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Banking euro area stress test model

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Abstract

The Banking Euro Area Stress Test (BEAST) is a large scale semi-structural model developed to assess the resilience of the euro area banking system from a macroprudential perspective. The model combines the dynamics of a high number of euro area banks with that of the euro area economies. It reflects banks' heterogeneity by replicating the structure of their balance sheets and profit and loss accounts. In the model, banks adjust their assets, interest rates, and profit distribution in line with the economic conditions they face. Bank responses feed back to the macroeconomic environment affecting credit supply conditions. When applied to a stress test of the euro area banking system, the model reveals higher system-wide capital depletion than the analogous constant balance sheet exercise.

Keywords: macro stress test, macroprudential policy, banking sector deleveraging, real economy-financial sector feedback loop

JEL Classification: E37, E58, G21, G28

Non-technical summary

A macroprudential stress test attempts to inform regulators and the public about potential risks originating in and propagating from the financial sector. Such a stress test aims to make sense of both complex balance sheets and most likely bank reactions to negative economic developments. Ultimately, it allows to timely alert the regulator and the market about capital and liquidity needs of the banking sector.

This paper introduces the Banking Euro Area Stress Test (BEAST) model developed for the purpose of macroprudential stress testing of the euro area banking sector. The model includes a macroeconomic block for 19 euro area economies and a representation of 91 systemically important banks with their individual balance sheets and profit and loss accounts. The model incorporates the interactions between banks and the real economy and, by following a semi-structural design, can provide a narrative for systemic risk transmission channels.

Two features make the BEAST particularly suitable for macroprudential stress testing. Banks in the model can adjust the size and composition of their assets, along with interest rates or dividend pay-outs. Thereby, banks behavioural response functions are estimated using historical bank-level datasets. This model feature deviates from the so-called constant balance sheet assumption in most of the microprudential stress-tests. Second, the model incorporates a feedback loop between the financial sector and the real economy. To counterbalance the realisation of capital shortfalls and the deterioration of asset quality, banks adjust their credit supply. These reactions of individual banks, once aggregated on a country level, translate into a negative credit supply shock and add to the initial scenario adversity.

To illustrate the working of the model, the BEAST is applied to evaluate the performance of the euro area banking sector under the adverse scenario of the 2018 EBA supervisory stress test. The adverse scenario for 2018–2020 considered a period of prolonged systemic stress, with a substantial drop in euro area output and in residential house prices, along with rising unemployment rates. By emphasizing the feedback between the banking sector and the real economy, the model amplifies the severity of the scenario and reveals higher bank capital depletion than the original EBA stress test results.

1 Introduction

Financial intermediation, and banking in particular, are highly complex activities. Many contracting decisions are based on trust, making them susceptible to drastic changes in the face of new information (Morris and Shin 2008). Such changes may occasionally give rise to sharp reversals in investors' actions resulting in financial distress and reduced private sector access to credit. To prevent such market disruption is the raison d'être of the macroprudential regulation and macroprudential stress testing.

A stress test can make sense of complex balance sheets and business models, uncover vulnerabilities of financial institutions, and timely alert regulators and the markets about capital and liquidity needs of institutions (Bookstaber et al. 2014). The focus of the microprudential regulator will be to minimise the cost to the tax-payer of bailing out insured deposits. The critical nuance is that from a microprudential perspective, the institutions are treated as isolated entities when aggregating this hypothetical cost across banks. In contrast, the macroprudential regulator aims to account for stress amplification mechanisms, such as deleveraging and credit crunches. Accordingly, macroprudential stress tests need to acknowledge a broader set of interactions between banks and their potential disruptive influence on the real economy (Claessens and Kose 2017), which we will refer to as real economy-financial sector feedback loop hereafter.

This paper introduces the Banking Euro Area Stress Test (BEAST) model developed for the purpose of macroprudential stress testing of the euro area banking sector. The model includes a macroeconomic block for the 19 euro area economies and a representation of 91 systemically important banks with their individual balance sheets and profit and loss accounts. Further, it captures the dynamic interdependencies between aggregate and bank-level variables including cross-border spillovers and the feedback loop between the financial sector and the real economy. The paper focuses on the model version that has been applied to the macroprudential stress test of the euro area banking system in 2018 (Budnik et al. 2019) and recalls the main takeaways from this exercise.

The BEAST has two ingredients that make it suitable for macroprudential stress testing. First, it incorporates banks' behavioural reactions to economic conditions. Among those, banks can adjust the size and composition of their assets, can reset interest rates on both loans and deposits, and scale up or down their dividend payments. This allows deviating from the so-called constant balance sheet assumption which is commonly applied especially in bottom-up stress tests. Second, the model incorporates a feedback loop between the financial sector and the real economy. A macroeconomic scenario impacts the quality of bank assets leading to changes in impairment losses and the adjustments of capital charges. Accordingly, an adverse scenario lowers bank profitability and increases the risk weighted exposure amounts, via both channels lowering the solvency level. In order to counterbalance the resulting capital shortfalls with respect to regulatory capital targets, banks adjust their credit supply (in terms of lending volumes and interest rates). Aggregated banks' credit supply responses translate into a change in aggregate credit conditions adding up to the initial scenario adversity.

Additional strength of the model is its ability to capture the heterogeneity of the euro area banking system. The model incorporates details of balance sheets and profit and loss statements of individual banks. Furthermore, banks' reactions depend on their own solvency, asset quality and profitability. And last, banks' behavioural equations involve a range of thresholds which are either identified econometrically (e.g. a tendency of banks to deleverage proportionately stronger once they hit their regulatory limits) or derived directly from the regulation (e.g. Maximum Distributable Amount limits). All three elements generate a high degree of heterogeneity in bank responses.

