examine how the leverage state of the economy can amplify or dampen the transmission of monetary policy shocks to the Irish economy. Specifically, we consider output, unemployment, and residential house prices to generate the corresponding trajectories, conditional on both high- and low-leverage states, as well as in the linear case.

The second module estimates how the balance-sheet components of banks similar to Irish ones would react to macroeconomic developments using data from European Banking Authority (EBA) EU-wide stress-test exercises. We interact the sensitivities of these components to macroeconomic outcomes with the scenario generated in the first module, or inputted from external sources, to obtain the final transitional common equity tier 1 (CET1) capital ratio and sub-components depletion, as a measure of the resilience of domestic Irish banks.

Finally, in the third module, we compare the outcomes of multiple scenarios in terms of severity and plausibility, to ensure we are considering scenarios which are both sufficiently severe and plausible in our stress-testing exercises. To that aim, we use a reverse stress-testing approach with Monte Carlo simulations to estimate the joint probability of any macroeconomic scenario conditional on its associated capital depletion.

By applying our methodology to Irish banks, we find that the economic state in which credit exceeds its long-run trend is associated with a stronger transmission of exogenous monetary policy shocks in the Irish economy. Overall, capital losses are driven by output and unemployment dynamics. The decomposition analysis indicates that credit risk is the dominant driver of capital depletion. In contrast, increases in residential house prices are linked to lower credit risk losses, possibly due to stronger collateral values, and are also associated with higher net interest income through increased credit volumes. Our plausibility assessment confirms that scenarios generating extreme capital depletion—such as those observed during the Global Financial Crisis or under the 2023 EBA stress tests assumptions—are less plausible on average than milder ones. Among scenarios associated with capital losses, only a small subset meets both severity and plausibility criteria, offering useful benchmarks for policy evaluation.

The remainder of this paper is as follows. Section 2 reviews the literature related to stress-test scenario design, while Section 3 outlines the methodology, detailing the three modules of our QST methodology. In Section 4, we present the results for each of the modules. Eventually, Section 5 concludes. Extensions and robustness checks of the framework are displayed in Section A.

2 Literature Review

From the existing literature, a closely related contribution for the first and second modules of the QST is Couaillier and Scalone (2024). Their Risk-to-Buffer framework generates scenarios based on cyclical risks, measured by the state of indebtedness of a given economy, and estimates bank sensitivities to GDP growth shocks in a stylised stress-test setup aimed at calibrating the countercyclical capital buffer (CCyB). We extend this approach by considering more granular data at the bank level and specific subcomponents of the CET1 capital ratio and profit and loss accounts, and we assess the specific impact of each macroeconomic variable featured in the input scenario. In our third module, we allow for the comparison of multiple scenarios in terms of severity and plausibility in a supplemental module, to ensure we are considering relevant exercises only. Therefore, our methodology relates to three streams of literature: first, on the generation of adverse scenarios suitable for stress-testing purposes; second, on the estimation of bank balance-sheet sensitivities to macroeconomic scenarios; and third, on the assessment of scenario severity and plausibility through reverse stress-testing.

2.1 Generation of Stress-Test Scenarios

The aim of stress-test exercises is to assess how the balance-sheets of banks would be affected by severe yet plausible macroeconomic shocks (Baudino et al., 2018). Adverse scenarios can be derived either from data-driven models or constructed narratively through expert judgment. In any case, according to Barbieri et al. (2022), stress-test scenarios become more severe during economic upswings, as financial-system vulnerabilities accumulate under these conditions, increasing the likelihood of pronounced cyclical downturns. This is consistent with empirical evidence showing that recessions following credit booms tend to be deeper, regardless of what triggers the recession. Stress-test scenarios should therefore be more severe during periods of exuberance, for instance when credit and asset prices are growing rapidly and risk premia are compressed, which usually coincides with times when markets and financial institutions perceive risks to be lowest. Accordingly, the Bank of England (BoE) conducts an annual exercise based on a countercyclical approach, where the severity of the stress-test scenarios is assumed to be higher as debt levels increase relative to GDP (Brazier, 2016).

An extensive literature has examined how the leverage cycle shapes the transmission of macroeconomic shocks, particularly those arising from monetary policy, with mixed evidence on its effects. Alpanda and Zubairy (2018), using a STLP model, found that high household indebtedness weakens the transmission of monetary policy *via* the home equity loan channel. Despite monetary stimuli positively influencing house prices and, consequently, home equity levels, high initial debt levels constrain borrowing capacity.[2] As follows, when debt stocks exceed equilibrium levels, borrowing constraints dampen the impact of lower interest rates on consumption and GDP. Similarly, Aikman et al. (2016), using a threshold VAR, observed that monetary policy tightening failed to reduce risk appetite, measured as the excess bond premium derived from corporate bond prices, during high credit cycle states, unlike in low credit-cycle states. Conversely, Rünstler and Bräuer (2020), Cloyne et al. (2020), and Jordà and Taylor (2019) documented a stronger monetary policy transmission under high leverage through the interest-rate channel. This effect is specific to mortgagors, excluding debt-free homeowners and renters, and operates when loans are adjustable-rate or fixed-rate loans can be refinanced at the reduced rate.

Although the leverage cycle is not commonly incorporated into stress-test models, second-round effects have recently been included in some exercises, such as the Central Bank of Ireland Macroprudential Stress Test (Morell et al., 2022), and also in Anderson et al. (2022); Budnik et al. (2023). These models capture the impact of deteriorating credit conditions—such as sharp increases in insolvencies and bankruptcies, rising real debt burdens, falling asset prices, and bank failures—all of which contribute to amplifying the initial shock by restricting credit supply.[3] In a first round, adverse macroeconomic scenarios affect the balance sheets and profit and loss accounts of individual banks, thereby reducing credit supply and demand. In a second round, this contraction in credit

[2] Borrowing constrains arise from the credit channel becoming non operational at high levels of debt. As agents become more leveraged, lenders increase the default risk premium charged, as described in the agency cost model of Bernanke et al. (1999).

[3] This perspective is known as the financial accelerator introduced in Bernanke et al. (1999), where endogenous pro-cyclical movements in borrower balance sheets can amplify and propagate business cycles.

supply and demand is fed back into the macroeconomic model, further amplifying the downturn. Accordingly, the initial state of leverage influences the propagation of the shock.

2.2 Sensitivities of Bank Balance-Sheets to Macroeconomic Scenarios

Given the complexity of the models and sensitivity of bank- and loan-level data required to integrate the dynamic bank-balance-sheet stress tests, macroprudential exercises are typically performed no more frequently than biennially (Hirtle et al., 2016; Kapinos et al., 2018). However, from a macroprudential policy perspective, it is desirable to have tools that allow for the assessment of bank resilience on a quarterly basis, thereby ensuring that the capacity of banks to absorb capital shortfalls remains aligned with evolving macroeconomic conditions.

Philippon et al. (2017) documented that the results of previous EBA EU-wide stress-tests exercises were informative and unbiased on average to inform realised bank-level losses associated to adverse macroeconomic developments. Similarly, Niepmann and Stebunovs (2024) displayed that EBA results were good estimators of realised banks credit losses. Accordingly, the "stylised stress-test" framework proposed by Couaillier and Scalone (2024) draws on the outcomes of the 2018 EBA EU-wide stress-test exercise to estimate the sensitivities of bank capital to macroeconomic developments. In particular, they estimate a reduced form pooled regression capturing the impact of GDP growth on the aggregate CET1 capital ratio of banks. The estimated coefficients can be interpreted as the sensitivities of the CET1 ratio to macroeconomic variables, allowing the evaluation of changes in the banks' capital position under various stress conditions.

2.3 Severity and Plausibility of Stress-Test Scenarios

Eventually, an important challenge in designing effective stress-test exercises lies in selecting scenarios that are both sufficiently severe and plausible (Basel Committee on Banking Supervision, 2009; Baudino et al., 2018). As such, macroeconomic scenarios should not only involve significant deviations in the macroeconomic variables of interest, but also remain consistent with the macro-financial structure of the economy, as well as with historical evidence (Breuer et al., 2009).

The trade-off between severity and plausibility has been explored in Breuer et al. (2009), Bonucchi and Catalano (2022), and Glasserman et al. (2014). In particular, Bonucchi and Catalano (2022) provided a method for computing the joint probability of observing a macroeconomic scenario, applicable to various structural models. To do so, they used a simultaneous macroeconometric equations model to capture the empirical distribution of the covariance of all endogenous macroeconomic variables, as well as their specific reaction to an exogenous macroeconomic policy shock. In this set up, the severity of each exogenous shock can be associated to the level of capital depletion it induces. Then, from Monte-Carlo simulations, the joint probability of observing the generated scenario for a given level of capital depletion is estimated, facilitating the comparison of multiple scenarios in terms of severity and plausibility. Recently, Aikman et al. (2024) propose a multiple-scenario reverse stress test, where stochastic simulations generate a collection of possible macro-financial and bank-level scenarios, with severity defined by the associated CET1 depletion.

3 Methodology

The QST methodology is based on three modules, with the primary goal of analysing the potential capital depletion domestic Irish banks would face in response to a range of macroeconomic developments. The methodology can be described as per the three following steps.

First, an adverse scenario is generated following an exogenous restrictive monetary policy shock, using a smooth-transition local-projection (STLP) model (Section 3.1). The principal purpose of this module is to generate scenarios in which the response of macroeconomic outcomes to exogenous and unanticipated monetary policy shocks is contingent on the leverage stage of the economy. This leverage stage can amplify or dampen the transmission mechanism, while the severity of the scenarios can also be proportionally adjusted—through the magnitude of the initial shock—by rescaling the impulse-response functions (IRFs) of the model. To account for any potential endogeneity concern, we identify the monetary policy shock considering an instrumental variables (IV) procedure. We acknowledge, however, that such scenarios may be insufficient to fully assess the resilience of banks under diverse macroeconomic stress events, such as those arising from geopolitical or supply-side shocks. Therefore, in the second module, our methodology also incorporates externally generated scenarios.

Second, the sensitivities of the subcomponents of the transitional CET1 capital ratio of banks to macroeconomic developments are estimated considering the bank-level outcomes of past EBA EU-wide stress-testing exercises, both under the baseline and adverse scenarios using panel regressions. To estimate the final capital depletion, as well as the relative contribution of each of the macroeconomic variables of interest, these sensitivities are interacted with the scenarios generated either in the first step or from external sources (Section 3.2).

Finally, by reproducing the second step across multiple scenarios, we estimate their plausibility. Severity is associated with the level of capital depletion linked to each scenario. The objective is to identify the most severe scenarios that also exhibit the highest plausibility. To this end, we estimate the joint probability of observing a specific combination of macro-financial outcomes and capital depletion through Monte Carlo simulations, relative to the historical response of the Irish economy to restrictive monetary policy shocks (Section 3.3).

3.1 Scenario Generation

3.1.1 Data

The three quarterly macroeconomic variables we consider for generating our in-house Irish adverse scenarios are output, unemployment, and residential house prices.[4] As Irish GDP variations are distorted by multinational profits, we consider the GNI* instead. The GNI* is interpolated to quarterly frequency using the Chow-Lin method (Chow and

[4] The three selected variables show consistent adverse paths across the 2018, 2021, and 2023 EBA exercises, which we use to extract sensitivities in the second module. By contrast, both increases and decreases in inflation and interest rates are treated as adverse across exercises, while commercial real estate prices are excluded to avoid potential collinearity with residential house prices.

Lin, 1971), with unemployment and the Modified Domestic Demand (MDD) serving as auxiliary variables.[5] We assume in the remainder that the GNI* is equivalent to GDP, as bank balance-sheet elasticities are computed on GDP using EBA data. All these three variables displayed historical patterns of large booms and busts associated to bank failures, notably during the global financial and sovereign debt crises, which make them relevant to draw plausible recessionary environments in our scenario generation module.

To model the exogenous unanticipated restrictive monetary policy shock, we use the *path* factor we extracted from the dataset of monetary policy surprises constructed by Altavilla et al. (2019), considering the full 'monetary event' window. This dataset gathers high-frequency variations in interest rates of various maturities around ECB monetary policy announcements, reflecting unexpected revisions in market expectations following such announcements. Monetary policy factors are ideal for representing exogenous shocks, as they capture the unexpected component of rate variations around a given central bank announcement and are orthogonal to each other by construction. Although the initial rate movements from these shocks are often small, they have significant economic impacts on various macroeconomic outcomes, such as GDP growth and inflation (e.g., Andrade and Ferroni, 2021; Miranda-Agrippino and Nenova, 2022). A full explanation of how we construct our monetary policy shock is featured in Section B.1.

The *path* factor is associated to unexpected restrictive forward guidance announcements. As such, it captures the reaction of market participants to unexpected changes in the future stance of monetary policy, and affects mainly medium-term (i.e. 1- and 2-year) rates (Figure 15). However, according to the signalling channel of monetary policy (Campbell et al., 2012; Melosi, 2016; Nakamura and Steinsson, 2018), which is particularly relevant in the context of the ECB (Jarociński and Karadi, 2020; Miranda-Agrippino and Nenova, 2022), monetary policy actions can convey information about economic fundamentals from central banks to market agents, leading to revisions in their expectations which are not necessarily related to monetary policy. These reactions are notably reflected by comovements between rate and stock price surprises around monetary policy announcements (Figure 16), which run counter what standard monetary theory predicts. Therefore, monetary policy factors are not equivalent to 'pure' monetary policy shocks. Following Jarociński and Karadi (2020), we extract the 'pure' monetary policy component of our *path* factor by exploiting such comovements in Section B.2. Then, when necessary, we aggregate our shock to a quarterly frequency. To ensure that it is not serially correlated, we regress it on its first two lags and take the residual from this regression.

Eventually, we integrate the 1-year Euribor in our model. This rate helps ensuring that we capture the response of Irish macroeconomic variables to a monetary policy tightening. It also enables us to adjust the severity of the scenario we generate by rescaling its response to the desired level, similar to the methodology of Tenreyro and Thwaites (2016). This variable is extracted from the ECB data portal on a quarterly basis.[6] In addition, data for the unemployment rate are extracted from Eurostat, while

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[5] The variables are retrieved from the Irish Central Statistics Office (CSO). The yearly Modified Gross National Income in million euros is identified by the code NA001 and the Modified Total Domestic Demand at current prices is identified as NAQ05. Data are available on the CSO website (https://www.cso.ie/en/index.html). The detailed definition of GNI* is available at: https://www.cso.ie/en/interactivezone/statisticsexplained/nationalaccountsexplained/modifiedgni/.

[6] Its identifier is FM.Q.U2.EUR.RT.MM.EURIBOR1YD_.HSTA.

residential house prices are sourced from the ECB.[7] In Table 2 in Section C, we display the summary statistics for these variables spanning the period from 2000Q3 to 2024Q4.

In line with Jordà and Taylor (2019), we propose a measure of the domestic credit cycle as a state variable. Specifically, we use the credit cycle estimated in Mugrabi and Rünstler (2025), which applies the multivariate unobserved components model introduced in Rünstler and Vlekke (2018) for the Irish case. Compared with alternative approaches—such as univariate filters (Hodrick–Prescott, Christiano–Fitzgerald) or parametric methods (e.g., VECM, alternative UCM specifications)—this model yields cycle turning points that align closely with key events in Irish macroeconomic history and exhibits favourable real-time and early-warning properties. Given the significant presence of multinational enterprises in the Irish GDP, the paper considers outstanding national credit, designed to capture credit extended to domestic households and firms. Specifically, the national credit is computed as the sum of loans granted to Irish households and the outstanding credit to non-financial firms provided by domestic financial institutions.[8] For simplicity, in the remainder, the national credit cycle will be referred to as the leverage or credit cycle.

3.1.2 Linear and Smooth-Transition Instrumental Variables Local Projections

We generate an adverse outlook for the Irish economy by estimating impulse response functions (IRFs) using the long-difference LP model of Jordà (2005) in response to an exogenous restrictive monetary policy shock. The initial sample period covers the 2000Q3-2024Q4 time span. The linear model is displayed in Equation (1).

$$\Delta Y_{t+h} = \tau_t + \alpha_h + \delta_h' L Y_t + \theta_h z_t + \sum_{i=1}^{2} \gamma_{h,i} L^i r_t + \mu_{t+h}, \Delta Y_{t+h} = Y_{t+h} - Y_{t-1}, h \in [\![1, h_{max}]\!]. \quad (1)$$

Where $Y_t = \{$GNI*, Unemployment rate, Residential house prices$\}$, r_t is the 1-year Euribor, and z_t is our proxy for the exogenous unanticipated monetary policy shock (ε_t^{MP}), that is, the quarterly *path* factor described in Section 3.1.1. L is the lag operator, α is an intercept, and τ_t is a time trend to account for structural changes in the Irish economy over the considered time span. To avoid non-stationarity issues, we take the year-on-year growth rate of the GNI* and residential house prices. Overall, our specification features one lag of all dependents variables but the Euribor, for which two lags are included. The IRFs are obtained from the coefficient θ_h, which captures the response of the dependent variable at horizon $h \in [\![1, h_{max}]\!]$ to a restrictive monetary

[7] The identifiers are: Unemployment rate, percentage of labour force, total, seasonally adjusted, age 15 to 74 (LFSI.Q.IE.S.UNEHRT.TOTAL0.15_74.T), and Residential House Prices, whole country, all dwelling types, existing (RESR.Q.IE._T.N._TR.TVAL.IE1.TB.N.IX).

[8] For the former, the data source is the ECB, with the identifier QSA.Q.N.IE.W0.S1M.S1.N.L.LE.F4.T._Z.XDC._T.S.V.N._T. For the latter, the data source is Central Bank of Ireland Statistics, Table A.1 'Summary Irish Private Sector Credit and Deposits,' Outstanding Credit advanced to the Irish private sector, available at: https://www.centralbank.ie/statistics/data-and-analysis/credit-and-banking-statistics/bank-balance-sheets/bank-balance-sheets-data). In the multivariate setup, the authors also employ GNI* and residential house prices, drawing on the sources mentioned above.

policy shock while accounting for other dynamics in the economy. We set h_{max} to 12 to generate three-year scenarios, as in the EBA framework.

Similar to Tenreyro and Thwaites (2016), we rescale the IRFs to achieve the desired final impact on the 1-year Euribor. Specifically, in our baseline analysis, we rescale our IRFs to obtain a 50-basis-point (bp) increase in the 1-year Euribor. This allows us to control the severity of our scenario by associating more adverse outlooks with higher increases in medium interest rates following unexpected restrictive changes in the future stance of the ECB monetary policy. Accordingly, we rescale standards errors using the delta method. Eventually, we smooth all the IRFs using a three-quarter rolling average.

In further analysis, we integrate a cyclical amplifier by accounting for the state of leverage of the economy, considering a STLP model. There are several reasons for considering such model where the state variable is the leverage cycle. Recent studies suggests that the credit cycle influences the transmission of monetary policy to macroeconomic variables (e.g., Alpanda et al., 2021; Rünstler and Bräuer, 2020). Furthermore, the misspecification test for vector smooth transition regression models, proposed by Teräsvirta and Yang (2014), provides evidence that a STLP model could be more appropriate given the presence of non linearities in the time series considered, as we reject the hypothesis of joint linearity at the 1% significance level.[9]

Following Auerbach and Gorodnichenko (2013), we allow for a smooth transition between both high- (H) and low-leverage (L) states.[10] Our STLP specification is presented in Equation (2).

$$\begin{aligned}\Delta Y_{t+h} = \tau_t + F(\zeta_t)(\alpha_h^H + \delta_h'^H LY_t + \theta_h^H z_t + \sum_{i=1}^{2} \gamma_{h,i}^H L^i r_t) \\ + (1 - F(\zeta_t))(\alpha_h^L + \delta_h'^L LY_t + \theta_h^L z_t + \sum_{i=1}^{2} \gamma_{h,i}^L L^i r_t) + \mu_{t+h},\end{aligned} \tag{2}$$

with $F(.)$ the smooth transition function, computed as the logistic transformation of ζ_t presented in Section 3.1.3, and the remaining specifications similar with those of the linear model.

However, to avoid any potential endogeneity between unexpected monetary policy shocks and the Irish economy, in our baseline analysis, we follow Ramey and Zubairy (2018) or Stock and Watson (2018), and adopt an instrumental variable (IV) identification procedure. According to Stock and Watson (2018), monetary policy factors must satisfy three conditions to serve as a valid instrument (z_t) for identifying the exogenous monetary policy shock (ε_t^{MP}).

First, they should satisfy the instrument relevance condition ($E[z_t \varepsilon_t^{MP}] \neq 0$). Monetary policy shocks represent the total amount of exogenous news about monetary policy over a given time period. Since ECB monetary policy announcements—on which monetary policy factors are based—constitute a significant portion of this news, z_t and ε_t^{MP} are likely positively correlated, thereby satisfying the relevance condition.

[9] The test can also be applied in the linear standard LP setup (Plagborg-Møller and Wolf, 2021; Li et al., 2024).

[10] Under the non-linear set up, an alternative model could be a threshold LP. However, as in Alpanda et al. (2021), where the credit cycle conditions the transmission of the monetary policy shocks, we opt for the STLP specification. Relying on a dummy state variable, as in Ramey and Zubairy (2018), would overlook gradual shifts in the credit cycle.

Second, they must meet the instrument exogeneity condition ($E[z_t \varepsilon_t^{\neg MP}] = 0$, with $\neg MP$ denoting any shock in ε_t unrelated to monetary policy). Given that monetary policy factors are based on monetary policy surprises—specifically, rate variations within narrow windows around ECB monetary policy announcements—it is unlikely that financial markets would simultaneously be influenced by other shocks unrelated to monetary policy. Finally, the lead-lag exogeneity condition ($E[z_t \varepsilon_{t+j}^{MP}] = 0 \; \forall j \neq 0$) is met under the assumption that monetary policy factors, which are based on monetary policy surprises, are uncorrelated with any information available to the markets prior to the ECB announcement.

Our linear instrumental variable estimation model is displayed in Equation (3).

$$\Delta Y_{t+h} = \tau_t + \alpha_h + \delta_h' LY_t + \theta_h r_t + \sum_{i=1}^{2} \gamma_{h,i} L^i r_t + \mu_{t+h}, \tag{3}$$

with similar notations as above, except that we now instrument the contemporaneous value of the Euribor with z_t, which represents an external instrument to the exogenous monetary policy shock (ε_t^{MP}), that is the quarterly *path* factor described in Section 3.1.1. Overall, that specification features one lag of all dependents variables but the Euribor, for which two lags are included in addition to the contemporaneous value.

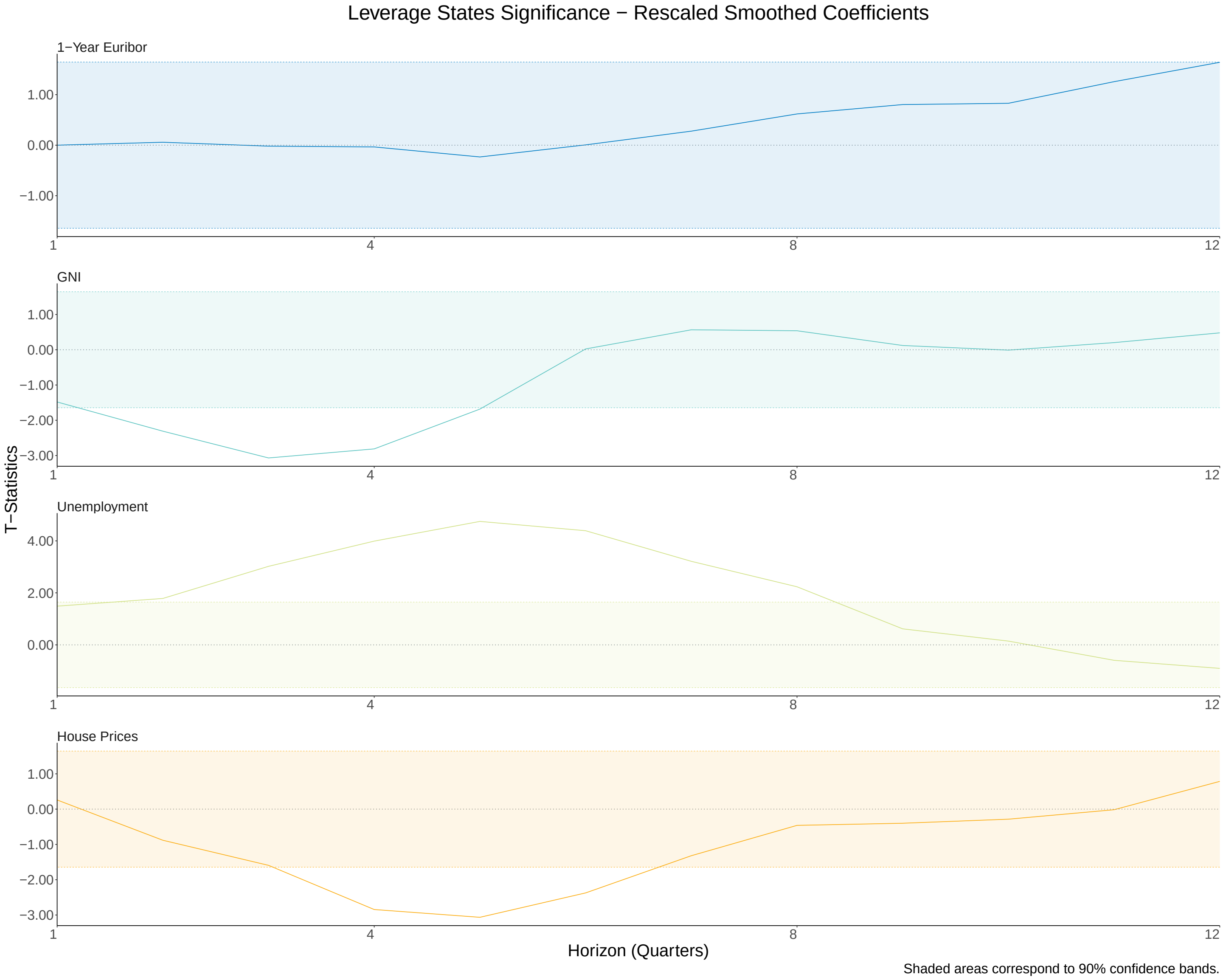
Then, our STLP specification is presented in Equation (4).

$$\begin{aligned} \Delta Y_{t+h} = \tau_t + F(\zeta_t)(\alpha_h^H + \delta_h'^H LY_t + \theta_h^H r_t + \sum_{i=1}^{2} \gamma_{h,i}^H L^i r_t) \\ + (1 - F(\zeta_t))(\alpha_h^L + \delta_h'^L LY_t + \theta_h^L r_t + \sum_{i=1}^{2} \gamma_{h,i}^L L^i r_t) + \mu_{t+h}, \end{aligned} \tag{4}$$

with all notations consistent with the above. In all cases, we correct standard errors with the Newey-West procedure with h lags to account for autocorrelation issues in the errors of the projections, and 90% confidence bands.

Figure 1 presents t-statistics to test whether the difference between the rescaled coefficients in a high- and low-leverage states are significantly different from zero in the IV specification, with shaded areas corresponding to 90% confidence bands. Values outside the shaded areas reflect statistically significant differences between both states. The STLP specification is particularly relevant in the IV case for the GNI*, the unemployment rate, and residential house prices, which is also why we consider it in our baseline case.

FIGURE 1. State Significance - IV Specification



3.1.3 *Transition Function*

Following Ramey and Zubairy (2018) and Tenreyro and Thwaites (2016), we consider the lagged Irish national credit cycle (ζ_t) as our state variable to capture the degree of leverage in the economy. The national credit cycle is estimated using the methodology of Mugrabi and Rünstler (2025), based on the multivariate unobserved components model of Rünstler and Vlekke (2018). The credit cycle can be interpreted as the deviation from its long-term trend, with positive values of our state variable indicating periods of leverage above trend. It is worth noting that, in a stationary cycle, leverage above trend should be observed approximately 50% of the time. Therefore, periods classified as being in the high-leverage state do not necessarily imply imminent systemic risk.

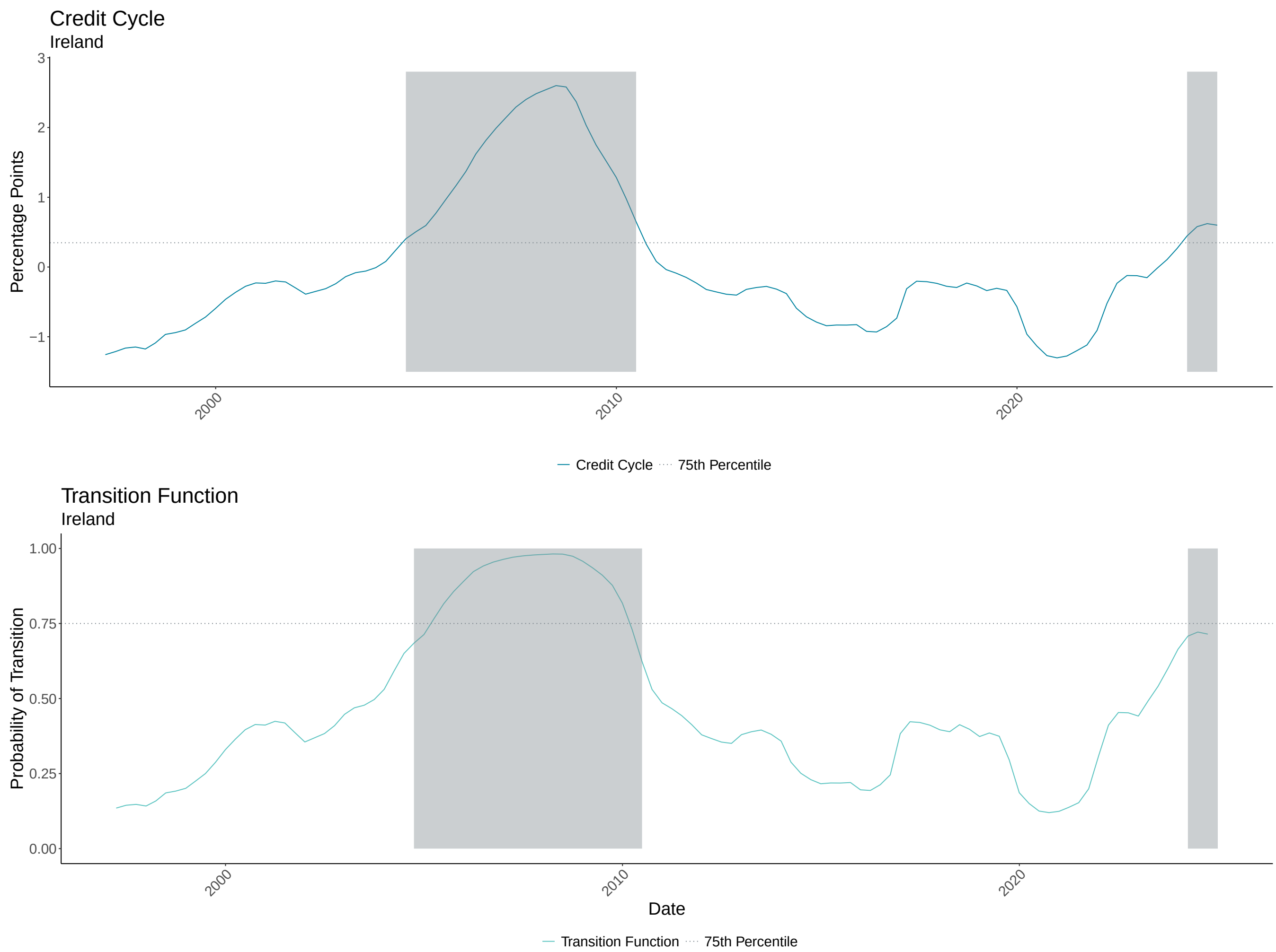
$F(.)$ is the smooth transition function, computed as the logistic transformation of ζ_t (Teräsvirta et al., 2010; Auerbach and Gorodnichenko, 2013), presented in Equation (5).

$$F(\zeta_t) = \frac{1}{1 + \exp(\varphi \times \zeta_t)}, \tag{5}$$

where φ is a regime-switching parameter. The higher the value of φ, the sharper the switch of one regime to another. The economy is classified as being in the high-leverage state when $F(\zeta_t) > 0.75$, that is, when the credit cycle lies above its long-run trend. To calibrate φ accordingly, using a grid search over φ, we minimise the distance between the probability of spending 25% of the time in the high-leverage regime and the transition function indicating a high leverage state (i.e. $\mathbb{P}[F(\zeta_{t-1}) > 0.75] = 0.25$). We obtain $\varphi = 1.5$, which translates into a rather smooth switch from one regime to another.

Figure 2 shows credit and monetary policy dynamics in Ireland over 2000–2024 in the upper panel, the state variable ζ_t in the middle panel, and the transition function $F(\zeta_t)$ in the lower panel. The shaded areas mark quarters in which credit is above trend. This occurs prior to the outbreak of the global financial crisis and again in the post-pandemic period, starting in 2022Q2. Accordingly, the remainder of the analysis focuses on results derived from the high-leverage state regime for conducting the macroeconomic projections.[11]

FIGURE 2. Credit and Monetary Policy Dynamics in Ireland



[11] Although the transition function has not exceeded the threshold, it is close to 0.75, while the credit cycle is above its long-term trend. Therefore, we focus on the high-leverage state hereafter.

3.2 Elasticities and Capital depletion

3.2.1 Data and Sample Selection

In the second module, we estimate the elasticities of the transitional CET1 capital ratio of Irish banks,[12] as well as their profit and loss accounts, using data from recent EBA stress test exercises. We focus on the most recent EBA stress test exercises (2018, 2021, 2023) as they are all based on the IFRS9 framework, so balance-sheet items remain consistent across exercises.[13] The initial dataset comprises 79 European banks.

To isolate the specific impact of macroeconomic developments on Irish banks, we restrict the sample to institutions with comparable business characteristics and balance sheet structures. We achieve this by clustering banks based on four key indicators: total assets, fully loaded leverage ratio, net interest income as a share of total operating revenue, and the ratio of customer deposits to total funding. These indicators ensure alignment in size, leverage, and business models. The latter two are particularly useful for distinguishing banks with a stronger focus on retail lending activities from those with investment-oriented operations (Köhler, 2015). These indicators are retrieved from BankFocus, covering the period from 2018 to 2023.

We compute the mean, as well as the 25th and 75th percentiles for Irish banks across these four indicators. Using these benchmarks, we select European banks with similar profiles ('EU selection'), ensuring that the Irish interquartile range is contained within the corresponding range for the EU selection, as shown in Figure 17 in Section D. By doing so, we refine the selection by excluding banks whose indicator values deviate significantly, beyond specific standard deviations from the Irish means, as detailed in Figure 18 (Section D). This process results in a final selection of 28 retail banks, representing approximately 35% of the total sample. The list of selected banks is reported in Table 3 (Section D).[14]

A caveat to this approach is that, by relying on EBA data, we remain bound by the assumptions embedded in their framework—such as the 'static balance sheet' assumption, which does not allow banks to adjust their behaviour in response to adverse macroeconomic shocks.

3.2.2 Sensitivity of Irish Banks to Macroeconomic Developments

We estimate the sensitivity of Irish banks to macroeconomic developments using the sample of 28 European retail banks similar to Irish banks described in Section 3.2.1. From this database, we consider the subcomponents of CET1 capital ratio at the bank level, and macroeconomic variables at the country level. These indicators are presented under both adverse and baseline scenarios.

The rationale for analysing individual subcomponents is to disentangle the specific

[12] We consider the three domestic Irish banks in this framework, namely Allied Irish Banks (AIB), Bank of Ireland (BoI), and Permanent TSB (PTSB). Yet, data from EBA stress-test exercises are only available for AIB and BoI as PTSB has been excluded from EBA samples after the 2014 exercise.

[13] Results hold when stress test exercises up to the 2014 one are included in the analysis.

[14] Further analysis displayed that considering the whole sample left the results unchanged owing to the introduction of a bank-fixed effect in the framework.

impact of each macroeconomic variable on the transitional CET1 capital ratio. For example, credit risk losses may decline in response to GDP growth, while retained earnings are likely to increase during periods of economic expansion. As a result, the overall CET1 ratio would increase owing to the combined effects of GDP growth on its underlying subcomponents.

We decompose our target measure, the transitional CET1 capital ratio, following two approaches. The first, which serves as our baseline specification, follows the 'Waterfall' decomposition methodology adopted by the EBA. Table 4 (Section E.1) lists the bank balance-sheet items included in this approach, such as net interest income (NII), credit risk losses, market risk losses, and distributed amounts, among others. Following this methodology, we start with the transitional CET1 capital ratio disclosed by banks prior the start of the exercises, and compute the contribution of these subcomponents to the final CET1 capital ratio observed one, two, and three years after the initial shock. Finally, all subcomponents, except the final CET1 capital ratio, are divided by total risk exposure amounts disclosed prior to the exercise. This allows us to capture the cumulative impact of macroeconomic developments on the transitional CET1 capital ratio over one, two, and three years following the shock.

In a second approach, we decompose the CET1 capital ratio into its numerator (transitional CET1 capital) and denominator subcomponents (total risk exposure amounts) separately, following the structure of EBA balance sheet templates. This approach is referred to as the 'Horizontal' decomposition in the remainder. We describe the methodology in Section E.2. In this Appendix, Table 5, outlines the specific items included. The subcomponents are aggregated separately for the numerator and the denominator, based on the relative share of each component from the realised data in the EBA exercises. These shares are reported in Figure 20.

The difference between these two approaches lies in the interpretation of how macroeconomic developments impact subcomponents of the transitional CET1 capital ratio. The Horizontal approach maintains a direct relationship with the balance-sheet structure of banks, allowing for the separate interpretation of the impact of macroeconomic variables on both the numerator, related to CET1 capital reserves, and the denominator, reflecting the different categories of risk exposures of banks. On the other hand, the Waterfall approach provides a more straightforward decomposition of the capital depletion associated with each of the macroeconomic developments. Therefore, we present results for the latter in our baseline analysis, while selected results for the Horizontal decomposition are reported in Section E.2.2. For both approaches, we find that the aggregate effects of macroeconomic developments across the subcomponents, along with their direct impact on the transitional CET1 capital ratio, move in the same direction. This outcome suggests that the estimation model does not exhibit substantial bias and that the specification is appropriately designed. These elasticities are presented in Section 4.1 for the Waterfall decomposition.