The BEAST falls between macroeconometric semi-structural models, used for e.g. inflation and output forecasting, and heterogeneous agent models. Regarding its semi-structural design, the model is a mixture of structural and data-driven equations. The latter are inspired by theory and estimated employing macro- and micro-economic data and identification techniques. Regarding its proximity to heterogeneous agent models, the BEAST incorporates the information about many individual banks and aggregates bank-level outcomes to arrive at system-wide variables that enter the macro block.

The original contribution of the paper is to propose a comprehensive semi-structural setup in the field so far dominated by sequential use of multiple unconsolidated approaches. These sequential approaches allow for a combination of several models that originally work on different levels of granularity and emphasize different transmission mechanisms. Examples of modular frameworks include the Bank of Canada's Macrofinancial Risk Assessment Framework (MFRAF) (Fique 2017), the Bank of England Risk Assessment Model of Systemic Institutions (RAMSI) (Alessandri et al. 2009), the Bank of France frameworks by Bennani et al. (2017) and Camara et al. (2015) or in the ECB Stress-Test Analytics for Macroprudential Purposes in the euro area (STAMP€)(Dees et al. 2017). The core weakness of a modular approach is its ingrained inconsistency and limited ability to describe amplification mechanisms. The convergence in these approaches is achieved by iterating the work flow. Our approach has the ambition to encapsulate all relevant elements of an amplification mechanism (in our case real economy-financial system feedback loop) in one, jointly solved, system. To this end it resembles the proposal of Krznar and Matheson (2017).

The paper is structured as follows. Section 2 provides a high-level introduction of the model. Section 3 describes the macro block. Section 4 describes the identification of core behavioural bank-level equations. Additionally, the identification of empirical equations describing the sensitivity of bank assets to macroeconomic developments is placed in Appendix A. All remaining model identities are listed in Appendix B. Section 5 elaborates on selected results of the euro area macroprudential stress test of 2018 as an example of model application. Section 6 concludes.

2 High level model description

This chapter introduces the main segments of the model and explains their interactions. The BEAST works on a quarterly frequency and, along with the logic of semi-structural modelling, it consists of a set of estimated behavioural equations whose specification is informed by theory, and a set of structural relationships.

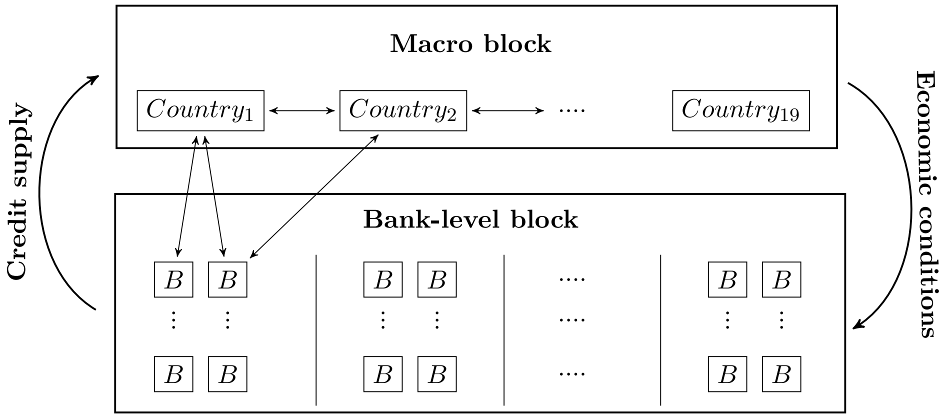


Figure 1: Basic model structure

The model can be thought of as a joint representation of 19 individual euro area economies (macro block) and over 90 largest euro area banks (bank-level block). The bank-level block is based on the templates submitted by banks in the EBA stress-test exercise in 2018, and focusses on bank lending, credit risk and net interest income. Less emphasis is put on modelling of the trading book, market and operational risk, and bank liabilities. The estimation of behavioural equations involves multiple datasets including iBSI/iMIR (individual Balance Sheet Items and MFI Interest Rate Statistics), COREP/FINREP information, and public databases such as Bankscope and SNL.

The two blocks are interlinked as illustrated in Figure 1. Economic conditions in the 19 euro area countries affect the quality of bank assets and credit demand. Bank lending decisions, aggregated on a country level, affect in turn the macroeconomic outlook.

2.1 Macro block

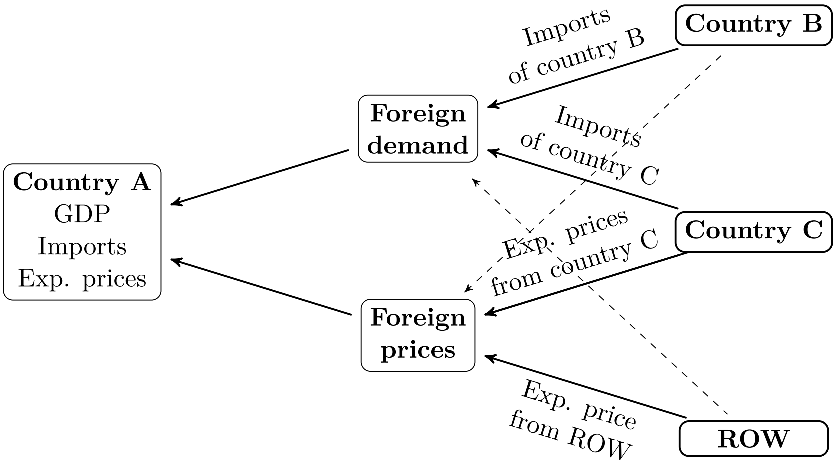


Figure 2: Cross-country trade spillovers

Each economy is represented by a set of macro-financial variables, such as GDP, inflation, house prices or government bond yields. The dynamics of these variables are modelled in a simplified fashion with a Vector Autoregression model (VAR). A detailed description of the underlying identification strategy can be found in chapter 3.

Cross-border trade spillovers are introduced via foreign demand and price variables entering country-level VARs. As outlined in Figure 2 foreign demand of a country depends on import volumes of its trading partners, while foreign prices depend on export prices of other countries (in both cases as weighted with the corresponding export or import shares). Beyond, the model involves country-specific rest-of-the-world (ROW) variables.[1]

[1]The methodology of introducing trade spillovers follows the proposal by Budnik and Runstler (2018) that allows for linking country level models into linearized multi-country systems in an easily tractable way. Same specification of trade spillovers enters as well the Stress Test Elasticities used in the European Banking Authorities stress test exercises since 2011. Trade shares of all euro area countries are assumed to remain constant.

2.2 Bank-level block

The asset side of each bank balance sheet is illustrated in Table 1. The BEAST models the evolution of exposures to the non-financial corporate sector (NFC), households backed by real estate (HHHP) and household for consumption purposes (HHCC), followed by exposures to sovereigns (SOV) and the financial sector (FIN). Exposures to the non-financial private sector are split by the country of exposure, while exposures to sovereign and financial sectors are aggregated across jurisdictions. The dynamics of other loans, equity exposures and securitized portfolios is exogenous.

Portfolio	Modelling approach
Loans to NFC Loans to HHHP Loans to HHCC	geographical breakdown
Loans to SOV Loans to FIN	aggregated
Other loans Equity exposure Securitized portfolio	exogenous

Table 1: Schematic illustration of banks' banking books

The model captures flows between the three IFRS9 asset impairment stages, i.e. performing, with increased credit risk since initial recognition, and credit-impaired, for each endogenous banking book portfolio. Changes in asset quality are reflected in respective flows of provisions which, aggregated up, enter the profit and loss statement. A detailed description of the impairment stages and the loan loss provisioning can be found in Appendices B.1 and B.2.

Each endogenous banking book portfolio has its assigned risk weight. Total risk weighted amounts are derived by adding the endogenous credit risk exposure amounts to exogenous assumptions regarding the evolution of capital charges related to market and operational risk (see Appendix B.7).

For each endogenous banking book portfolio t

On the bank liability side, the model tracks separately equity, sight and term deposits (to corporates NFC and households HH), wholesale funding including interbank liabilities and debt securities (Table 2). It is assumed that the structure of debt funding (deposits, market funding and debt securities) remains constant while the total debt funding changes in proportion to the size of banks' assets.

Liability class	Modelling approach
Capital	
Sight deposits HH	geographical breakdown
Sight deposits NFC	
Term deposits HH	
Term deposits NFC	
Wholesale funding	exogenous

Table 2: Schematic illustration of banks' liabilities

For each bank, net profit is broken down into impairments arising from credit risk, net interest income performance, the devaluation of assets due to market risk and net-fee-commission income. Bank dividend pay-outs of banks follow an estimated behavioural equation taking into account regulatory payout restrictions (see subchapter 4.3 and Appendix B.5 for additional information on the profit and loss account).

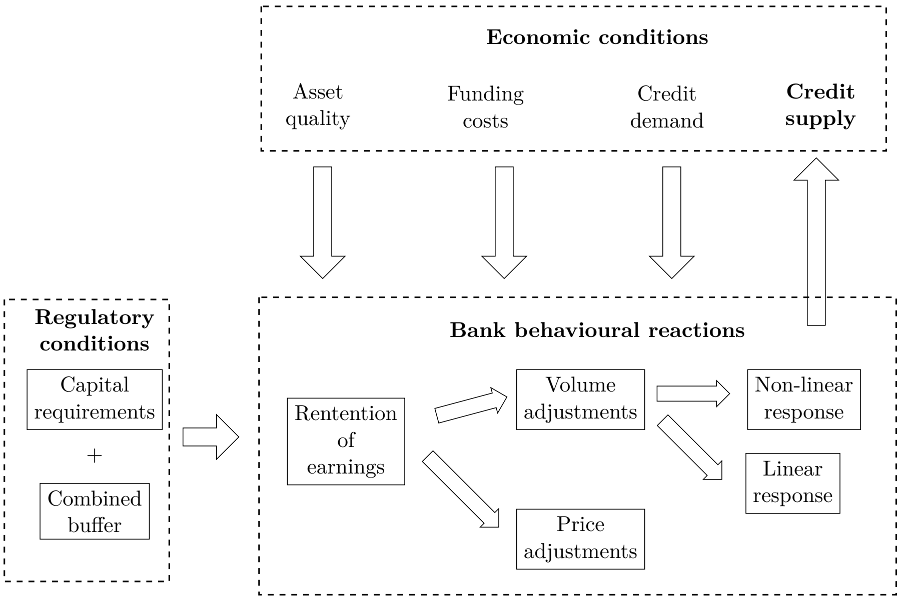


Figure 3: Schematic illustration of model dynamics focusing on bank reactions

The important element of the BEAST is the relaxation of the static balance sheet assumption. As illustrated in Figure 3, banks adjust their loan volumes and interest rates in response to a given scenario. These behavioural reactions take into account changes in bank asset quality, profitability, solvency rate with respect to their regulatory requirements, and the evolution of sector and country specific credit demand. In particular loan volume adjustments involve a linear and non-linear response to capital shortfall and changes in asset quality (see chapter 4).