The elasticities for each component of the CET1 ratio, as well as for the ratio itself, are estimated using a panel regression displayed in Equation (6) for each year of the exercises (i.e. one, two, and three years after the start of the exercise).

$$Y_{i,j} = \alpha_i + \mu_j + \sum_{m=1}^{m_{max}} \beta_m M^{\Delta}_{m,c,j} + \sum_{l=1}^{l_{max}} \gamma_l X^{\Delta}_{l,i,t-1} + \varepsilon_{i,j}, \tag{6}$$

where i denotes the bank, whose headquarters are located in country c, and $j \in \{2018, 2021, 2023\}$ refers to the EBA stress-testing exercise. The subindex t

corresponds to the actual year relative to the post-shock period. As such, a specific year is associated to each year of exercise j (e.g., for the 2023 exercise, which started in 2022, the first year following the shock corresponds to the year $t = 2023$). $Y_{i,j}$ represents the cumulative proportion of each subcomponent of the CET1 capital ratio, as well as the ratio itself (Table 4). $M^{\Delta}_{m,c,j}$ represents the cumulative variation of each of the three macroeconomic variables we consider from the start of the exercise, in percentage points (pps). These variables are GDP growth ($m = 1$), the unemployment rate ($m = 2$), and residential house prices growth ($m = 3$) at the country level (c), where the headquarters of bank i are located. Therefore, $m_{max} = 3$. α_i and μ_j are bank- and exercise-fixed effects. These fixed effects control for unobservable characteristics at the bank and addresses potential biases due to differences between the exercises. Furthermore, $X^{\Delta}_{l,i,t-1}$ represents the l-th bank- or country-specific one-year lagged control. We consider the variation of the natural logarithm of total assets and return on equity (RoE) to account for the size and profitability of each institution. We also capture the business model of each banks by adding the customer deposits to funding and non-interest income to operating revenue ratios. All these data are extracted from BankFocus. Eventually, we account for the financial and regulatory environment by adding the Moral Hazard Index from the World Bank Deposit Insurance dataset,[15] which is the first principal component of deposit insurance design features for each country (Demirgüç-Kunt and Detragiache, 2002), and the bank concentration index, computed as the assets of three largest commercial banks as a share of total commercial banking assets, also extracted from the World Bank.[16] We lag all controls by one year to mitigate any potential endogeneity issue. Therefore, $l_{max} = 6$.

The sensitivities of the subcomponents of the CET1 capital ratio of banks similar to Irish ones are obtained from the coefficients β_m for each macroeconomic variable (m) and relative period after shock (one, two, and three years). To obtain the overall effect, we sum the coefficients obtained from the regressions of each contributor to the CET1 capital ratio. Results are presented in Section 4.1. The obtained elasticities represent the change in percentage points of the CET1 capital ratio and its subcomponents resulting from a one-percentage-point increase in GDP growth, residential house prices growth, or the unemployment rate.

3.2.3 Capital Depletion

The capital depletion associated with a macroeconomic scenario is computed using the elasticities estimated with the model introduced in Section 3.2.2. We define partial capital depletion as the specific effect of a macroeconomic variable on the CET1 capital ratio or one of its subcomponents. To compute this partial effect, the estimated coefficients β_m are multiplied by the cumulative outlook variation of the corresponding macroeconomic variables (m) for the post-shock period. The overall capital depletion, for a given period, is the aggregated effect across all the macroeconomic variables considered.

Our framework allows for the estimation of capital depletion associated with both

[15] `https://datacatalog.worldbank.org/search/dataset/0040209/Deposit-Insurance-dataset`.

[16] `https://databank.worldbank.org/source/global-financial-development/Series/GFDD.OI.01`.

internal and external scenarios. For the former, we employ the quarterly outcomes generated with the model presented in Section 3.1.2, which covers a twelve-quarter horizon. Assuming that the elasticities remain constant within the year, the quarterly estimated depletion is computed using the yearly betas corresponding to the quarterly horizon. For the external scenarios, we rely on alternative sources, such as the scenarios of previous EBA stress-testing exercises. Results for our baseline in-house scenario are presented in Section 4.2, and those for different severities and alternative sources are presented in Section A.2.

3.3 Scenario Plausibility

In this section, we identify the scenarios that combine the most severe outcomes with the highest plausibility. To this end, we compare a wide range of scenarios and their associated estimates of capital depletion. We draw on the in-house outlooks generated with the model described in Section 3.1.2, and we also consider scenarios derived from external forecasts, such as past EBA stress-test exercises.

We employ a non-parametric model with multiple simultaneous equations to compute the joint probability of observing a given combination of macro-financial outcomes and capital depletion. Monte-Carlo simulations allow us to derive these joint probabilities using a frequentist approach, relying on the multivariate distribution of a set of quarterly endogenous variables. Specifically, the historical joint dynamics between the macro-financial variables considered in Section 3.1.2 and the aggregate CET1 capital ratio are assumed to follow a multivariate normal distribution with mean zero and a finite covariance structure. The estimated plausibility is relative to the historical response of the Irish economy to macroeconomic shocks, specifically a restrictive monetary policy shock. Because our identification relies on an exogenous monetary policy disturbance, any other type of shock that cannot be associated to this type would present a plausibility tending to zero.

The covariance matrix of the joint multivariate normal distribution is derived using realised macroeconomic data for the Irish economy over the 2009Q2-2024Q4 time span. The selection of this starting date reflects the fact that CET1 requirements gained importance following the Global Financial Crisis (GFC), while Irish macroeconomic dynamics in the post-crisis period provide a closer approximation to current conditions than earlier data. As we employ country-level indicators, the aggregate transitional CET1 capital ratio is computed as the sum of the transitional CET1 capital of the three domestic Irish banks[17] divided by the sum of their risk-weighted assets (RWA), based on COREP data. The set of endogenous variables includes GNI* growth, the unemployment rate, residential house prices growth, and the 1-year Euribor, yielding a total of five endogenous variables. Data sources are reported in Section 3.1.1. We compute the year-on-year variation of these variables and standardise them. In the robustness check, we compute plausibility using a subsample starting in the post-GFC recovery phase (2011Q1).

We build the compact system of equations, based on the reverse stress test proposed in Bonucchi and Catalano (2022), and displayed in Equation (7).

$$\mathbf{Y} = \mathbf{MZ}+\mathbf{E}, \tag{7}$$

[17] AIB, BoI, and PTSB.

where **Y** gathers the standardised year-on-year ($N = 5$) endogenous variables, **Z** the exogenous restrictive monetary policy shocks proposed in Section 3.2, and **E** i.i.d. residuals. The endogenous variables are vertically stacked into the vector Y_t of length N and the vectors in bold are vertically stacked across T quarters, such that **Y** is a vector of length $(N \times T)$ and **Z** of length T.

The matrix **M** represents the reaction of the endogenous variables to exogenous contemporaneous and previous shocks, for what we define the multiplier at time t as $m_{i,t} = \frac{y_{i,t}}{z_t}$ $\forall\, i \in [\![1, N]\!]$. The compact model is built by collecting each M_t of length N in a matrix as follows:

$$\mathbf{M} = \begin{bmatrix} M_t & 0 & \cdots & 0 \\ M_{t+1} & M_t & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ M_T & M_{T-1} & \cdots & M_t \end{bmatrix}.$$

The multivariate normal distribution of **Y** is assumed to be $\mathbf{Y} \sim \mathcal{N}(\mathbf{0}, \mathbf{M}'\Xi\mathbf{M})$, with:

$$\Xi = \begin{bmatrix} \sigma^2_{z_{t,t}} & \sigma_{z_{t,t+1}} & \cdots & \sigma_{z_{t,T}} \\ \sigma_{z_{t+1,t}} & \sigma^2_{z_{t+1,t+1}} & \cdots & \sigma_{z_{t+1,T}} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{z_{T,1}} & \sigma_{z_{T,t+1}} & \cdots & \sigma^2_{z_{T,T}} \end{bmatrix},$$

for what the errors and the exogenous variable are required to be uncorrelated and that **E** and **Z** are assumed to follow a Gaussian distribution.

As in Bonucchi and Catalano (2022), this approach allows us to compute the probability of observing a specific combination of variables exceeding a certain threshold a_i for each endogenous variable $i \in [\![1, N]\!]$. For example, the probability along the GNI* dimension can be measured at the left tail $(GNI^* \leq a_{GNI^*})$ while the area of interest for the unemployment rate, could be set at the right tail $(UR \geq a_{UR})$ for a given time period. However, in our extension, the specification of the tail of interest (right or left) can be determined either *a priori*, for instance based on specific adverse scenarios, or derived from the realised data, particularly through Monte Carlo simulations. Furthermore, we can admit different thresholds for each quarter before and after the capital depletion under consideration.

The advantage of the estimated distribution capturing the joint dynamics throughout the considered period is that it allows the tail of interest to differ for each specific period. For instance, it is plausible that in quarters leading up to a substantial capital depletion, interest rates may increase beyond a certain threshold, followed by a sharp correction a few quarters later. Consistent with the previous sections, we assume that the propagation of a shock varies across the macro-financial variables over time but also that capital depletion may exhibit a lagged response to the macroeconomic conditions.

We perform L =5,000 Monte-Carlo simulations, generating this way 5,000 joint random paths of the N endogenous variables for T quarters. From these simulations, we identify the tail of interest for each quarter, both before and after a substantial capital depletion. To do so, we focus on the left tail of the variation of the transitional CET1 capital ratio at a specific threshold. This threshold can be, for example, its historical minimum. Other thresholds can also be considered, such as the CET1 capital ratio depletion associated with an external macroeconomic forecast or our in-house scenarios. Under the condition of the simulated CET1 capital variation exceeding the threshold, we retrieve the corresponding simulated values of the macro-financial variables for all preceding and subsequent quarters. Given that the endogenous variables are standardised, a positive (negative) median across all simulations indicates that the tail of interest lies on the right-hand side (left-hand side).

The expected combination of macro-financial outcomes at quarter t, when the CET1 capital ratio falls below a certain threshold ($\overline{CET1}$) in quarter t^*, can be expressed as in Equation (8).

$$\hat{Y}_t = E\left[\bigcap_{i=1}^{N}([Y_{i,t} \geq a_{i,t}] \times \mathbb{1}_{\{a_{i,t}>0\}} \vee [Y_{i,t} \leq a_{i,t}] \times \mathbb{1}_{\{a_{i,t}<0\}}) \middle| CET1_{t^*} \leq \overline{CET1}\right], \quad (8)$$

for every $i \in [\![1, N]\!]$ and $t \in [\![1, T]\!]$. The indicator functions $\mathbb{1}_{\{a_{i,t}>0\}}$ and $\mathbb{1}_{\{a_{i,t}<0\}}$ take the value of one when the medians across the L simulations are positive and negative, such that:

$$a_{i,t} = \text{median}(\overline{Y_{i,t}}^{(1)}, \overline{Y_{i,t}}^{(2)}, ..., \overline{Y_{i,t}}^{(L)}).$$

The medians of the simulated values of the macroeconomic variables, conditioned on the CET1 falling below its historical minimum, are presented in Figure 7, Section 4.3. Note that this is equivalent to what is commonly referred to as a reverse stress test, as for a given level of capital depletion, we infer the associated combination of macroeconomic variables.

In order to compute the plausibility of observing the endogenous variables jointly exceeding their corresponding thresholds at quarter t, we consider the cumulative multivariate Gaussian distribution function in Equation (9).

$$F(A_t) = P(|Y_t| \geq A_t), \quad (9)$$

where $A_t = [a_{1,t}, \ldots, a_{N,t}]$ is the vector of thresholds for the N variables. Similarly, $a_{i,t}$ can be specified either from our in-house model or from external scenario sources.

We integrate this model with the previous sections, allowing us to infer the joint probability of observing the scenarios and capital depletion generated in Section 3.1 and Section 3.2. Furthermore, this model provides the flexibility to assess the plausibility of a wide range of alternative scenarios when estimates for the same set of endogenous variables are available.

4 Results

4.1 Estimated Elasticities

The elasticities for the Waterfall decomposition, derived from Equation (6) (Section 3.2.2) are presented in Figure 3. For clarity, all components of the transitional CET1 capital ratio are shown as positive values. This allows us to interpret the elasticities as the impact of an increase of one percentage point in the independent variables on each component. However, credit risk, market risk losses, distributed amounts, and total risk exposure amounts, contribute to a decrease in the final ratio. This implies that an increase in these components results in a higher capital depletion. All components are divided by realised RWAs.

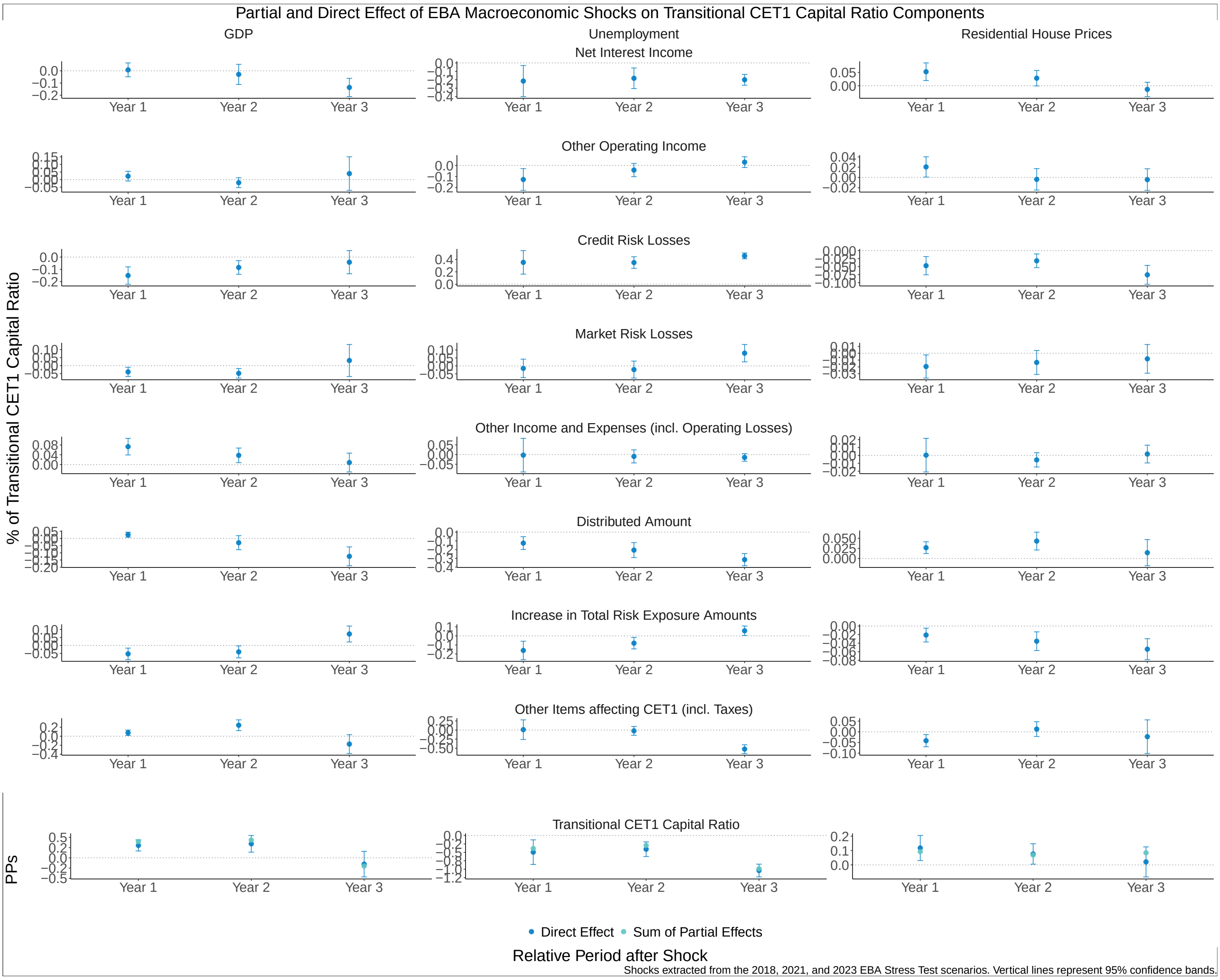
The components contributing most to the final capital variation are net interest income, credit risk losses, and other items, including taxes. A 1 percentage point (pp) increase in GDP growth (left-hand side column) leaves net interest income essentially unchanged in the first two years of the exercise, before leading to a 0.15pp drop in the third year. Credit risk losses, by contrast, decline by 0.15pp in year 1 and remain broadly unchanged in years 2 and 3, as stronger economic activity typically reduces the probability of default of households and corporates (Buch et al., 2014; Ali and Daly, 2010; Ioannidou et al., 2014), thereby contributing positively to the final capital variation. Other items increase by 0.2pp in year 2 and then decrease by the same amount in year 3. Summing all these effects, the transitional CET1 capital ratio rises by 0.3pp in years 1 and 2, before falling by 0.2pp in year 3, mostly due to the sharper declines in net interest income and other items in that year. This overall effect is similar to Couaillier and Scalone (2024), although their estimation pools all years and banks.[18]

Results are of similar magnitude following a 1pp increase in the unemployment rate (middle column), which leads to a consistent decrease in net interest income of 0.2pp across the three years and a steady increase in credit risk losses of up to 0.4pp in year 3. Other items, by contrast, decrease significantly by 0.5pp only in year 3, resulting in a larger drop of 1pp in the transitional capital ratio that year, compared with 0.5pp in years 1 and 2. Distributed amounts also decline meaningfully following a 1pp increase in unemployment, as banks become less profitable, which contributes positively to the final capital ratio.

Eventually, results following an increase by 1pp of the growth rate of residential houses prices (right-hand side column) are aligned to those of GDP, yet with a lesser magnitude, as such increase would lead to credit expansion and lower credit risk through the rise in the collateral value of household. As a result, the increase in risk exposure amounts emerges as a relatively large contributor to capital depletion, up to 0.06pp. Yet, the overall capital ratio would consistently rise by 0.1pp following an increase in residential house prices. These results are consistent with the existing literature showing how downturn periods affect bank-level metrics negatively by reducing their profitability and asset quality, as well as increasing the risks they face, notably through increases in non-performing loans (e.g., Demirguc-Kunt and Detragiache, 1998; Altavilla et al., 2018; Mody and Sandri, 2012).

[18] The authors, considering GDP as the sole independent variable and excluding bank fixed effects or bank-specific controls, estimate an average annual elasticity of the CET1 ratio to GDP of 0.45.

FIGURE 3. Elasticities - Waterfall Decomposition



Importantly, when we sum these coefficients across all the components, we obtain an effect similar to the one achieved by directly regressing the final transitional CET1 capital ratio on the selected macroeconomic outcomes (represented by the light- and dark-blue dots in the last row of Figure 3, respectively). This suggests that the errors at each equation level are not substantial enough to alter the overall direction of the CET1 ratio response to the macroeconomic variables.