2.3 The feedback loop

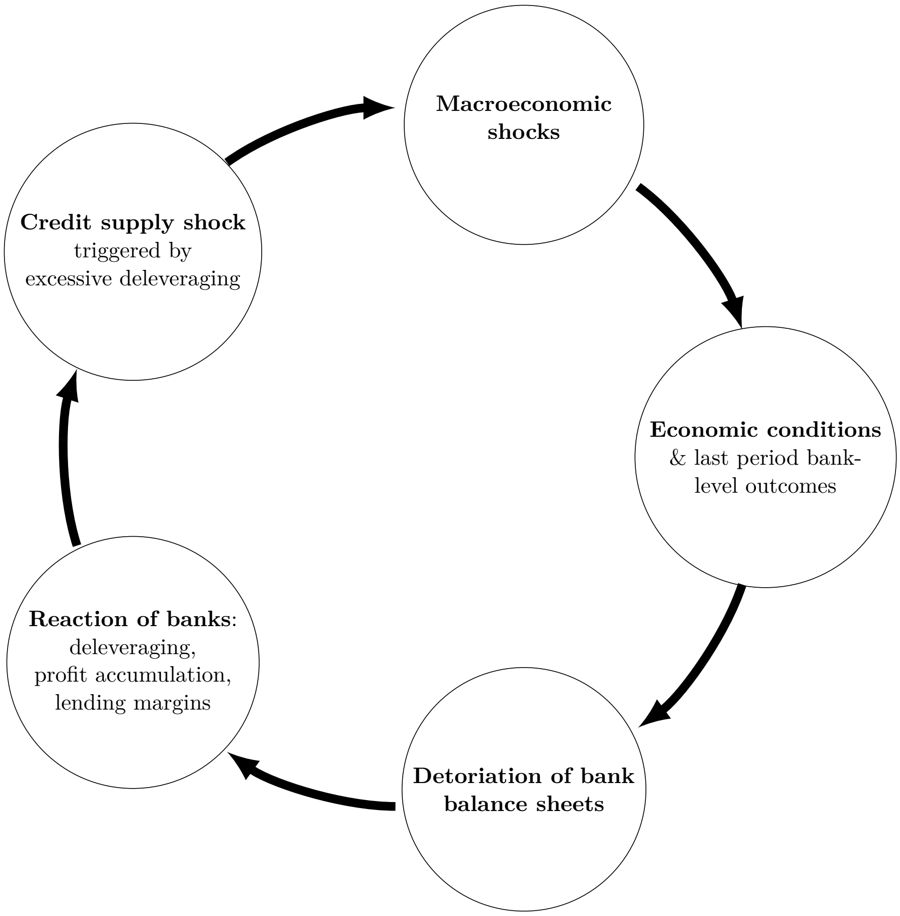


Figure 4: Schematic illustration of model dynamics focusing on the real economy – banking sector feedback loop

Next to the relaxation of the static balance sheet assumption, the model incorporates the impact of bank lending decisions on the real economy. It is achieved by aggregating the non-linear elements of bank credit supply responses, interpreted as excessive deleveraging, and mapping these into a credit supply shock affecting the real economy as illustrated in Figure 4.

The main mechanism of the real economy-financial sector feedback loop can be described in several steps as illustrated in Figure 4. At first, selected macroeconomic shocks affect the real economy. The resulting economic conditions influence bank asset quality and credit demand conditions. Following the changes on their balance sheets, banks are allowed to rebalance their assets in order to restore their solvency levels. The resulting credit supply shocks add to the initial macro-financial shocks and change the economic outlook in the following periods.

3 Macroeconomic module

The macroeconomic module of the BEAST can be described as a reduced-form multi-country setup. The dynamics of single euro are economies are estimated with a structural panel vector autoregressive model. The VAR equations are later interlinked via trade spillovers.

3.1 Empirical approach

The estimation of the macroeconomic block rests on a structural panel vector autoregressive model (SPVAR) for 19 euro area countries. For each economy i, the model includes 11 endogenous variables in vector $Y_{i,t}$ and 2 exogenous variables in vector $X_{i,t}$. The reduced form panel VAR has the following form:

$$Y_{i,t} = c_i + \sum_{j=1}^{p} A_{i,j} Y_{i,t-j} + B_i X_{i,t} + \epsilon_{i,t} \tag{1}$$

where c_i is a vector of country-specific intercepts, $A_{i,j}$ is a country-specific matrix of autoregressive coefficients for lag j, p corresponds to the number of lags (it is assumed that $p = 2$) and $\epsilon_{i,t}$ is a vector of reduced–form residuals.

The estimation relies on the Bayesian estimator proposed by Jarocinski (2010). The estimator allows for different VAR coefficients across units ($A_{i,j}$ and $B_{i,j}$) but assumes that they are drawn from a distribution with similar mean and variance.

The structural representation of the panel VAR model is derived combining zero and sign impact restrictions. Following the methodology developed by Arias et al. (2018) we identify 8 structural shocks based on the identification scheme in Table 3.

Aggregate demand, aggregate supply and monetary policy shocks are identified using a standard set of restrictions as in Hristov et al. (2012). An aggregate demand shock is described as a shock that moves inflation and GDP in the same direction (and triggers an increase in short-term interest rates). An aggregate supply shock moves inflation and GDP in opposite directions. An accommodative monetary policy shock is reflected in lower interest rates and an increase in inflation and output.

The identification of credit supply shocks follows Hristov et al. (2012), Barnett and Thomas (2013) and Duchi and Elbourne (2016). The identification scheme assumes that a credit supply shock moves lending rates and volumes in opposite directions. Such a credit supply shock is

	Aggregate supply	Monetary policy	Aggregate demand	Credit supply	Long-term interest	Residential prices	Unem-ployment	Stock prices
Real GDP	+	+	+	+			0	0
HICP	–	+	+	0	0	0		
Unemp. rate				0			–	
Short-term int. rate		–	+	0	0			0
Long-term interest rate				0	+	0		
Import volumes				+				
Export prices				0				
Residential property prices				0		+		0
Bank lending rates				–				
Bank loan volumes				+				
Equity price index				+				+

Table 3: Summary of identifying restrictions in SPVAR

consistent with either a decline in banks capital (Gerali et al. 2010) or deterioration of bank asset quality (Gertler and Karadi 2011). The identification is strengthened by imposing zero contemporaneous response restrictions on inflation, unemployment rate, short- and long-term interest rates. The residential price shock identification follows Buch et al. (2014). All remaining shocks, therein stock prices shock, unemployment shock and long-term interest rate shock, are delineated by imposing the relevant zero restrictions.

Macroeconomic scenarios are replicated within the model using structural shock decomposition. Thereby, the macroeconomic module not only allows introducing second-round effects originating in the banking sector via the credit supply shock but also provides a clear narrative of each scenario.

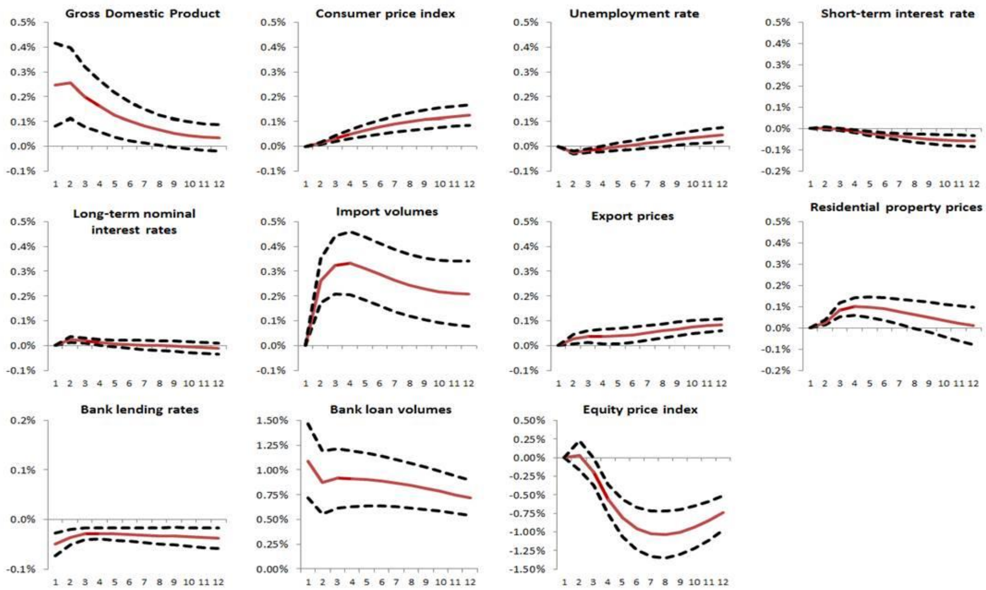
3.2 Data

The quarterly data from 2002Q1 to 2017Q4 are sourced from the ECB Statistical Data Warehouse (SDW) macroeconomic projection database.[2] Endogenous variables consist of real gross domestic product, unemployment rate, consumer price index, nominal residential property prices, long-term nominal interest rates[3], equity price index , import volumes and export prices, bank lending rates, bank loan volumes, short-term money market rates. Two exogenous variables

[2] If the information in the SDW was missing, the dataset was completed using data from national sources.
[3] 10-year government bond rates.

include country-specific foreign demand and competitors prices. All variables except unemployment and interest rates enter the VAR model in log levels.

3.3 Results



Note: Units are in percentage point deviation, except the interest rates and unemployment rate, which are in terms of percentages. The solid red line depicts the mean of country specific response at each horizon, while the dashed lines represent mean +/- one standard deviation.

Figure 5: Impulse responses to credit supply shock

Impulse responses of the model's endogenous variables to a one standard deviation adverse credit supply shock are presented in Figure 5. A favourable credit supply shock leads to a credit boom that causes bank loan volumes to increase and bank lending rates to decrease. On average, favourable credit supply shocks increase loan volumes by about 1.1% on impact and decreases lending rates by 5 basis points on impact. After the credit supply shock, GDP increases by about 0.25% on impact before slowly returning to baseline. The effect of the credit supply shock on other variables is relatively limited.

4 Bank-level behavioural equations

This section presents the main equations describing banks' behavioural reactions. It starts with the description of adjustments in bank lending volumes. Then, it summarises the estimates of lending and deposit margin equations. Last, it lays down the dynamics of dividend pay-outs. In each case, and similar to the section on the macro block, we first describe the specification, then the data, and finally the results of the estimations.

4.1 Loan evolution

The evolution of bank lending should relate both to the macroeconomic environment (a stress test scenario) and banks' own situation such as their profitability, solvency or estimates of credit risk. The desired specification of lending equations should encapsulate all this factors in a common setup. However, the estimation of such equations with bank-level information is hindered by data availability.