4.2 In-House Scenario

4.2.1 Scenario Generation

Our in-house scenario is derived from the model described in Section 3.1. We analyse the responses of the three macroeconomic variables selected in Section 4.1 and the 1-year Euribor to an exogenous restrictive monetary policy shock. We rescale these

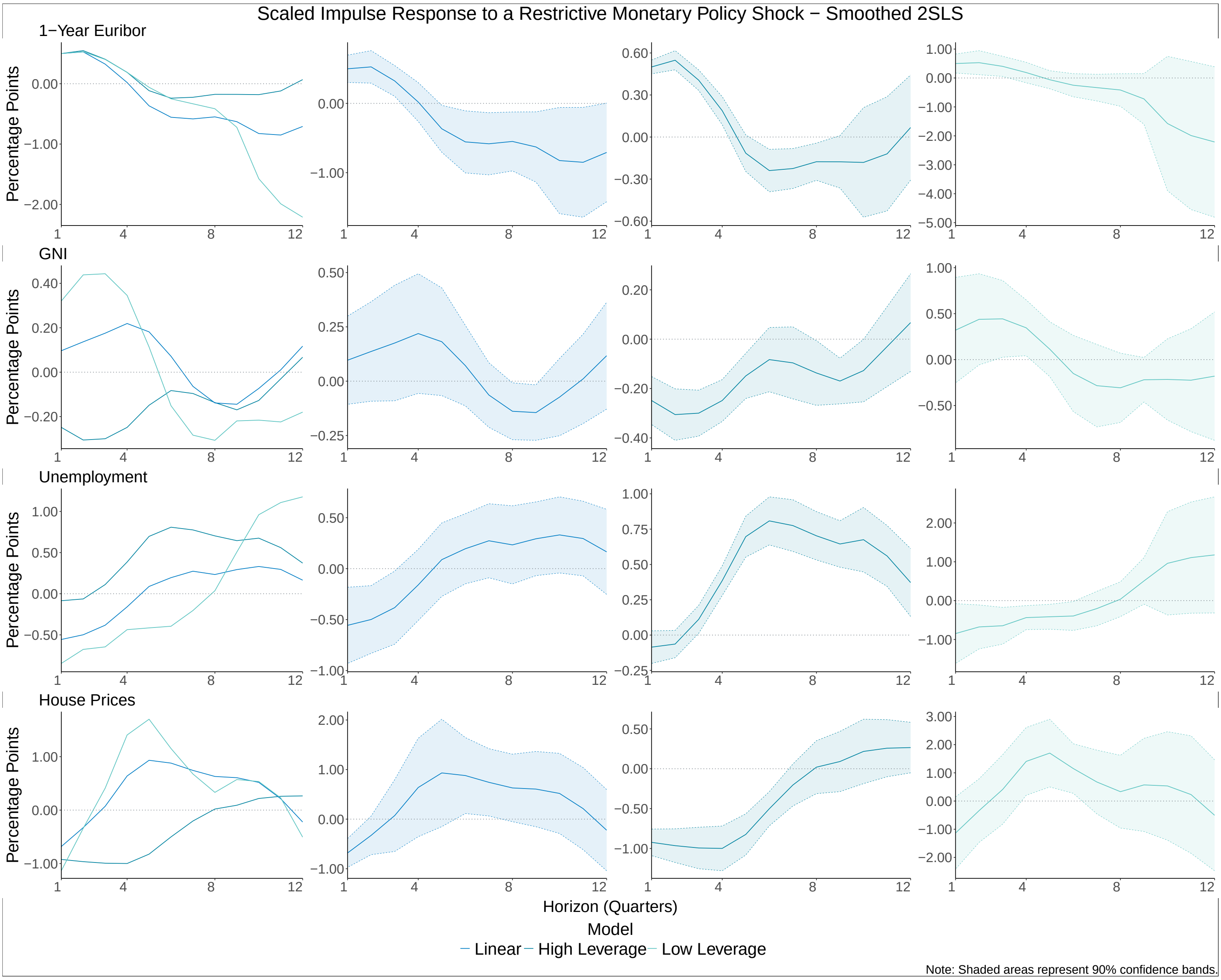
IRFs to correspond to a 50bp increase in the 1-year Euribor on impact for the linear and smooth transition models. Figure 4 presents the quarterly scenarios generated under the linear, low- and high leverage states models. The IRFs are reported in cumulative year-on-year differences, together with their 90% confidence intervals. Results are expressed in percentage points for consistency. The scenario at annual frequency is presented in Table 7 in Section G (year-on-year).

As displayed in Figure 1, we find meaningful differences between the low- and high-leverage states for all variables but the 1-year Euribor, notably in the IV specification. Consistent with the literature documenting that monetary policy becomes more effective in high-leverage states through the interest rate channel (Rünstler and Bräuer, 2020; Cloyne et al., 2020; Jordà and Taylor, 2019), we find that the IRFs are statistically significant under this regime. When credit is above trend, an exogenous restrictive monetary policy shock leads to a decline in output, an increase in unemployment, and a fall in house prices in the Irish economy. By contrast, neither the low-leverage state nor the linear specification yield statistically significant IRFs; therefore, we refrain from interpreting these results further (Montiel Olea and Plagborg-Møller, 2021; Ramey, 2016).

As shown in Figure 2, the national credit cycle has remained above its trend level since 2022Q2. Hence, all subsequent analysis is conducted in the state where the credit is above its long-run trend. In this regime, a restrictive monetary policy shock is followed by a continuous increase in the Euribor over four consecutive quarters. GNI* year-on-year growth declines persistently, reaching a cumulative drop of -0.25pp in quarter 4 before gradually recovering. Residential house price growth also falls markedly, cumulating -0.99pp after four quarters. Finally, cumulative unemployment increase peaks in quarter 6, at 0.81pp.

Our results are consistent with previous findings, although, to the our knowledge, no study explicitly accounts for the leverage state when examining the transmission of monetary policy shocks in the Irish economy. Lozej et al. (2023), in a simulation exercise using a semi-structural model, apply an exogenous Euro Area monetary policy shock leading to a raise in interest rates by about 360bps over four quarters. The authors find a reduction of around 2.2% in GDP in the first year, with the maximum impact of 3.2% occurring in the second year, relative to a baseline scenario without an interest rate increase. In our case, a shock of similar magnitude would lead to a maximum cumulative decline in GNI* of about 1.8pps in the first year. This somewhat milder response may reflect the use of GNI*, which abstracts from multinational activities and is therefore expected to be less affected by exogenous shocks. With respect to house prices, Corsetti et al. (2021), using a data-rich factor model, evaluate the effects of common monetary policy shocks across euro area countries. They find that, for Ireland, a 25bps contraction in the Eonia is associated with a 1.1% decline in house prices in quarter 10. Furthermore, Goncharenko and Lukmanova (2025) find a moderate interest rate pass-through, where only 0.2pp of a 1pp increase in the monetary policy rate are passed through to lending rates. While there is some variation across loan categories, the pass-through remains modest and never exceeds 0.5pps. Since we identify that monetary policy remains effective when the credit is above its long-run trend, where the interest rate channel operates, this moderate pass-through to lending rates may help explain the mild transmission of monetary policy to the Irish economy.

FIGURE 4. Scaled Response to a Restrictive Monetary Policy Shock (50bps)



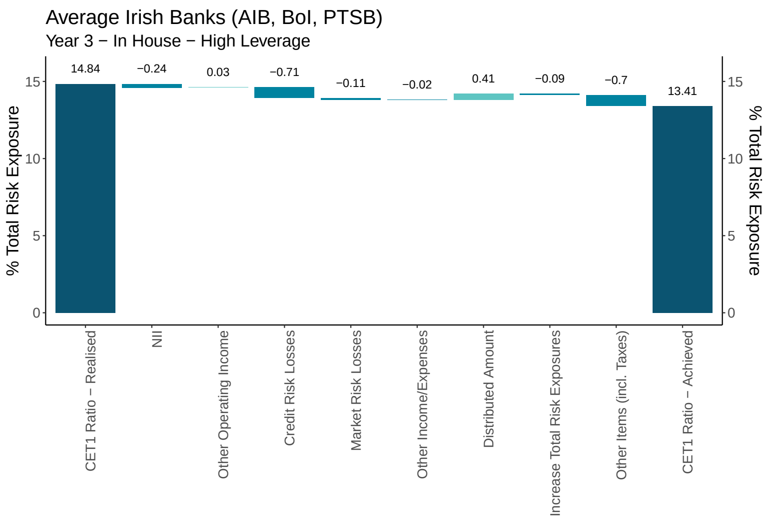
4.2.2 *Capital Depletion*

Figure 5 presents the cumulative depletion of the system wide Irish CET1 capital and its main contributor under the high-leverage state model three years after the restrictive unanticipated exogenous shock. All metrics are computed as a share of the total risk exposure amounts in 2024Q4, the starting point of our projections. At that date, the aggregate transitional CET1 capital ratio stood at 14.8%.[19] For an adverse macroeconomic scenario consistent with a 50bp increase in the policy rate, the cumulative CET1 capital depletion is estimated at 1.43pps. The chart reveals that the main contributors to the cumulative depletion are credit risk losses, followed by other

[19] Data come from the 2024Q4 COREP update, considering AIB, BoI, and PTSB.

items (including taxes and transitional arrangements, when relevant).

FIGURE 5. Total CET1 Capital Ratio Depletion - High-Leverage State

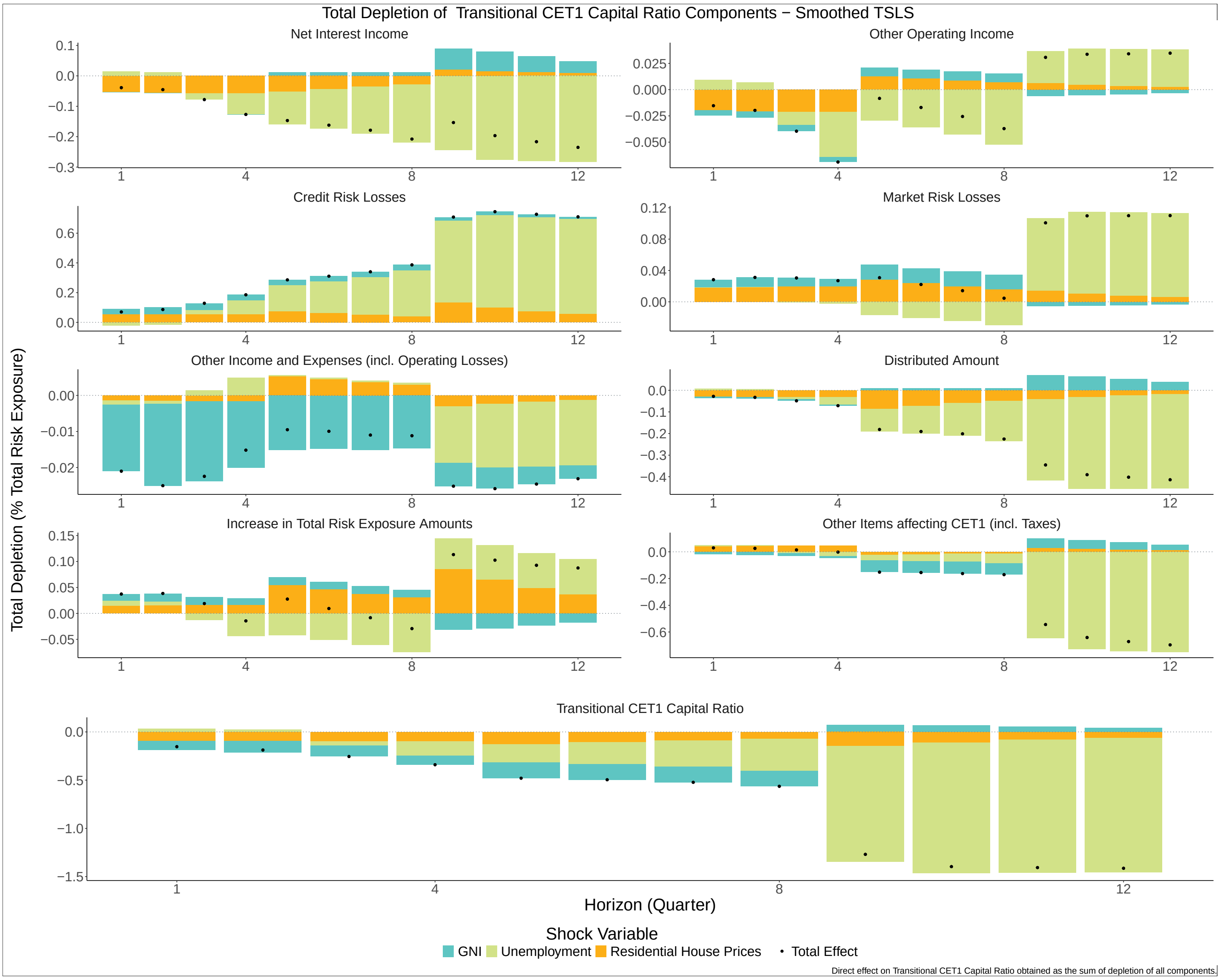


Note: Average cumulative depletion three years following a 50bp increase in the 1-year Euribor. CET1 Ratio: Transitional CET1 capital ratio, NII: Net interest income.

As our objective is to provide a timely assessment of capital depletion, we also present the results for the cumulative quarterly depletion. Figure 6 shows the outcome for the high-leverage state following an unexpected exogenous restrictive monetary policy shock leading to a 50bp increase in the 1-year Euribor. In terms of quarterly CET1 capital depletion, the maximum cumulative depletion occurs at the end of the horizon. As reported in the lower panel of the figure, during the first and second years following the shock, the CET1 capital ratio is predominantly influenced by declines in the GNI* and house prices. Conversely, in the third year after the shock, unemployment becomes the main driver of total capital depletion, while GNI* and house prices return to positive growth. This is consistent with the estimated IRFs, which show that the increase in the unemployment rate becomes more pronounced from the beginning of the second year following the shock, whereas the other variables reverse their dynamics (Figure 4). The increasing contribution of unemployment mainly affects credit and market risk losses, while also reducing net interest income, distributed amounts, and other items. By contrast, the effects of GNI* and residential house prices are transmitted primarily through the income components of the balance sheet, as well as via increases in total risk exposure amounts.

As shown in the previous section, since the IRFs are statistically significant only under the high-leverage state, we refrain from providing interpretations for the other regimes. For comparison purposes, however, Figure 21 in Section F reports the capital depletion under the linear specification (left-hand side) and the low-leverage state specification (right-hand side), while the quarterly decomposition is displayed in Figure 22 and Figure 23 for the linear and low-leverage specifications, respectively. Under the linear specification, capital depletion remains low, at 0.16pp, whereas in the low-leverage state it reaches 0.62pp, with the main contributors being credit risk losses, net interest income, and other items.

FIGURE 6. Total CET1 Capital Ratio Depletion - High-Leverage State

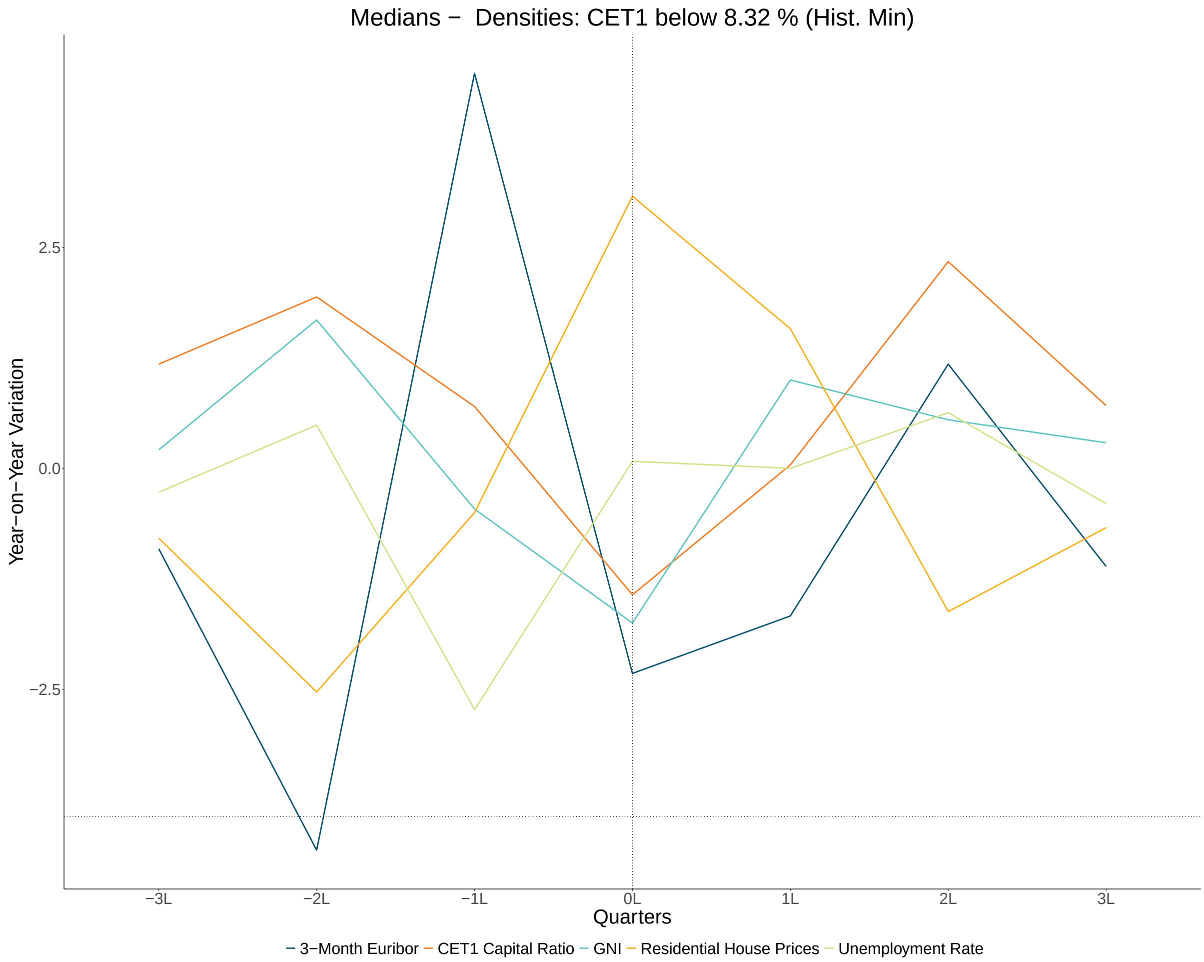


4.3 Scenario Plausibility

In this section, we compare severity and plausibility across a wide range of scenarios. The yearly scenarios and their associated capital depletion are reported in Table 7 (Section G). Our benchmark results are based on data from 2009Q2 to 2024Q4. As a robustness check, we also use a subsample beginning in the post-GFC recovery phase (2011Q1).

We first conduct a reverse stress test to identify the values of the macro-financial variables consistent with the CET1 ratio reaching its historical minimum of 8.32%, observed in 2011Q1. Figure 7 shows the median simulations conditioned on the left tail of capital variation. As the variables are standardized, the figure displays the standard deviations of the five endogenous variables considered. The exercise focuses on the simulations where the aggregated CET1 ratio fells below its historical minimum, spanning three quarters before and after (−3L to 3L). With the historical mean of the aggregated CET1 ratio being 13.73%, a year-on-year depletion of 3.94 standard deviations would result in the ratio reaching its historical minimum.