To overcome data shortages, the process of estimating lending equations separates the impact of credit demand and credit supply factors. Loan demand will depend on aggregate economic conditions, like GDP growth, unemployment and interest rates. Loan supply, in turn, will depend on individual bank characteristics, like bank's profitability, solvency and asset quality.

The demand-side equation is estimated using iBSI/iMIR data collected for a sufficiently long time to allow identification of bank lending inertia and its dependency on macroeconomic aggregates. The supply-side equation is estimated using the supervisory reporting datasets COREP/FINREP that covers only a three year horizon but includes all relevant variables reflecting banks' internal situation. The demand-side equation is later reinterpreted as an autoregressive component and the supply-side equation as a medium-run relationship. Both are merged in the final equation in a way analogous to an error correction model.

4.1.1 Loan demand

4.1.1.1 Methodology

Loan demand equations involve a set of macroeconomic variables and an index capturing time variation in credit supply factors. The latter index is later replaced by sector-specific loan supply equations. However, for estimation purposes it is necessary to derive a measure of changes in credit supply factors that would be available for a longer time horizon. To this end, we use semi-consolidated information on bank lending volumes and interest rate margins and identify a structural credit supply shock in a series of bank-level VARs. More precisely, we estimate a series of bank-level VAR models similarly as in Altavilla et al. (2016) for each ultimate parent bank:

$$Y_{i,t} = c_i + \sum_{j=1}^{p} A_{i,j} Y_{i,t-j} + \sum_{j=1}^{p} B_{i,j} X_{i,t} + \epsilon_{i,t} \tag{2}$$

where $Y_{i,t}$ is a vector of the endogenous variables for bank i including total lending volumes to the non-financial private sector as well as the average interest rate on loans to the non-financial private sector. c_i is a vector of bank-specific intercepts. $X_{i,t}$ is a vector of exogenous variables with natural logarithm of exposure weighted real GDP and changes in short-term rates. $A_{i,j}$ is a bank-specific matrix of autoregressive coefficients for lag j, p is the number of lags (and is set to $p = 1$) and $\epsilon_{i,t}$ is a vector of reduced–form residuals. Relying on these banking group specific VARs we identify a credit supply shock index via sign restrictions as described in Table 4:

	Credit supply
Loan volumes	–
Avg. interest rate	+

Table 4: Summary of identifying restrictions

Lending demand equation is estimated via a fixed-effect panel regression of bank-level loan growth rates on country-specific aggregate economic conditions. The sectors s considered are: financial institutions (FIN), non-financial corporates (NFC) and households (HH). We postulate the following functional relationship for quarterly log change of bank i loan exposures to sector s in country j at time t denoted by $\Delta Loans^s_{ij,t}$:

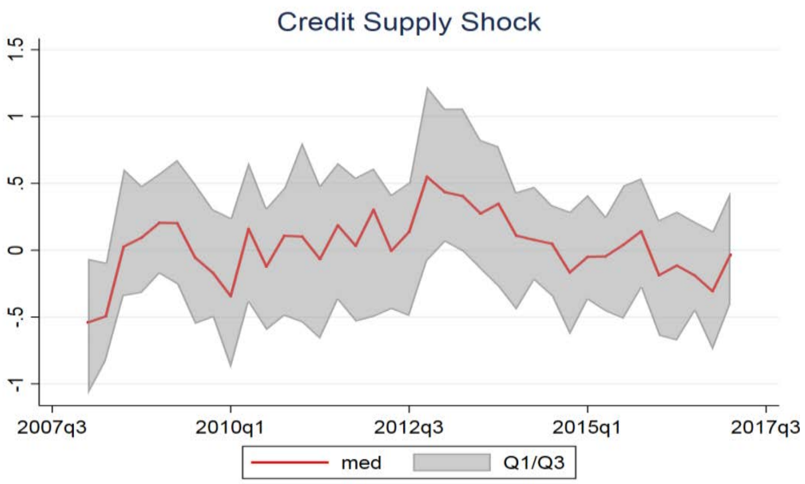
$$\Delta Loans^s_{ij,t} = c_i + \sum_{j=1}^{p} \alpha^p \Delta Loans^s_{ij,t-j} + \sum_{j=1}^{p} \beta^p X_{j,t-j} + \tau Supplyshock_{i,t} + \epsilon_{ij,t} \tag{3}$$

where $X_{j,t}$ is a vector of macroeconomic variables including GDP growth, inflation (based on HICP), short-term rate, unemployment rate, and the spread between long and short-term rate in country j. α^p, β^p and τ stand for regression coefficients. Before applying a general-to-specific procedure of excluding insignificant lags of dependent variables, the panel includes two lags ($p = 2$) of all covariates. The panel is estimated subject to dynamic homogeneity restrictions (see Jensen (1994)) to ensure a stable long-run relationship between nominal GDP growth and loan growth. The specification includes the supply shock index $Supplyshock_{i,t}$ from eq. 2 and is estimated with bank level clustered standard-errors.

4.1.1.2 Data

The first stage of the analysis is based on semi-consolidated iBSI/iMIR loan and interest rate data, while the second stage uses individual reporting and differentiates between loans and interest rates to households, non-financial and financial corporations as well as the public sector. The loan and interest rate data were seasonally and outlier-adjusted using the X-12-ARIMA algorithm both on individual branch and consolidated bank level. The monthly iMIR/iBSI data are then transformed to quarterly time series in line with the frequency of the model framework. The macroeconomic variables are sourced from SDW.

4.1.1.3 Results



Note: The red line illustrates the median cumulative shock index of all 70 semi-consolidated banking groups reporting in iBSI/iMIR while the grey area represents the interquartile-range.

Figure 6: Aggregate time variation in credit supply shock series

Figure 6 plots the evolution of credit supply shock series. It appears that the proxy for omitted bank-specific credit supply factors performs reasonably well in capturing the impact of the recent financial crisis in 2007–2008 and later of the European debt crisis in 2010.

Table 5 presents the estimation results from for the fixed-effect panel. The final specifications

Sector	Non-financial corporates		Financial corporates		Sovereign		Households	
Regressor	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Loan growth $(t-1)$	0.193***	(0.000)					0.375***	(0.000)
Loan growth $(t-2)$	0.200***	(0.000)					0.294***	(0.000)
GDP growth $(t-1)$	0.317***	(0.000)	0.595***	(0.000)	0.567	(0.428)	0.189***	(0.000)
GDP growth $(t-2)$	0.290***	(0.000)	0.405**	(0.010)	0.308	(0.627)	0.142***	(0.000)
GDP growth $(t-3)$					0.126	(0.843)		
Inflation $(t-1)$	0.0870	(0.376)	0.404	(0.546)			0.331***	(0.000)
Inflation $(t-2)$	0.520***	(0.000)	0.596	(0.372)	0.862	(0.613)		
Inflation $(t-3)$					0.138	(0.936)		
Δ STN $(t-1)$	-0.229	(0.105)	−1.168*	(0.097)	−3.904**	(0.014)	−0.664***	(0.000)
Spread $(t-1)$	-0.0141	(0.660)	-0.130	(0.579)				
Unemp. rate $(t-1)$	−0.031*	(0.077)						
Δ Unemp. rate $(t-1)$			−1.430*	(0.066)			-0.00230	(0.970)
Supplyshock (t)	−0.0005**	(0.033)	−0.007***	(0.000)	−0.005*	(0.069)	0.00001	(0.898)
Constant	−0.0006**	(0.042)	0.002	(0.147)	-0.001	(0.731)	−0.0005***	(0.000)
Bank fixed effects	Yes		Yes		Yes		Yes	
Banks	84		91		81		86	
Obs.	2925		3172		2755		2994	

Table 5: Loan demand model

differ between sectors. For instance, the regressions for financial and sovereign exposures do not include lagged dependent variables, whole household loans exhibit high inertia. The procyclicality of corporate lending is stronger than the procyclicality of lending in any other market segments as reflected in the relative impact of output growth on corresponding loan volumes.

4.1.2 Loan supply

4.1.2.1 Methodology

In order to uncover the relationship between bank lending and bank characteristics, we rely on a pooled bank-level regression inspired by Khwaja and Mian (2008). The original work of Khwaja and Mian (2008) (see also Jiménez et al. (2017)) uses loan level information on firms, which are indebted to at least two banks, to establish how two (or more) banks, which are differently affected by a policy change, adjust their lending to firms. In order to control for firm level characteristics that can affect their loan holdings (such as loan demand and borrower risk) the authors saturate the regressions with firm-level fixed effects.

In our case, the rich set of fixed-effects will control the regressions for credit demand factors. A counterparty of a bank is a specific lending segment such as a corporate sector in one of the jurisdictions.[4] By using data for counterparties that borrow from at least two banks, we can identify counterparty-time fixed effects, which capture counterparty-time variation likely related to the evolution of the macroeconomic environment. The salient assumptions behind this methodology is that all entities within the same sector-counterparty class face the same demand for loans and that loan demand is not bank specific, i.e. it is equal across all banks that lend to a counterparty. In the model, fixed-effect estimates are dropped and effectively replaced by the loan demand equation estimated earlier.

The general model specification is the following:

$$\Delta Loans^{s}_{ij,t} = f(CET1Shortfall_{i,t-1},\ NPL^{s}_{ij,t-1},\ ROA_{i,t-1},\ \delta^{s}_{jt}), \tag{4}$$

where $\Delta Loans^{s}_{ij,t}$ is quarterly log change of sector s loans to counterparty j by bank i in time t, $CETShortfall_{i,t}$ is a measure of CET1 capital surplus or shortfall (see subsection 4.1.2.2 for its definition) [5], $NPL^{s}_{ij,t}$ is sector-counterparty specific share of non-performing loans, $ROA_{i,t}$ is return on assets and δ^{s}_{jt} are counterparty-time fixed effects.

In addition to the linear effect of capital surplus or shortfall we are interested in three types of non-linearities. First, a bank close to its regulatory requirements may be more prone to deleverage. To capture this effect we interact $CETShortfall_{i,t}$ with a dummy variable equal to one if bank i experiences capital shortfall in time t denoted by $I(CETShortfall_{i,t})$. Second, banks may be more likely to deleverage on non-domestic exposures. To pin down this effect we interact $CETShortfall_{i,t}$ with dummy variables for domestic $I(Domestic)$ and foreign $I(Foreign)$ exposures. Finally, we distinguish between the cases where the share of bank NPLs increased in the last year and cases where such a share decreased, and introduce the interactions with the corresponding dummies $I(NPL\ increase)$ and $I(NPL\ decrease)$.

4.1.2.2 Data

The estimation rests on COREP/FINREP reporting templates. These include relevant bank characteristics such as lending at bank-counterparty-sector level, capital, profitability, share of

[4]Similar approach is used by Mésonnier and Monks (2015) in their study of the effect of 2011's EBA capital exercise.