FIGURE 7. Medians Conditional to Transitional CET1 Capital Ratio Exceeding its Historical Minimum



Prior to the CET1 ratio reaching its historical minimum, the Irish economy experiences a moderate expansion, i.e. positive GNI* growth, declining unemployment, and increasing house prices. Just one quarter before the substantial capital depletion in Irish banks, the ECB adopts a restrictive monetary policy stance, reflected in an increase in the 1-year Euribor by 4.47 standard deviations above the historical mean. One quarter after the monetary policy tightening house prices decrease continuously, while GNI* react two quarters later.

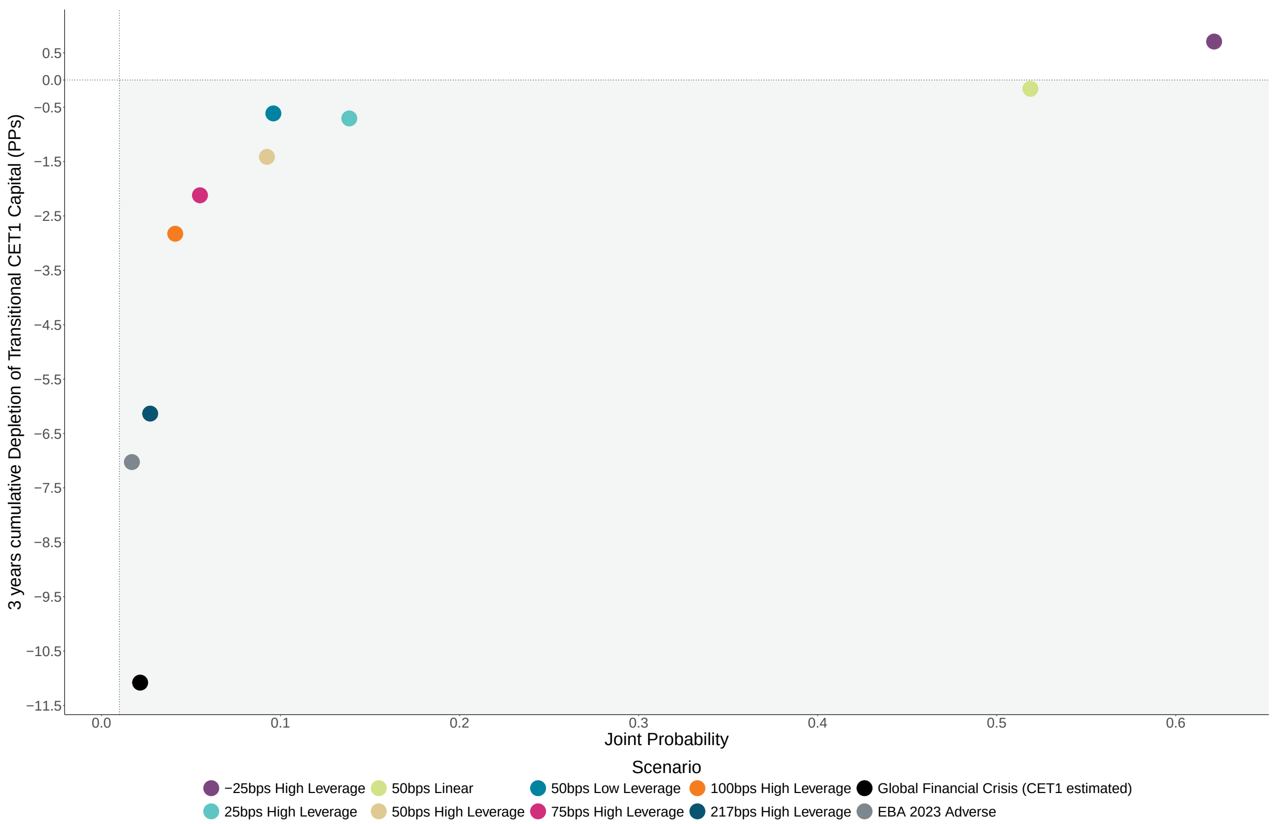
We compute the likelihood of macroeconomic variables exceeding the medians reported in Figure 7, corresponding to the aggregated CET1 ratio falling below its historical minimum. This likelihood is assessed relative to whether the simulations are below or above the medians when the medians are positive or negative, respectively. For all quarters, this probability remains below 0.01%. These medians can be interpreted as estimates of the macroeconomic values required to reach a specific capital depletion, which is typical of the objective of a reverse stress test.

Secondly, we focus on evaluating the plausibility of a range of scenarios, including those generated in-house using the model presented in Section 3.1 and external outlooks for the Irish economy derived from the EBA 2023 scenarios.[20]

We consider the realised values for the years following the GFC, taking 2009Q1 as the first quarter of the crisis period (Laeven and Valencia, 2020). Based on the macro-financial conditions observed during the three years following the shock, we compute capital depletion using the elasticities estimated in Section 4.1. Our calculations indicate that the transitional CET1 capital ratio depletes by 6.26pps year-on-year in the first year, reaching a cumulative depletion of 11.08pps (2011Q1) over the three years considered. We denote this scenario as *Global Financial Crisis (CET1 estimated)*. For the in-house scenarios, we incorporate various monetary policy shocks, including a 25bp decrease in the 1-year Euribor and increases of 25, 50, 75, 100, and 217bps under the high-leverage regime (linear- and low-leverage states for the 50bps scenario). In particular, the 217bp increase coincides with the adverse scenario of the 2023 EBA stress test, for which we estimate a capital depletion of 6.14pps, compared with the 7.03pps reported by the EBA—a 0.89pp difference.

Figure 8 presents the estimated plausibility and severity—measured as the cumulative capital depletion over the three-year horizon—for each scenario considered.

FIGURE 8. Severity and Plausibility



Note: The vertical dotted line marks a probability threshold of 0.01%. Scenarios in the lower quadrant with CET1 capital ratio depletion and to the right of the vertical line report both severe and plausible scenarios.

The most plausible outcome corresponds to a 25bps decrease in the 1-year Euribor, which is associated with a cumulative capital increase of 0.71pp. In terms of plausibility,

[20] EBA scenarios are retrieved from the EBA website (here for 2023).

this is followed by the 50bps linear exercise, yielding a cumulative depletion of 0.16pp. Considering the high-leverage state, scenarios linked to higher interest rates consistently display lower plausibility but greater severity. The EBA 2023 adverse scenario exhibits low plausibility (slightly above 0.01) and a cumulative depletion of 7.03pp, while the GFC scenario is the most severe, with plausibility above zero and a cumulative depletion of 11.08pp.

5 Conclusion

We develop a QST methodology, designed to provide timely and data-driven assessments of the resilience of Irish banks to a broad range of macroeconomic scenarios. This framework aims at complementing the Central Bank of Ireland MPST framework (Morell et al., 2022) and addresses the need for more frequent evaluations of potential vulnerabilities in the banking sector. Its flexibility allows for the integration of both internal and external macroeconomic outlooks, supporting experts in making data-driven and timely macroprudential policy decisions.

The QST methodology consists of three modules. In the first module, we generate recessionary environments triggered by monetary policy shocks, whose severity depends on the state of leverage in the Irish economy. We focus on three variables—output, unemployment, and residential house prices. In the second module, we estimate the sensitivities of bank capital to these macroeconomic developments based on a sample of banks comparable to domestic Irish banks, using outcomes from past EBA EU-wide stress-testing exercises. We then compute the expected capital depletion by interacting these sensitivities with our in-house scenarios, or external adverse scenarios representing tail events. This approach allows us to integrate externally generated scenarios and thereby examine a broader set of macroeconomic shocks relevant for stress-testing exercises. Finally, in the third module, we evaluate the likelihood of a wide range of scenarios materialising to ensure we consider only the most plausible and severe enough scenarios.

We show that, when the credit is above its long-run trend, restrictive monetary policy shocks transmit significantly to the Irish economy, though without generating material capital depletion. A decomposition of capital effects shows credit risk as the dominant channel, with unemployment as the main driver, while the income components of the balance sheet and total risk exposure amounts are primarily influenced by output and residential house prices. Finally, both in-house and external scenarios are found to be plausible, with more adverse shocks associated with lower plausibility and greater severity. The GFC remains the most severe case, and the 2023 EBA stress test adverse scenario emerges as the least plausible.

While the QST methodology can be readily extended to other European macroeconomic environments and provides a flexible and timely tool for assessing capital resilience, it is not without limitations. Reliance on EBA stress-test results implies that the estimated elasticities inherit the assumptions of that framework, including the “static balance sheet” constraint, under which banks’ behavioural adjustments to shocks are not modelled. Moreover, our econometric approach does not allow for the explicit modelling of individual balance sheet components and their interactions, particularly when these may be non-linear. The use of linear regressions to estimate sensitivities further limits the ability to capture potential non-linear relationships between macroeconomic conditions and bank capital dynamics. Nonetheless, the fact that our methodology closely replicates the outcomes of more comprehensive stress-test models in a quick and efficient manner makes it a valuable complement for policy-making purposes.

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Appendix

A Extensions and Robustness Checks

We conduct multiple robustness checks, structured around the three key components of the framework. The first two focus on the generation of in-house macroeconomic scenarios. The following four assess the robustness of the estimated capital elasticities. The final one relate to the plausibility assessment conducted in the reverse stress testing module. We report the results of three robustness checks in the following subsections. All additional results are available upon request from the authors.

Within the scenario generation module, we first explore an alternative specification of our monetary policy shock with the monetary policy factor derived from Jarociński and Karadi (2020), and find similar results. Then, we consider the OLS specifications displayed in Equation (1) and Equation (2) in which the monetary policy factor is directly incorporated into the regression. While results are similar, the identification of the shock is less precise in that case, as displayed by the wider confidence bands around the IRFs.

Turning to the second component of the framework, we apply the Horizontal decomposition of the CET1 capital ratio presented in Section 3.2, also considering profit and loss accounts. We find that the final transitional CET1 capital depletion, estimated from the aggregation of partial effects through each of its components, is similar in terms of both direction and magnitude to results obtained under the Waterfall decomposition (Section A.1). Next, we expand our analysis to include all 79 banks from the 2018 EBA stress-testing exercise and extend the sample period to include data from all exercises since 2014. These additional checks yield results consistent with our baseline—particularly as our elasticity regressions include bank- and exercise-fixed effects—while producing slightly narrower confidence intervals. Detailed results are available upon request.

We also compare the official capital depletion reported in EBA 2018, 2021 and 2023 exercises with our own estimations when using the same adverse scenarios finding non significant difference, i.e. 0.5pp, 0.6pp, and 0.8pp respectively, as shown in Section A.2. In Section A.3, we expand our estimation of capital depletion to alternative variables, namely commercial real estate prices and short- and long-term interest rates, which led to an increase in the overall severity of the exercise. These results should be interpreted with caution, as the strong correlation between house and commercial real estate prices may introduce multicollinearity, potentially biasing coefficient estimates.

Finally, to assess the robustness of the reverse stress testing module, we reduce the sample period for estimating the joint distribution of endogenous variables. Employing an alternative subsample starting in the post-GFC recovery phase (2010Q4), we find that all scenarios remain plausible (Section A.4).

A.1 Horizontal Decomposition of the CET1 Capital Ratio and profit and loss Accounts

The intent of this robustness check is on demonstrating consistency at each level of the numerator and denominator of the CET1 capital ratio and profit and loss accounts within the single-equation specifications in Section 3.2.2.

The methodology and considered components are described in full detail in Section E.2. The capital depletion obtained considering this approach is presented in Figure 9. In contrast to the Waterfall approach, the effect of residential house prices is more substantial, notably on total risk exposures in the second and third years of the exercise. Transitional CET1 capital decreases constantly during the exercise, while total risk exposures remain flat in the first two years of the scenario. As a result, the capital depletion mostly arises from the drop in CET1 capital in our scenario. Overall, unemployment remains the main driver of the depletion. The cumulative drop in the transitional CET1 capital ratio reaches 1.6pps at the end of the exercise, compared to 1.43pps under the Waterfall approach. Profit and loss accounts are mostly hit in the first and second years, and partly recover to reach a final cumulative loss of EUR 0.16bn at the end of the exercise.

FIGURE 9. Total CET1 Capital Ratio Depletion - High-Leverage State

A.2 Alternative External Scenario

A.2.1 External Scenario

Our QST methodology is designed to incorporate a broad range of scenarios, including both in-house and external ones. As an example, we report in this section the adverse scenario for Ireland, derived from the 2023 EBA EU-wide stress-testing exercise. The frequency of the scenario is yearly.

We display the outcomes for the year-on-year variation of the GDP growth, unemployment rate, and house price growth and CET1 capital ratio, in Table 7 (Section G). In this scenario, cumulative decline in GDP growth and residential house prices is 12pps and 14.4pps, respectively, while the unemployment rate rises by 7.7pps. Unlike our in-house scenarios in Figure 4, the EBA scenario remains particularly severe two years after the shock, although it eventually reverts to positive growth for both GDP and house prices.

A.2.2 Capital Depletion

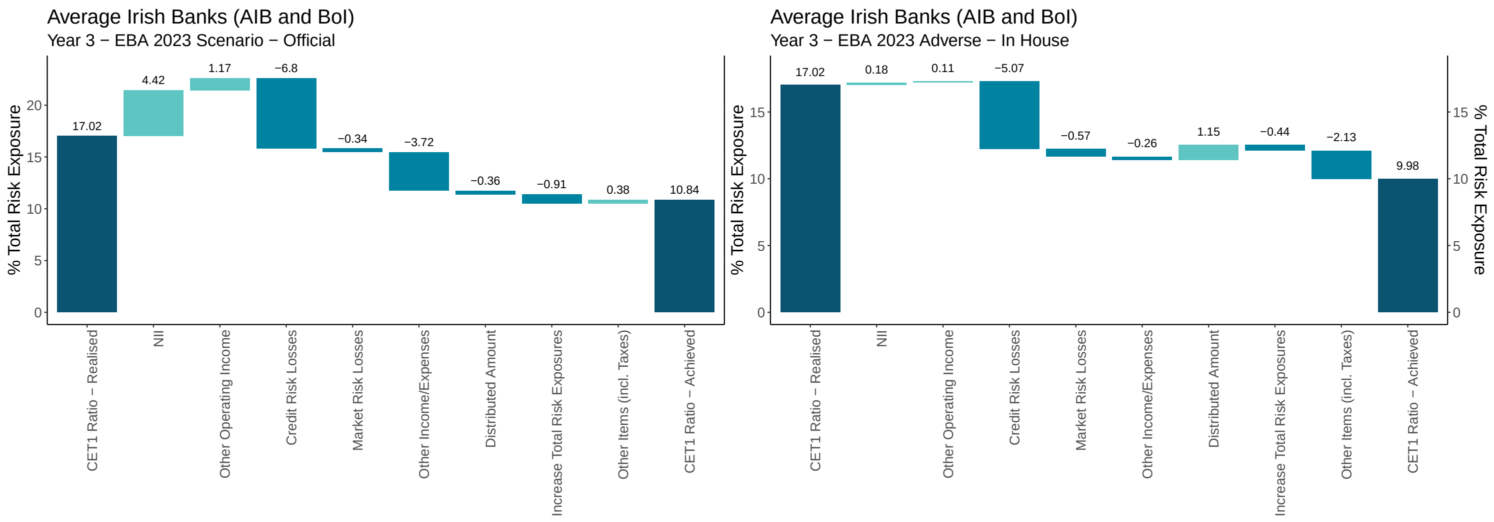
Figure 10 compares the cumulative capital depletion reported in the EBA 2023 exercise (left-hand side panel) with our own estimations using the same macroeconomic scenarios (right-hand side panel). Starting from an average CET1 capital ratio of 17.02% for Irish banks as of 2022Q4 (AIB and BoI only, as PTSB was excluded from this exercise), the EBA reports an average ratio of 10.84% after three years, implying a cumulative depletion of 6.2pps. Similarly, our in-house estimation for the same scenario yields an average depletion of 7pps, that is, a deviation of 0.8pp.

Going further, we replicate this exercise using the EBA 2018 and EBA 2021 stress test results, and find deviations to EBA results of 0.5pp and 0.6pp, respectively. This highlights the robustness of our econometric approach and the sample selection in capturing the capital sensitivities embedded in EBA exercises.

Furthermore, we find that in both cases the composition of capital depletion is similar overall, with the main driver being the increase in credit risk losses. Comparable magnitudes are observed for market risk losses and the increase in total risk exposure amounts. The main divergence arises from the income component (i.e. the sum of net interest income, other operating income, and other income and expenses), which contributes positively, but marginally, in our estimates (0.03pp), in contrast to a large positive contribution in the EBA results (1.87pps). On the contrary, the contribution of distributed amount is positive and large in our case, while in the EBA case it is negative and marginal as banks distribute less dividends when facing a drop in their profitability, an effect we cannot capture. Indeed, we assess how the components of bank balance sheets would react when facing monetary shocks under a linear assumption following an econometric approach. As a result, a drop in distributed amount linked to the drop in bank profitability results in a large positive contribution to the final CET1 ratio, given that distributed amounts strongly react to macroeconomic shocks (Figure 3). Conversely, EBA results are obtained from a static balance-sheet specification modelling most items of bank balance sheets, leaving more latitude on the contribution of each item to the final transitional CET1 ratio depletion over the three years of the scenario.

Figure 11 show the decomposition of the estimated cumulative capital depletion using EBA 2023 scenarios. The initial decline is primarily driven by the fall in GDP, followed by the increase in unemployment, while house prices play a marginal role, except on the income components of the balance sheet, and the increase in total risk exposure amounts.

FIGURE 10. Total CET1 Capital Ratio Depletion



Note: Results from the adverse scenario of the EBA 2023 Exercise. CET1 Ratio: Transitional CET1 capital ratio, NII: Net interest income. Starting point: 2022Q4.

FIGURE 11. Total CET1 Capital Ratio Depletion - EBA 2023 Adverse Scenario

A.3 Contributions of Commercial Real State and Short- and Long-Term Interest Rates

We explore the impact of alternative shocks on the capital depletion of banks, namely commercial real estate prices, as well as short- and long-term rates, extracted from the scenarios of the 2018, 2021, and 2023 EBA exercises. As a proxy for the policy rate, the short-term rate is represented by the 3-month euro swap rate, while the long-term rate is the 10-year Irish government bond yield.

We reproduce our baseline analysis by considering these three additional variables in the extraction of bank sensitivities in Equation (6) (Section 3.2), with m_{max} now amounting to six (GDP, unemployment, residential house prices, commercial real estate prices, and short- and long-term rates). Table 1 displays the variation of these six variables in the EBA scenario. Over the three years of the scenario, commercial real estate price growth drop heavily in the first year, and slightly recover in the second and third years, while remaining in negative territories. Short- and long-term rates increase in the first year of the exercise, then revert partly to their equilibria.

TABLE 1. EBA 2023 Scenario - All Variables

	GDP	U	RRE	CRE	STR	LTR
Year 1	−14.17	1.61	−14.20	−10.58	2.06	2.37
Year 2	−1.99	4.92	−7.82	4.53	−0.39	−0.51
Year 3	4.12	1.17	7.66	6.99	−0.14	−0.41

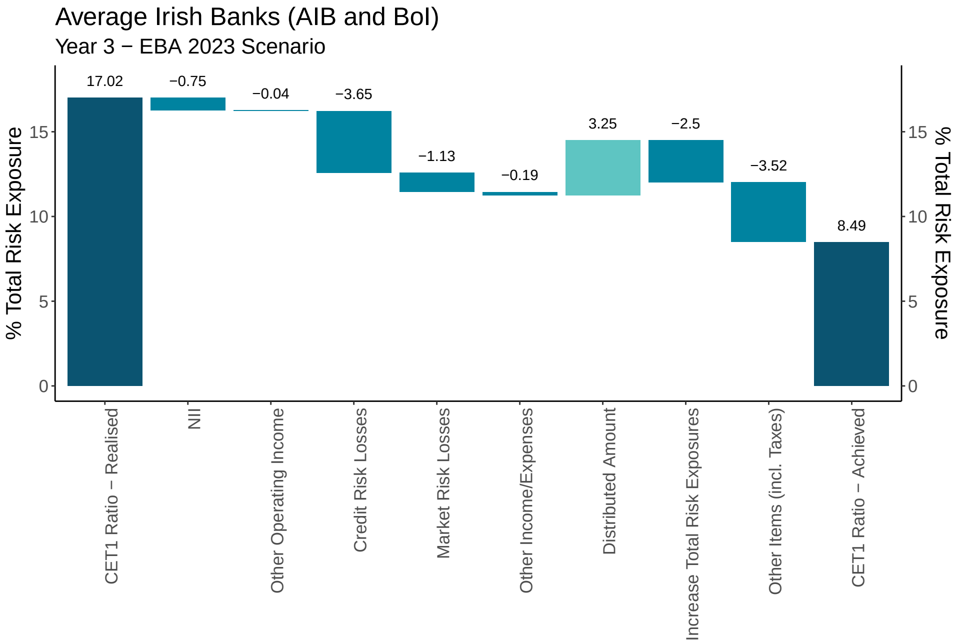
Note: U: Unemployment rate. RRE: Residential real estate prices. CRE: Commercial real estate prices. STR: Short-term rate. LTR: Long-term rate. Year-on-year variations reported in percentage points. Cumulative variation obtained as the sum of yearly variations.

The estimated reaction of CET1 capital ratio to an increase in commercial real estate prices is similar to the one of residential real estate prices, but of lower magnitude. A 1pp increase in the short-term rate is associated with a rise in the CET1 capital ratio over the three-year scenario horizon, whereas a 1pp increase in the long-term rate leads to a decline—larger than for any other variable. This is likely owed to the way these rate variables are considered within the EBA stress-testing framework. Indeed, instead of modelling their adverse path directly, as for other outcomes, the EBA departs from a given baseline outlook and applies a specific spread to define the adverse path, depending on its willingness to generate a high or low rate environment.

Figure 12 presents the total capital depletion we obtain from that exercise. The severity of the exercise is substantially higher than the one featuring three variables (Figure 11), with a cumulative 8.5pps depletion three years after the shock, compared to 6.4pps when considering three variables only. This is notably owed to the additional negative impact of commercial real estate prices on other income and expenses, while both the short- and long- term rates tend to reduce the interest income generation of banks, while increasing market risk losses, as displayed in Figure 13.

FIGURE 12. Total CET1 Capital Ratio Depletion - EBA 2023 Adverse Scenario

FIGURE 13. Total CET1 Capital Ratio Depletion - Alternative Variables

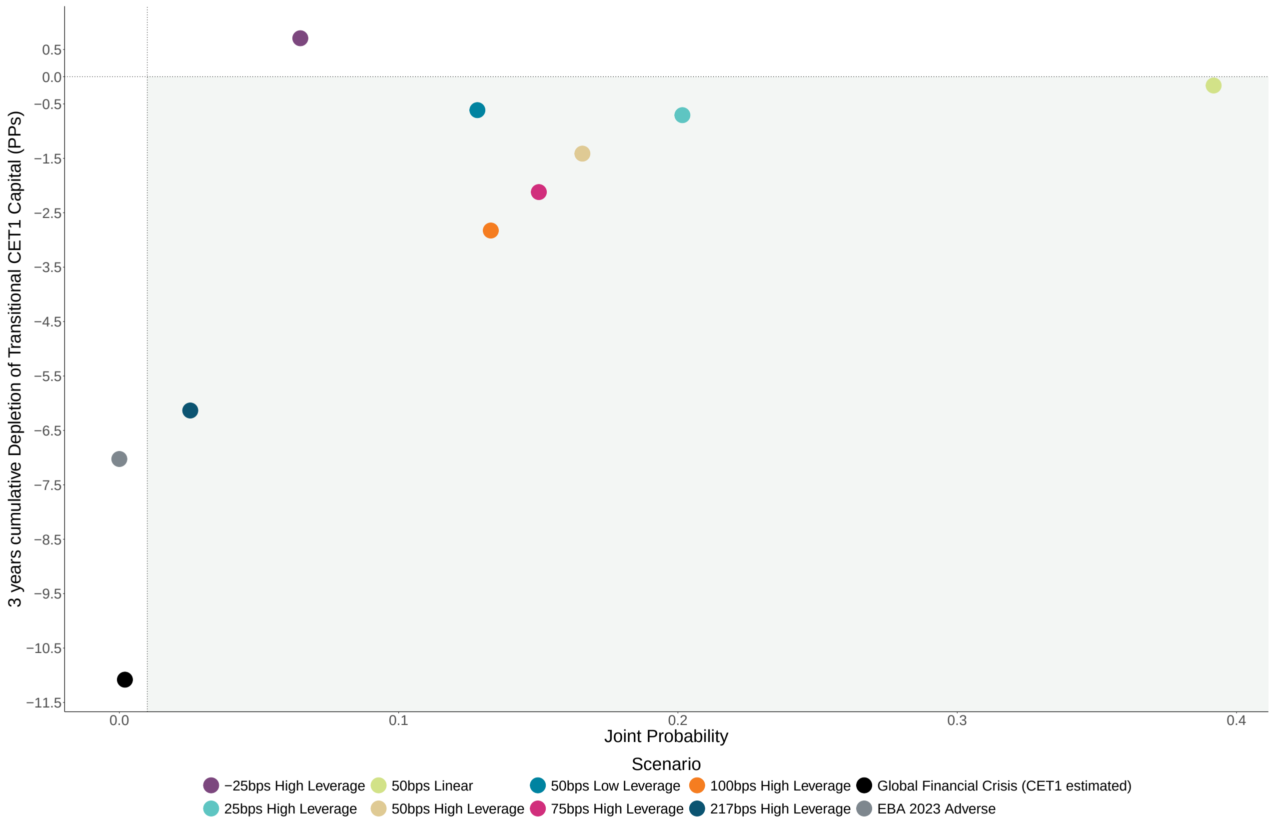


Note: Results from the adverse scenario of the EBA 2023 Exercise. CET1 Ratio: Transitional CET1 capital ratio, NII: Net interest income. Starting point: 2022Q4.

A.4 Severity and Plausibility - Reduced Sample Period

We re-estimate scenario plausibility using a reduced sample that begins in the post-GFC recovery phase (2011Q1). Excluding the GFC period removes extreme tail events from the distribution, which mechanically increases the relative plausibility of most scenarios. The only exception is the expansionary monetary policy shock in the high-leverage state, which becomes less plausible. This result reflects the fact that the excluded period corresponds to the pre-GFC phase, when the credit was above the long-term trend. Consequently, both the GFC and EBA adverse scenarios are now classified as non-plausible (Figure 14).

FIGURE 14. Severity and Plausibility - Post-GFC sample



Note: The vertical dotted line marks a probability threshold of 0.01%. Scenarios in the lower quadrant with CET1 capital ratio depletion and to the right of the vertical line report both severe and plausible scenarios. The system of equations and the plausibility assessment are performed using an alternative subsample starting in the post-GFC recovery phase (2011Q1).

B Extraction of Monetary Policy Factors

B.1 Factor Extraction

Identifying a shock that is both exogenous to the state variables and unanticipated is crucial for ensuring the validity of the results of the scenario generation module. Failure to meet these criteria could result in residuals that are correlated with the endogenous variables, leading to biased estimates and inconsistent standard errors. In state-dependent LP setups, a significant attention has been devoted to the identification of exogenous shocks (Alpanda and Zubairy, 2018; Hussain and Malik, 2016; Ramey and Zubairy, 2018). In the QST methodology, we consider a monetary policy factor as our exogenous restrictive monetary shock. Accordingly, we follow the methodology of Gürkaynak et al. (2005), Swanson (2021), and Altavilla et al. (2019). We refer the reader to the online appendix of Brana et al. (2024), on which this section borrows, for further information.

Monetary policy factors summarise the effects of monetary policy measures by capturing the unexpected ('surprise') component of the high-frequency reaction of markets around monetary policy announcements among rates of different maturities. We extract these factors from high-frequency surprises retrieved from the Euro Area Monetary Policy Event-Study Database (EA MPD) of Altavilla et al. (2019).[21] The EA-MPD gathers high-frequency changes of various rates and assets, which are extracted from ten-minute windows around monetary announcements beginning in 1999.[22] Three monetary announcements are considered, denoted as the *press release*, *press conference*, and *monetary event* windows in Altavilla et al. (2019). In the remainder, we consider the latter, encompassing the two former ones, to extract our monetary policy factors.[23]

The idea behind the extraction of monetary policy factors is to assess how many dimensions are necessary to adequately characterise monetary policy announcements given that the ECB has announced more than one policy decision in close to half meetings over the 1999-2025 time span. Equivalently, we aim at estimating how many latent factor would be necessary to describe a matrix encompassing a wide range of monetary policy surprises. The underlying identifying assumption is that monetary policy does not respond to intra-day asset price changes. Consequently, causality goes from monetary policy to asset prices only.

Following Altavilla et al. (2019), we depart from a base matrix, which incorporates OIS rates of 1-, 3-, 6-month, 1-, 2-, 5- and 10-year maturities with data beginning in 1999. We consider the monetary event window only, to ensure capturing all the dimensions of monetary policy events. We remove three outliers: the meeting following 9/11 (17 September 2001), and the two meetings that took place at the beginning of the Global Financial Crisis (8 October 2008, when a coordinated action of major central banks was announced, and 6 November 2008, when the Bank of England subsequently announced a 150bps cut in its bank rate). Missing values in OIS rates and bond yields are replaced by surprises in German bond yields of similar maturities following Altavilla et al. (2019). To assess how many latent factors underlie the response of asset prices or yields to monetary policy announcements, we first perform a Cragg and Donald (Cragg and

[21] The database can be found at: `https://www.ecb.europa.eu/pub/pdf/annex/Dataset_EA-MPD.xlsx`.

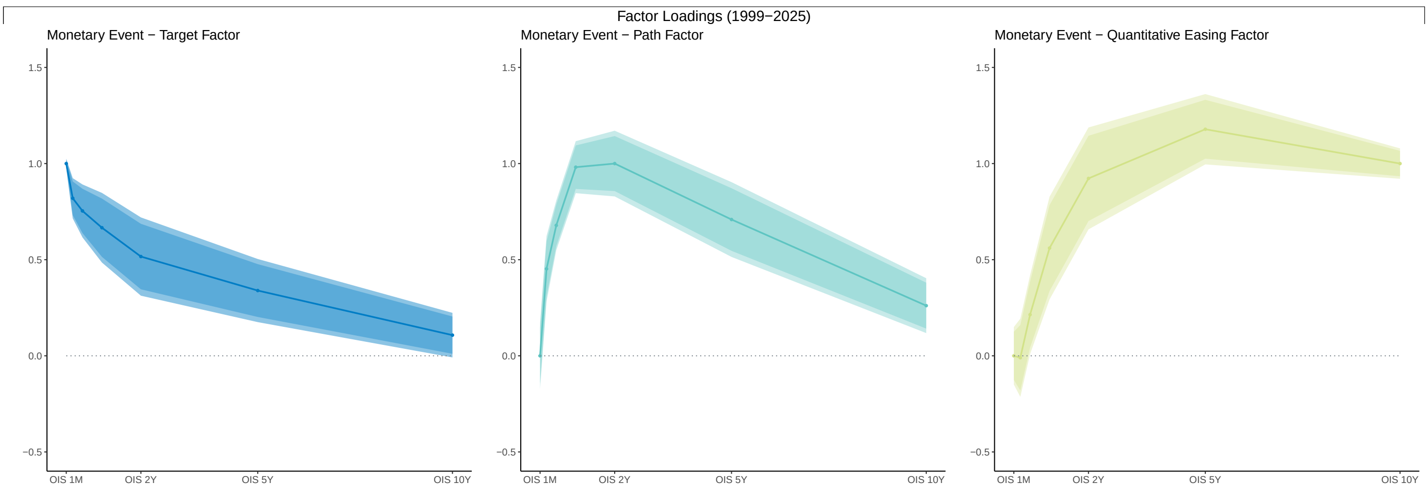
[22] OIS rates (1-week, 1-, 3-, 6-month, 1- to 20-year maturities), German (3-, 6-month, 1 to 30-year maturities), French, Italian and Spanish sovereign bond yields (2-, 5-, 10-year maturities), the STOXX 50 and SX7E as well as the EUR:USD, EUR:JPY, and EUR:GBP exchange rates.

[23] The ECB communication procedure proceeds can be divided in two steps. First, at 1:45pm (local time), the ECB releases a short note about the evolution of the key policy rates denoted the *press release*. Second, at 2:30pm (local time) begins the *press conference*, in which the measures adopted are commented by the president of the ECB, until 3:30pm. The *monetary event* window encompasses both windows. As such, it reports the difference of the median rate levels between the 3:40-3:50pm and 1:25-1:35pm windows.

Donald, 1997) rank test. Then, we perform a singular value decomposition of our base matrix, with the k first column of the factor matrix corresponding to the k latent factors needed to adequately describe the base matrix. We then rotate the factors to grant them an interpretation and ensure they are orthogonal to one another, following Gürkaynak et al. (2005), Swanson (2021), Altavilla et al. (2019), and Brana et al. (2024). To facilitate their interpretation, factors are then scaled to unit variance, while they already display zero mean by construction.

The economic interpretation of our factors is then granted on the basis of the rates they significantly load on, displayed in Figure 15. Similar to Brana et al. (2024), our factors can be interpreted as being *target*, *path*, and *quantitative easing* ones. They are scaled accordingly to have a unit impact on the 1-month, 2-, and 10-year OIS rates surprises, respectively. The *target* factor loads more on short-term rates and reflects surprises about the current policy rate, while the *quantitative easing* factor, which loads more on long-term rates reflects information on the long-end part of the yield curve. Lastly, the *path* factor loads heavily on the 2-year OIS rate and captures revisions in market expectations about the future path of policy rates. Therefore, this factor relates to forward guidance and reflect medium-term expectations of market participants.

FIGURE 15. Factor Loadings (1999-2025)



Note: Shaded areas correspond to 90% and 95% confidence bands.

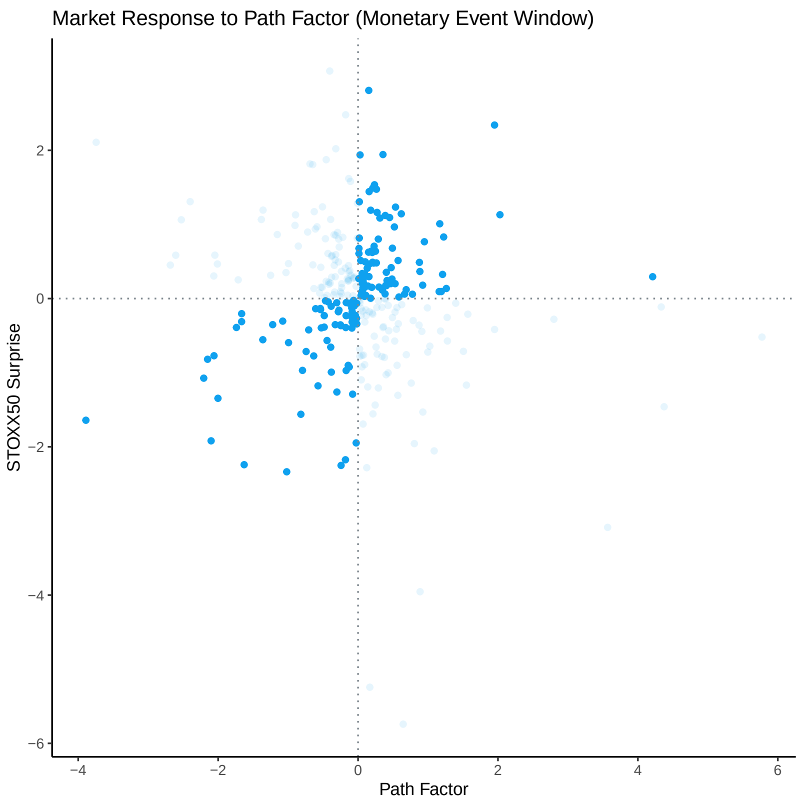
Given that they are based on interest rate surprises, an increase in each factor reflects a restrictive monetary policy stance.

B.2 Information Shocks

In Section B.1, we assumed that factors derived from monetary policy surprises are equivalent to ‘pure’ monetary policy shocks. However, these shocks may be contaminated by confounding elements, as noted by Miranda-Agrippino and Ricco (2021) and Jarociński and Karadi (2020). Specifically, assuming that that central banks possess greater information-processing capabilities compared to private forecasters and market agents (Romer and Romer, 2000), monetary policy actions can convey information about economic fundamentals from central banks to market agents, leading to revisions in their expectations. This is known as the signalling channel of monetary policy or the central bank information effect (Campbell et al., 2012; Melosi, 2016; Nakamura and Steinsson, 2018), which is particularly relevant in the context of the ECB (Jarociński and Karadi, 2020; Miranda-Agrippino and Nenova, 2022). To account for such contamination, we disaggregate them into 'pure' monetary policy and information shocks following Jarociński and Karadi (2020), that is to say, ex post.

We begin with exploiting comovements between short-term interest rates and stock prices in the EA MPD to extract two factors. The first reflects monetary policy shocks *per se* (monetary policy factor) and is associated with opposite movements between interest rates and stock prices, as expected by standard monetary policy theory. The second one implies comovements in rates and stock prices, which is interpreted as the central bank revealing private information about current and future demand conditions and tightening its policy to counter their impact on the economy (central bank information). For instance, Figure 16, in the *path* factor case, displays that such comovements arouse in a numerous number of instances in over the 1999-2025 time span.

FIGURE 16. *Path* Factor and Stock Surprises



First, we disaggregate all our monetary event factors with regard to opposite variations between the 2-year OIS rate and STOXX 50 surprises—associated with monetary policy shocks—to extract their monetary policy component. The information component is then obtained as the residual of the regression of the factor over its monetary policy component to ensure both are orthogonal to each other. This allows both shocks to be present in each monetary policy announcement. That approach is equivalent to the 'poor man's' proxy approach in Jarociński and Karadi (2020). However, their base matrix is slightly different as it encompasses 1-, 3-, 6-month and 1-year OIS rates, and the STOXX 50 surprises from the monetary event window, while they do not allow both shocks to be present in a given announcement.

Additionally, Jarociński and Karadi (2020) followed a rotational approach and set an angle $\alpha = \arccos \sqrt{\frac{\text{Var } i^{MP}}{\text{Var } i^{Total}}}$ to pin a unique decomposition. We refer to Appendix B of Jarociński (2020) for more detail. Data come from Marek Jarociński's website.[24]

C Summary Statistics

TABLE 2. Summary Statistics (2000Q3-2024Q4)

Variable	Unit	Average	StDev	Min	Max	N
ΔGNI*	%	0.61	1.04	−1.91	2.50	97
ΔHouse Prices	%	0.92	2.98	−6.93	6.44	97
Unemployment Rate	%	7.66	3.97	3.91	16.14	97
1-Year Euribor	%	1.76	1.73	−0.50	5.37	97
Aggregated CET1 Ratio	%	13.73	2.86	8.32	18.38	97
Standardised Credit Growth	%	2.17	0.18	1.66	2.43	97
Credit Cycle	%	0.13	1.00	−1.30	2.60	97

Note: Data sources in Section 3.1.1. Δ: Year-on-year log growth.

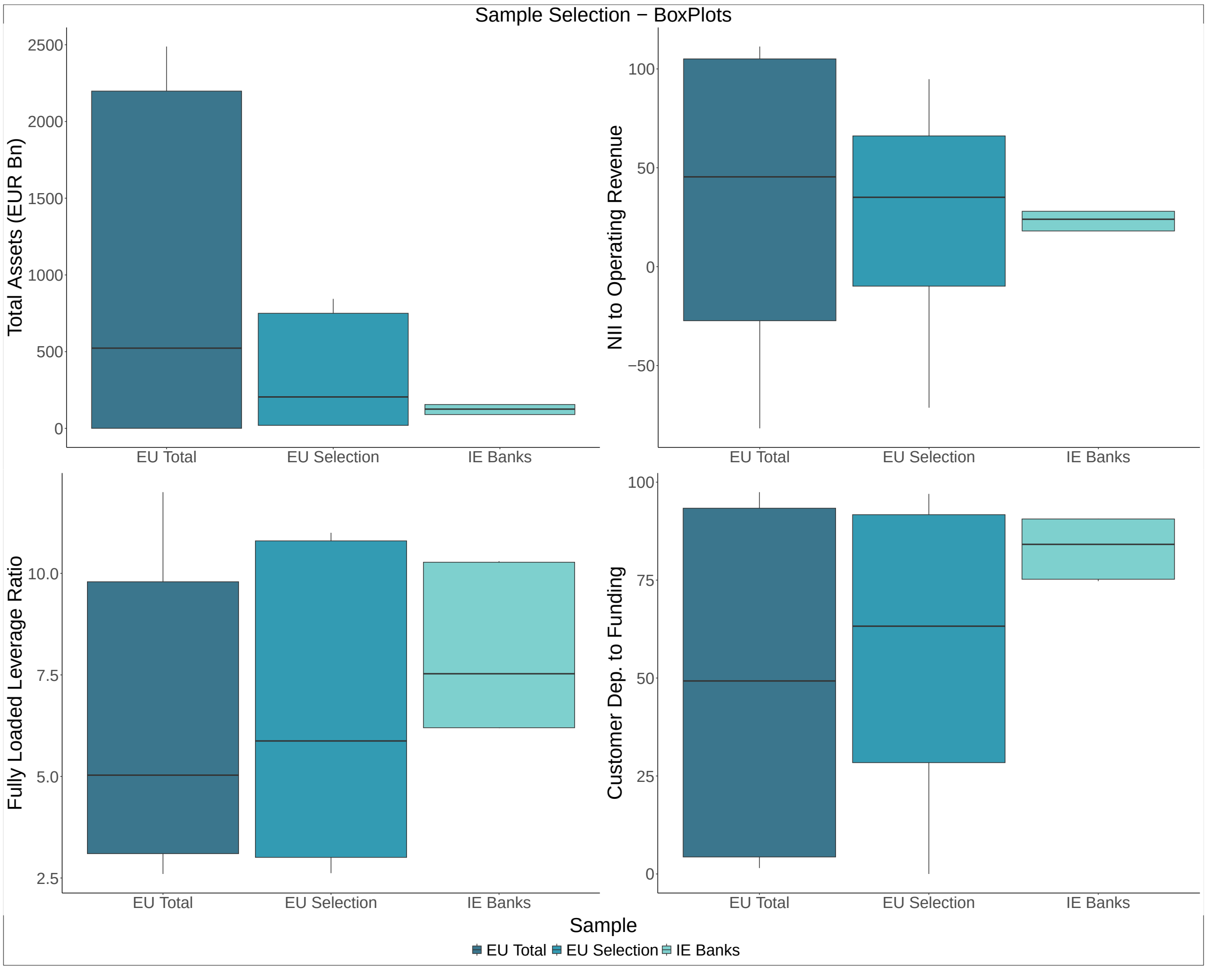
D Sample of Banks for Elasticities

TABLE 3. Sample of Banks for Elasticities

Name	Country (ISO2)
Erste Group Bank AG	AT
Raiffeisen Bank International AG	AT
Belfius Banque SA	BE
KBC Group NV	BE
Commerzbank AG	DE
Deutsche Apotheker- und Ärztebank eG	DE
Norddeutsche Landesbank-Girozentrale	DE
Sydbank	DK
Banco Bilbao Vizcaya Argentaria S.A.	ES
Banco de Sabadell S.A.	ES
Bankinter, S.A.	ES
Caixabank SA	ES
MPCA Ronda	ES
Alpha Bank	GR
Eurobank Ergasias	GR
National Bank of Greece	GR
Piraeus Bank	GR
Allied Irish Banks Group plc	IE
Bank of Ireland Group plc	IE
Banca Monte dei Paschi di Siena S.p.A.	IT
Banca Popolare Dell'Emilia Romagna - Società Cooperativa	IT
Banco BPM S.p.A.	IT
Unione di Banche Italiane Società Per Azioni	IT
ABN AMRO Bank N.V.	NL
Coöperatieve Rabobank U.A.	NL
SNS Bank N.V.	NL
DNB Bank Group	NO
Caixa Geral de Depósitos SA	PT

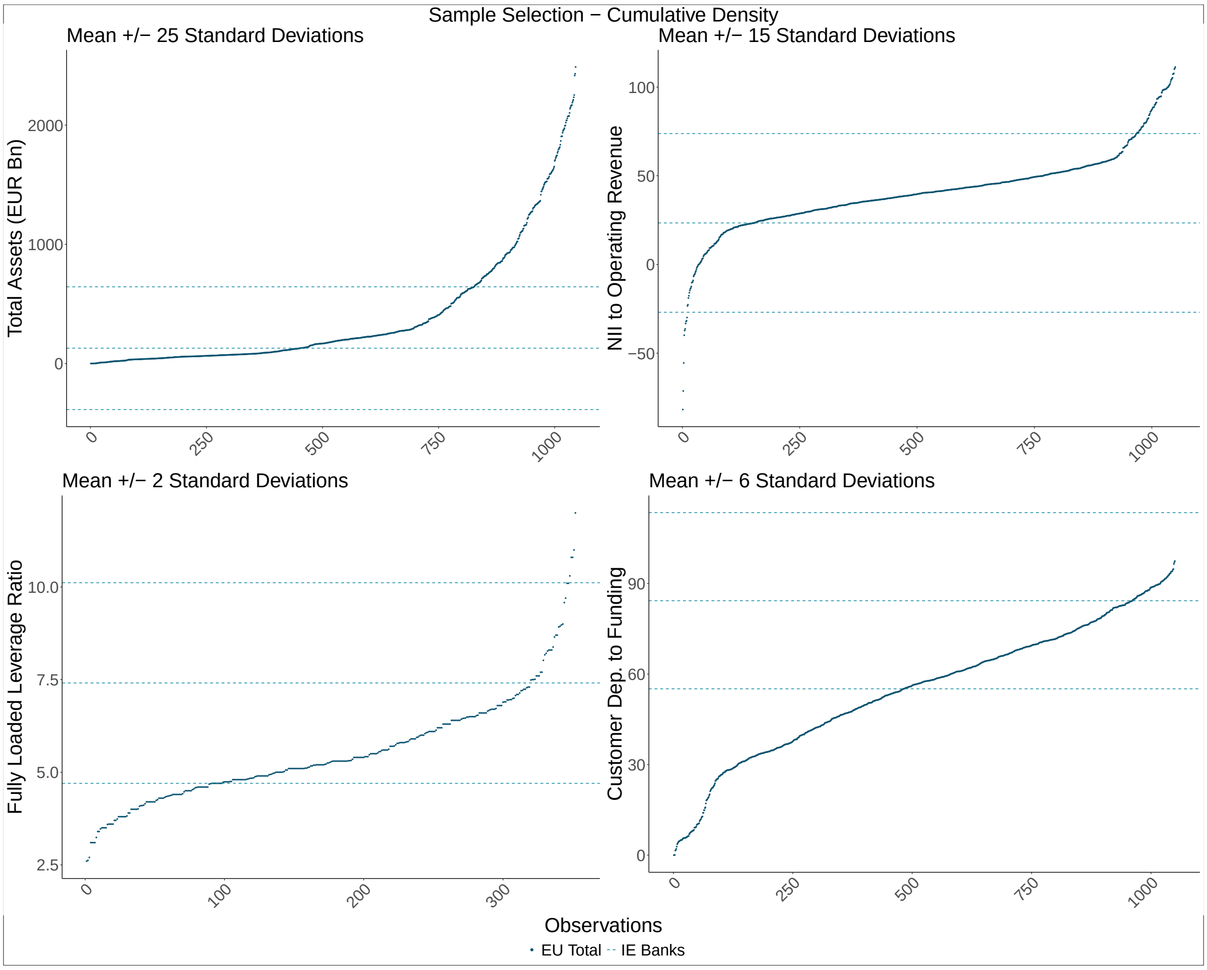
24 https://marekjarocinski.github.io/jkshocks/jkshocks.html.

FIGURE 17. EU Bank Selection - Mean and Interquartile Range



Note: The figures show the distributions of the bank indicators considered for the sample selection among the 79 European retail banks included in the EBA 2018, 2021, and 2023 exercises. The middle light blue line represents the mean values for Irish banks, while the upper and lower lines correspond to the selected +/- standard deviations. The specific standard deviations used are detailed in the respective figures. The 28 selected banks are concentrated between the light blue lines.

FIGURE 18. Distribution of Bank Indicators for Sample Selection



Note: The figures show the distributions of the bank indicators considered for the sample selection among the 79 European retail banks included in the EBA 2018, 2021, and 2023 exercises. The middle light blue line represents the mean values for Irish banks, while the upper and lower lines correspond to the selected +/- standard deviations. The specific standard deviations used are detailed in the respective figures. The 28 selected banks are concentrated between the light blue lines.

E Decomposition of the CET1 Capital Ratio

E.1 Waterfall Decomposition of the CET1 Capital Ratio - Items

TABLE 4. Waterfall Decomposition of the CET1 Capital Ratio

Index	Label	EBA Identifier						
Exercise		**2010**	**2011**	**2014**	**2016**	**2018**	**2021**	**2023**
C1	*Transitional CET1 Capital*	10001	30014	993402	1690802	183702	213702	2337002
O1	*Total Operating Income*	10004	30045	993005	1690709	183609	213609	2336009
R1	*Total Risk Exposure Amounts*[1]	10003	30016	993434	1690845	183756	213508	2335008
W1	Transitional CET1 Capital Ratio[1]	10008	30015	993441	1690847	183759	213761	2337061
W2	Net Interest Income		30040	993001	1690701	183601	213601	2336001
W3	Other Operating Income[2]							
W4	Credit Risk Losses	10005	30046	993007	1690710	183610	213610	2336010
W5	Market Risk Losses		30042	993003	1690706	183606	213606	2336006
W6	Other Income and Expenses (incl. Operating Losses)		30048	993011	1690711	183611	213611	2336011
W7	Distributed Amount		30051	993017	1690717	183616	213616	2336016
W8	Increase in Total Risk Exposure Amounts[3]							
W9	Other Items affecting CET1 (incl. Taxes)[4]							

Note: Items C1, O1, W2 to W7 are divided by $R1^{Start}$. [1]Realised value and values obtained under both scenarios considered as starting and ending points. [2]Other Operating Income is O1−(W2+W5). [3]Increase in Total Risk Exposure Amounts is computed as $C1\times\left(\frac{1}{R1^{Start}}-\frac{1}{R1^{End}}\right)$. [4]Other Items affecting CET1 (incl. Taxes) are $W1^{End}-(W1^{Start}+W2+W3+W4+W5+W6+W7+W8)$. As such, they include transitional arrangements when relevant.

E.2 Horizontal Decomposition of the CET1 Capital Ratio and Profit and Loss Accounts

E.2.1 Methodology

We decompose the transitional CET1 capital ratio using an alternative ‘Horizontal’ decomposition. This method separates the capital ratio into its numerator (transitional CET1 capital) and denominator (total risk exposure amounts) components, following the structure outlined in the EBA balance-sheet templates. The specific items considered are listed in Table 5. We also follow the same approach to decompose profit and loss, with items considered listed in Table 6 (Section E.2.2). Unlike the Waterfall approach, the Horizontal decomposition allows for a clear distinction between the impact of macroeconomic developments on the numerator (capital reserves) and the denominator (risk exposures) of the balance sheet. However, a limitation of this approach is that certain items, such as capital instruments eligible as CET1 capital and other reserves, are not typically modelled by the EBA, despite being important contributors to the transitional CET1 capital ratio.

In order to identify the total effect on the CET1 capital ratio, we consider the relative share of each subcomponent in both its numerator and denominator. Based on these observations, we compute the average share of each component by summing the amounts of each subcomponent across banks and exercises, then dividing by the total numerator or denominator for each period following the shock.[25] The resulting average

[25] This method of computing the average reduces the variance across banks and mitigates the influence of outliers, as opposed to averaging the ratios across banks and exercises. Additionally, by focusing on banks similar to those in Ireland, we are accounting for institutions with

shares are presented in Figure 19 and Figure 20 in Section E.2.3, with the sum of all components totalising one.

We compute the final effect of macroeconomic developments on the transitional CET1 capital and total risk exposures by multiplying the elasticities of all the components of the numerator, denominator, and profit and loss by their corresponding relative shares and summing them together. Specifically, the transitional CET1 capital ratio is obtained as $\beta_{CET1} = \frac{1+\sum_{n=1}^{N}\beta_n \times S_n}{1+\sum_{d=1}^{D}\beta_d \times S_d} - 1$, for each time period and macroeconomic variable. β is the sensitivity obtained from the regression of each subcomponent of the numerator and denominator in Equation (6) (Section 3.2.2). The only difference is that we now consider the cumulative variation of all the components instead of the level in the Waterfall approach.

E.2.2 Considered Items

TABLE 5. Horizontal Decomposition of the Transitional CET1 Capital Ratio

Index	**Label**	**EBA Identifier**						
Exercise		**2010**	**2011**	**2014**	**2016**	**2018**	**2021**	**2023**
		Numerator						
C1	Transitional CET1 Capital	10001	30014	993402	1690802	183702	213702	2337002
C2	Capital Instruments eligible as CET1 Capital*		30011	993403	1690803	183703	213703	2337003
C3	Retained Earnings		30050	993405	1690805	183705	213705	2337005
C4	Accumulated Other Comprehensive Income			993406	1690806	183706	213706	2337006
C5	Other Reserves*			993409	1690809	183710	213710	2337010
C6	DTAs		30052	993415	1690814	183715	213718	2337018
C7	Other CET1 Capital[1]							
		Denominator						
R1	Total Risk Exposure Amounts	10003	30016	993434	1690845	183756	213508	2335008
R2	Credit Risk Exposure			993101	1690601	183501	213501	2335001
R3	Market Risk Exposure			993104	1690604	183504	213504	2335004
R4	Operational Risk Exposure			993105	1690605	183505	213505	2335005
R5	Other Risk Exposure (incl. Transitional Adjustments)[2]							
		Ratio						
I1	Transitional CET1 Capital Ratio	10008	30015	993441	1690847	183759	213761	2337061

Note: [1]Other CET1 Capital is C1−(C2+C3+C4+C5+C6).[2]Other Risk Exposure (incl. Transitional Adjustments) is R1−(R2+R3+R4). *Not modelled by the EBA.

TABLE 6. Decomposition of After-Tax Profit and Loss Account

Index	**Label**	**EBA Identifier**						
Exercise		**2010**	**2011**	**2014**	**2016**	**2018**	**2021**	**2023**
O1	*Total Operating Income*	10004	30045	993005	1690709	183609	213609	2336009
P1	Interest Income				1690702	183602	213602	2336002
P2	Interest Expenses				1690703	183603	213603	2336003
P3	Net Fees and Commissions Income				1690705	183605	213605	2336005
P4	Market Risk Losses		30042	993003	1690706	183606	213606	2336006
P5	Other Operating Income[1]							
P6	Credit Risk Losses	10005	30046	993007	1690710	183610	213610	2336010
P7	Other Income and Expenses		30048	993011	1690711	183611	213611	2336011
P8	Tax Expenses			993013	1690713	183613	213613	2336013
L1	Net Profit and Loss		30049	993014	1690715	183104	213104	2331004

Note: [1]Other Operating Income is O1-(P1+P2+P3+P4).

comparable balance sheets, resulting in more consistent shares.

E.2.3 Balance-Sheet Proportions

FIGURE 19. Aggregate Share of CET1 Capital Ratio Components

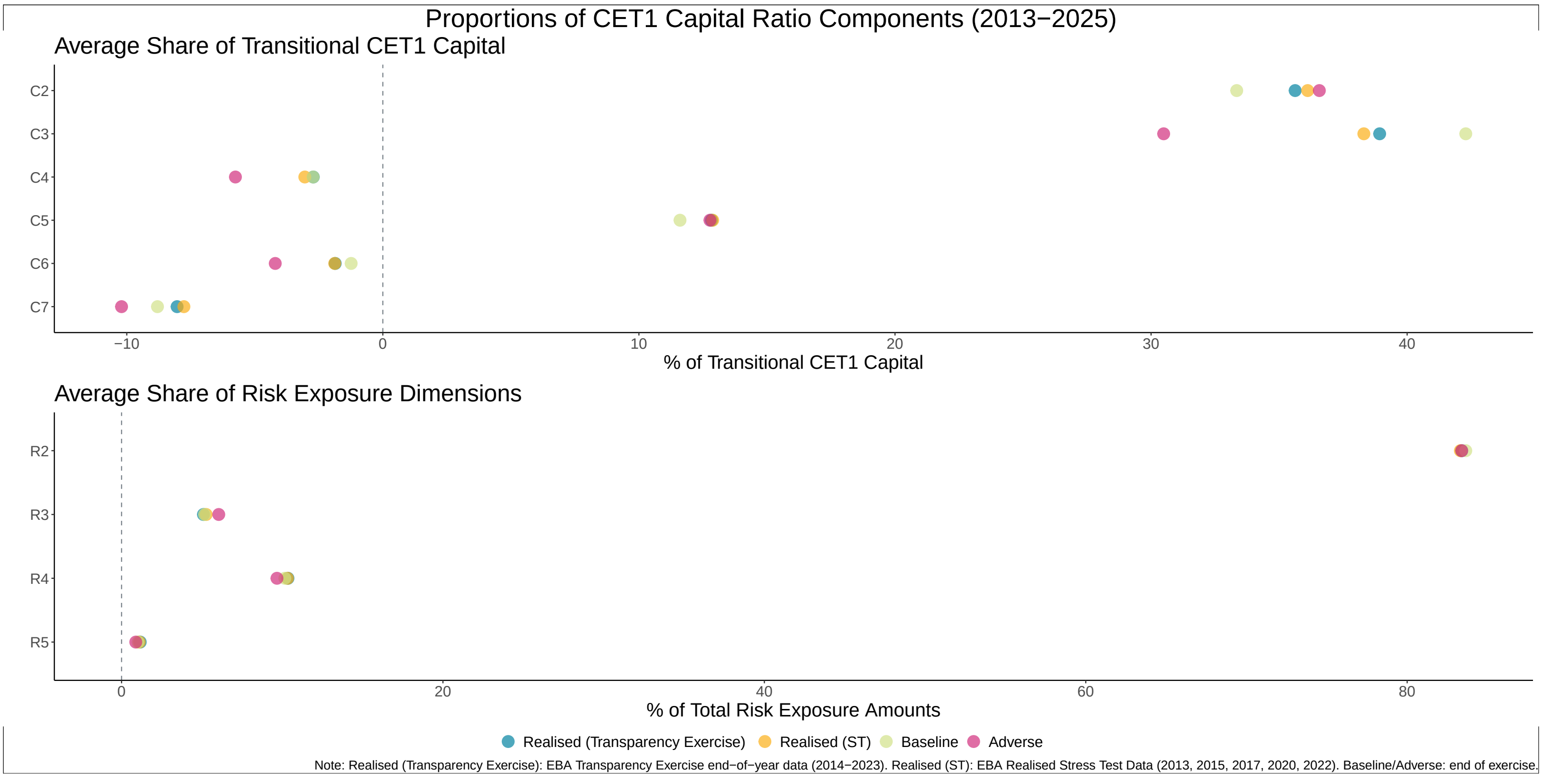
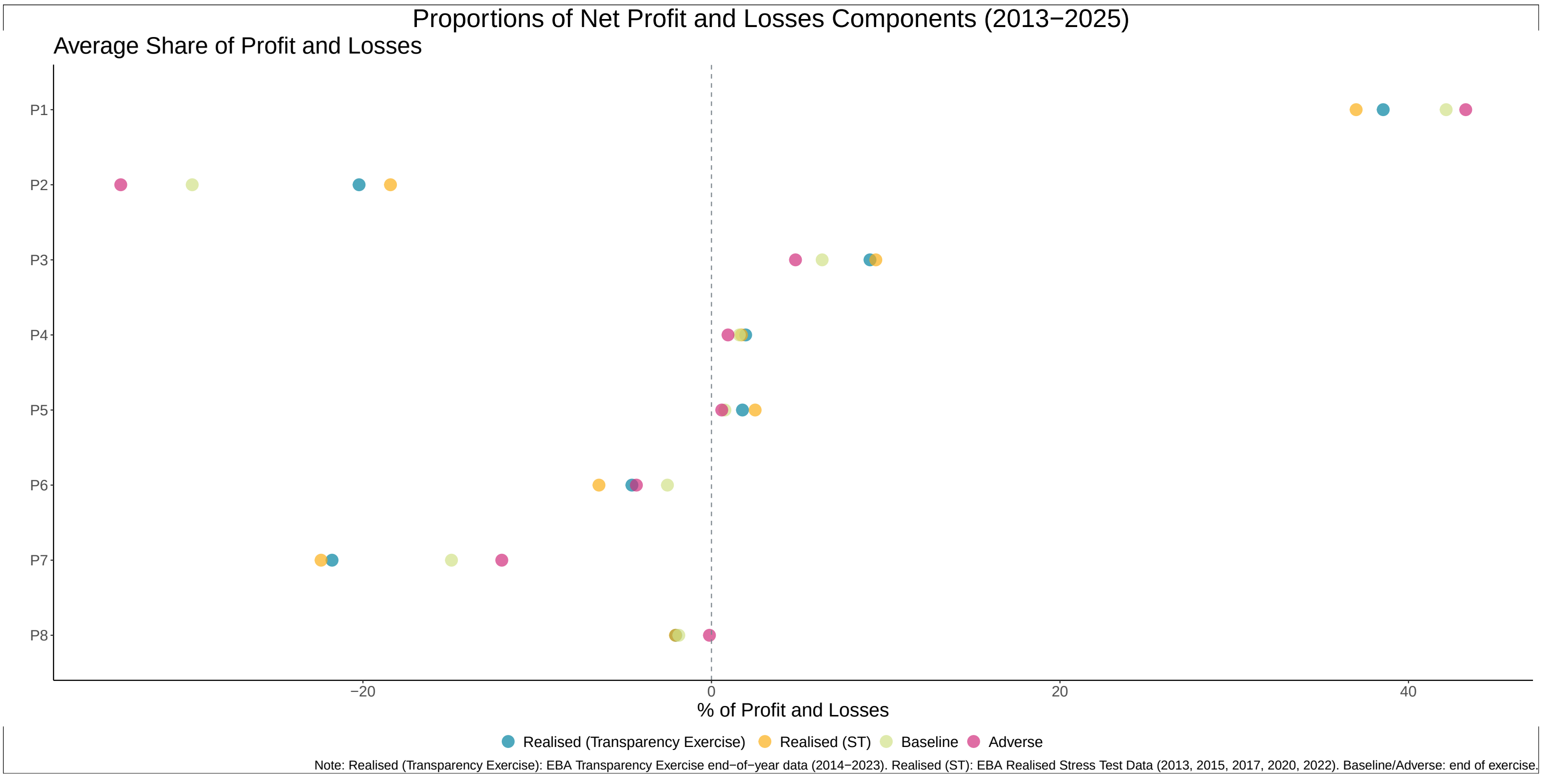
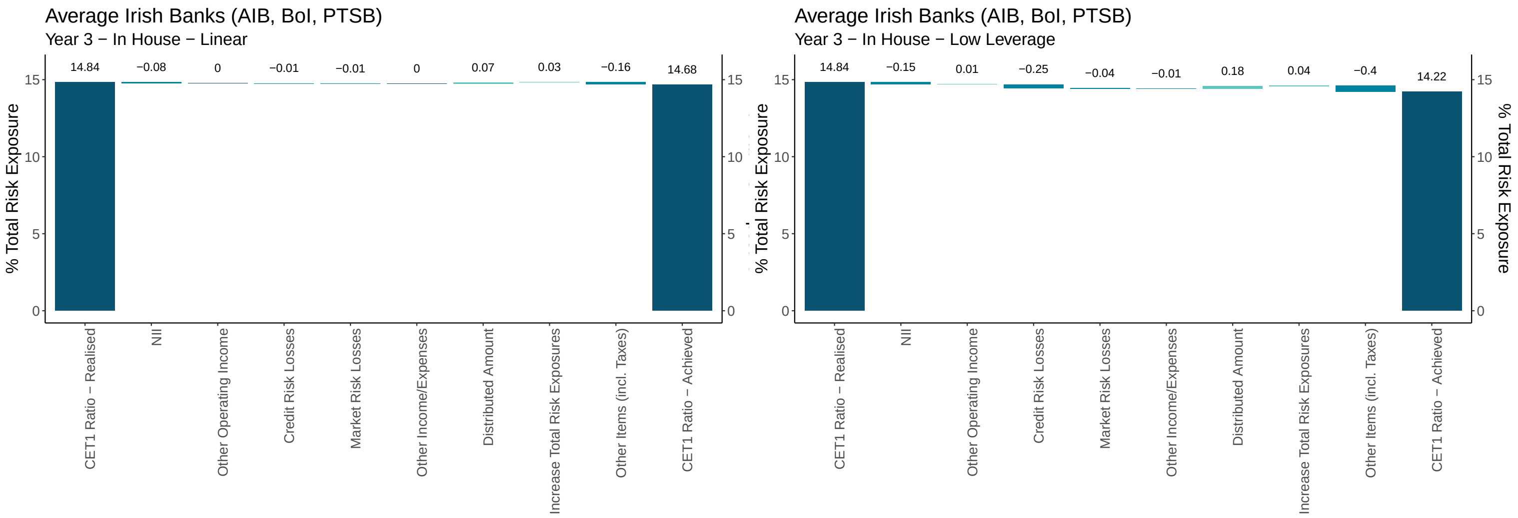


FIGURE 20. Aggregate Share of Profit and Loss Accounts



F Linear and Low-Leverage State Results

FIGURE 21. Total CET1 Capital Ratio Depletion (Linear and Low-Leverage)



Note: Average cumulative depletion three years following a 50bp increase in the 1-year Euribor. CET1 Ratio: Transitional CET1 capital ratio, NII: Net interest income.

FIGURE 22. Total CET1 Capital Ratio Depletion - Linear Model

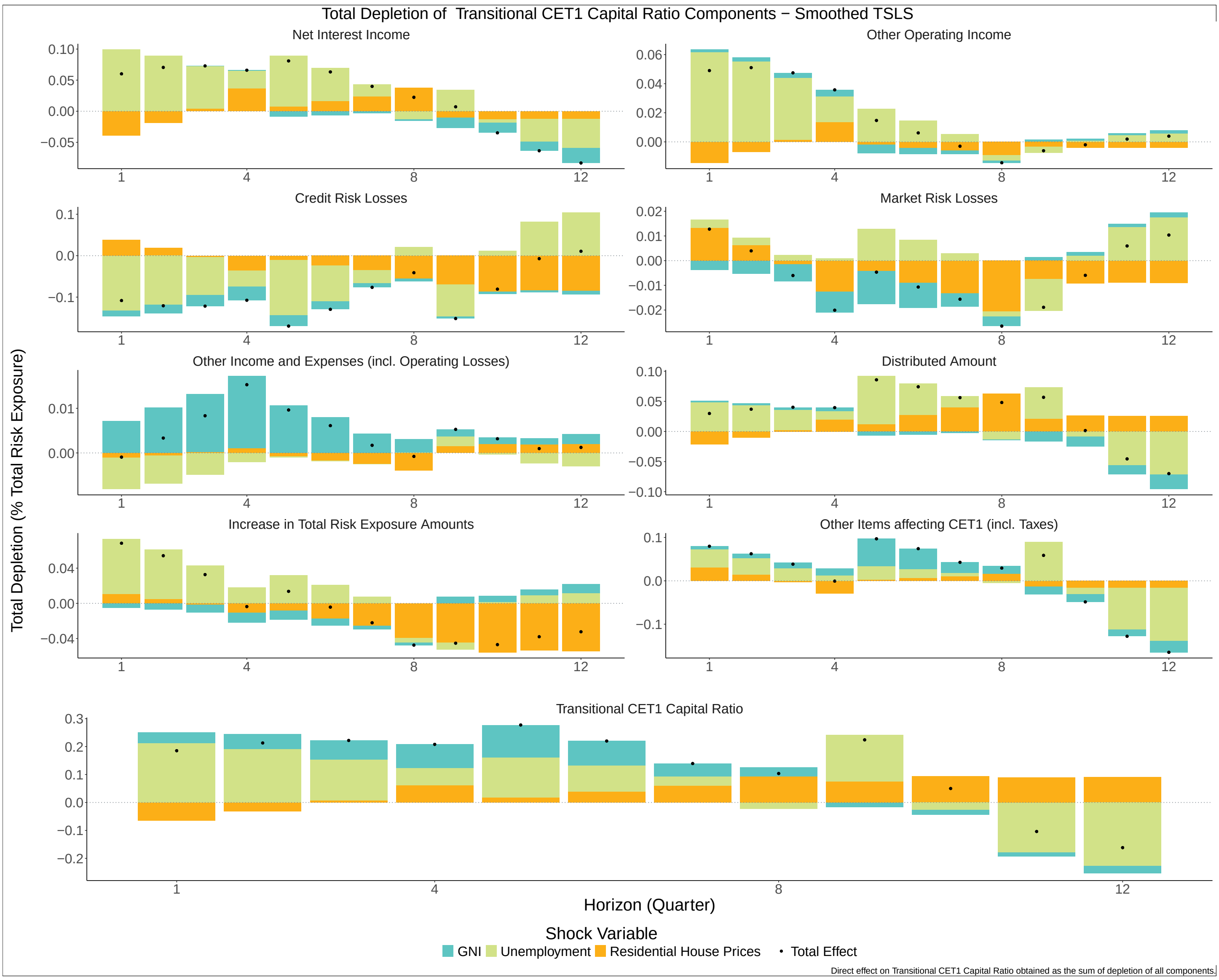
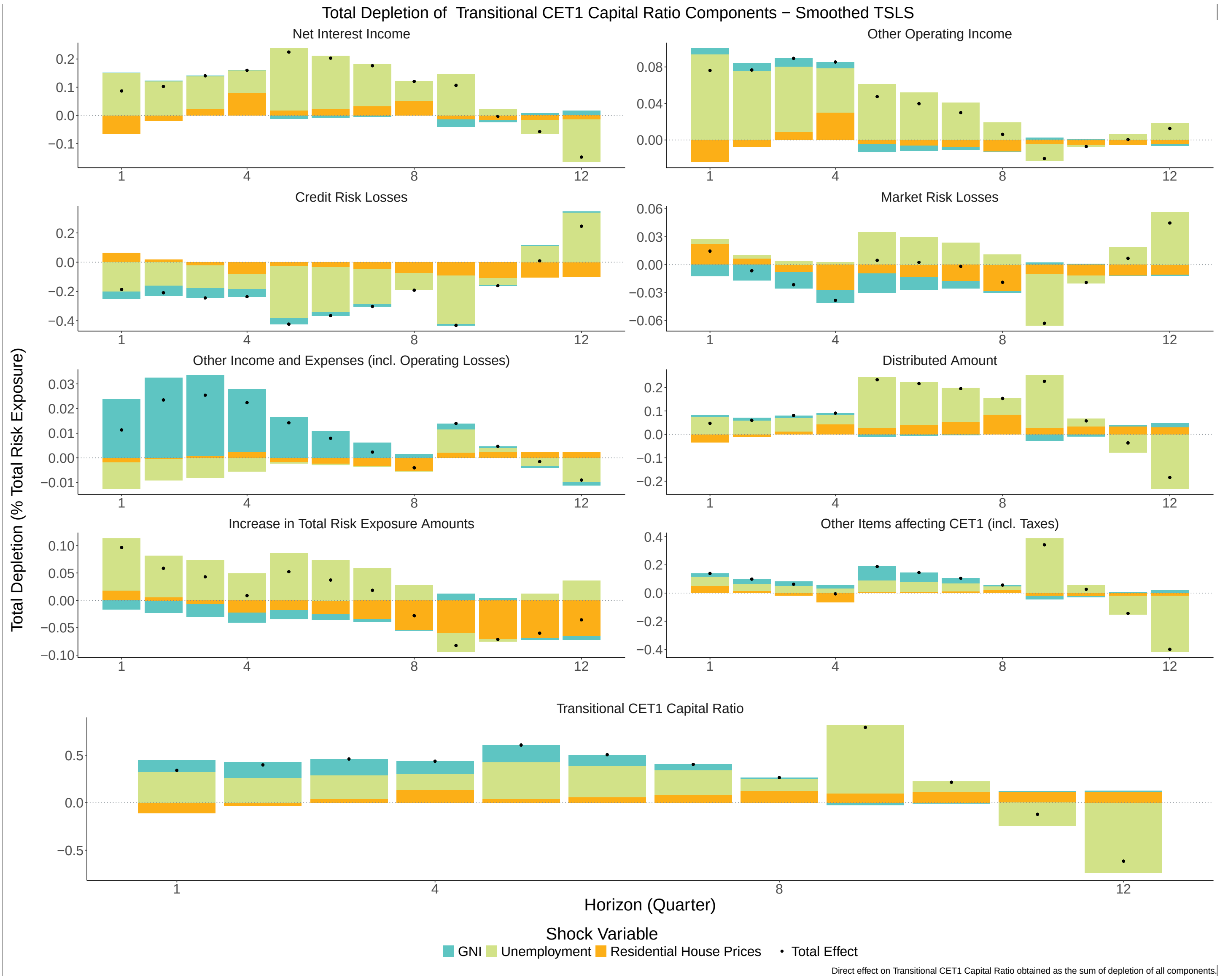


FIGURE 23. Total CET1 Capital Ratio Depletion - Low-Leverage State



G Relevant Scenarios and Estimated Capital Depletion

TABLE 7. In-House and External Scenarios and Estimated Capital Depletion

		Year after Shock		
Outcome (Δ)	**Scenario**	**1**	**2**	**3**
GDP/GNI* Growth	GFC (2009Q1)	−7.11	6.00	6.55
	EBA 2023 Adverse	−14.20	−2.00	4.10
	−25bps High Leverage	0.12	0.07	−0.03
	25bps High Leverage	−0.12	−0.07	0.03
	50bps Low Leverage	−0.25	−0.14	0.07
	50bps Linear	0.22	−0.14	0.12
	50bps High Leverage	0.35	−0.31	−0.18
	75bps High Leverage	−0.37	−0.21	0.10
	100bps High Leverage	−0.50	−0.27	0.13
	217bps High Leverage	−1.08	−0.59	0.29
Unemployment Rate	GFC (2009Q1)	5.54	2.96	1.27
	EBA 2023 Adverse	1.60	4.90	1.20
	−25bps High Leverage	−0.19	−0.35	−0.19
	25bps High Leverage	0.19	0.35	0.19
	50bps Low Leverage	−0.44	0.04	1.18
	50bps Linear	−0.16	0.23	0.16
	50bps High Leverage	0.39	0.70	0.37
	75bps High Leverage	0.58	1.05	0.56
	100bps High Leverage	0.77	1.41	0.74
	217bps High Leverage	1.67	3.05	1.61
Residential House Prices	GFC (2009Q1)	−14.10	0.69	1.34
	EBA 2023 Adverse	−14.20	−7.80	−7.70
	−25bps High Leverage	0.50	−0.01	−0.13
	25bps High Leverage	−0.50	0.01	0.13
	50bps Low-Leverage	1.41	0.33	−0.51
	50bps Linear	0.64	0.63	−0.22
	50bps High-Leverage	−1.00	0.02	0.27
	75bps High Leverage	−1.50	0.03	0.40
	100bps High Leverage	−2.00	0.04	0.53
	217bps High Leverage	−4.34	0.09	1.15
Transitional CET1 Capital Ratio	GFC (2009Q1)	−6.26	2.34	−7.82
	EBA 2023 Adverse	−7.56	−2.92	4.08
	−25bps High Leverage	0.17	0.11	0.42
	25bps High Leverage	−0.17	−0.11	−0.42
	50bps Low Leverage	0.44	−0.17	−0.88
	50bps Linear	0.21	−0.10	−0.27
	50bps High Leverage	−0.34	−0.22	−0.85
	75bps High Leverage	−0.51	−0.34	−1.27
	100bps High Leverage	−0.68	−0.45	−1.70
	217bps High Leverage	−1.48	−0.97	−3.69

Note: Δ: Year-on-year variations reported in percentage points. EBA 2023 Adverse: 2023 EBA adverse stress-test scenarios starting in 2022. GFC (2009Q1): Macroeconomic conditions experienced during the GFC in Ireland, with estimated and realised CET1 capital ratio values starting in 2008Q1. −25bps, 25bps, 50bps, 75bps and 100bps Linear, High- and Low-Leverage: In-house scenarios rescaled to obtain the corresponding basis-point change in 1-year Euribor on impact.

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