[5]Several studies have shown an importance of the link between bank capital and lending activity (see for example Gambacorta and Mistrulli (2004), Jonghe et al. (2016) and Aiyar et al. (2016)). A general finding of these studies is that less capitalised banks provide less funding sources to the real economy.

non-performing loans. The data are available for the period 2014–2018, at quarterly frequency. These data is supplemented with the information on capital requirements from which we derive our measure of $CET1Shortfall$:

$$CET1Shortfall_{i,t} = CET1REA_{i,t} - TCET1REA_{i,t} \tag{5}$$

where $CET1REA$ is the actual CET1 ratio defined as in Appendix B.6 and $TCET1REA$ is a capital target defined as:

$$TCET1REA_{i,t} = P1CR + P2CR_{i,t} + ComB_{i,t} + P2G_{i,t} \tag{6}$$

where $P1CR$ and $P2CR$ denote Pillar I and Pillar II minimum CET1 capital requirements. $ComB$ is the combined buffer requirement following the definition as in CRD and including capital conservation buffer, countercyclical capital buffer, Systemic Risk Buffer, O-SII and G-SII buffers. For estimation purposes, we assume that Pillar 2 guidance ($P2G$) equals 2% of Risk Weighted Amounts.

4.1.2.3 Results

Regressor	Coefficient	p-value
Effect of CET1 surplus/shortfall on domestic/foreign exposures		
$CET1Shortfall \times I(Foreign)$	0.098	0.006
$CET1Shortfall \times I(Domestic)$	0.038	0.660
$I(CET1Shortfall)$	−0.044	0.000
$CET1Shortfall \times I(CET1Shortfall)$	0.227	0.644
Effect of NPLs depending on their increase/decrease in last year		
$Sector - countryNPL \times I(NPLdecrease)$	0.005	0.828
$Sector - countryNPL \times I(NPLincrease)$	−0.068	0.001
ROA	0.428	0.108
Constant	0.000	0.953
Counterparty-time fixed effects	Yes	
R^2	0.10	
Obs.	9208	

Table 6: Loan supply model for non-financial corporates

Tables 6–8 present the estimation results for the corporate, household and sovereign sector, respectively. Few comments are in order. First, there is a difference in bank responses between

Regressor	Coefficient	p-value
Effect of CET1 surplus/shortfall on domestic/foreign and consumer/mortgage exposures		
$CET1Shortfall \times I(Foreign) \times I(Consumer)$	0.179	0.128
$CET1Shortfall \times I(Foreign) \times I(Mortgage)$	0.110	0.132
$CET1Shortfall \times I(Domestic) \times I(Consumer)$	0.135	0.086
$CET1Shortfall \times I(Domestic) \times I(Mortgage)$	-0.043	0.480
$CET1Shortfall \times I(CET1Shortfall)$	0.065	0.772
Effect of NPLs depending on their increase/decrease in last year		
$Sector - countryNPL \times I(NPLdecrease)$	-0.058	0.019
$Sector - countryNPL \times I(NPLincrease)$	-0.072	0.000
ROA	0.074	0.549
Constant	0.006	0.000
Counterparty-time fixed effects	Yes	
R^2	0.21	
Obs.	3428	

Table 7: Loan supply model for households

Regressor	Coefficient	p-value
Effect of CET1 sur./short. on domestic/foreign exposures		
$CET1Shortfall \times I(Foreign)$	-0.088	0.010
$CET1Shortfall \times I(Domestic)$	-0.033	0.529
Effect of NPLs depending on their increase/decrease in last year		
$TotalNPL \times I(NPLdecrease)$	-0.085	0.039
$TotalNPL \times I(NPLincrease)$	-0.091	0.086
ROA	0.134	0.647
Constant	0.001	0.661
Counterparty-time fixed effects	Yes	
R^2	0.15	
Obs.	3535	

Table 8: Loan supply model for sovereigns

the three sectors. The effect of CET1 surplus/shortfall is the strongest for corporates and consumer loans, whereas it becomes negative for sovereign exposures and for domestic mortgage loans. This tells us that banks with CET1 shortfall shift their lending from corporates and consumer credit to sovereigns and partially also to mortgage loans. This likely reflects higher risk weight charges on the former exposures compared to the latter. Second, the lending effect of CET1 surplus/shortfall is amplified when a bank experiences a capital shortfall. As expected, this non-linearity is more pronounced for riskier corporate loans. Third, the effect of capital surplus/shortfall is stronger for foreign exposures. Banks with capital shortfall will first reduce their loan supply abroad and only later in the domestic market. Lastly, negative effect of NPLs is stronger for banks that recently experienced an increase in the share of NPLs.

4.2 Lending and deposit interest rate margins

The intention of including endogenous equations for bank-level interest rate margins in the model is to better capture the evolution of net interest income under different macroeconomic scenarios. Bank-level interest rates consist of two components, the reference rate linked to 3 month EURIBOR (STN) in the macro block, and margins. This split is aimed to recover two risks affecting bank net interest income under stress: (i) the risk related to a change in the general "risk-free" curves; (ii) the risk related to a change in the "premium" that the market requires or the bank sets for different types of instruments and counterparties.

4.2.1 Methodology

Lending margins on new business $EIRAssetNew$ are modelled separately for three loan segments: loans to NFC, loans for households for house purchases and consumer credit. For simplicity they are each time defined as teh difference between the bank specific lending interest rate for new business and the reference rate equal to 3 month EURIBOR. The general dynamic panel model specification for the sector s lending margins has the following form:

$$EIRAssetNew^{s}_{i,j,t} = f(EIRAssetNew^{s}_{i,j,t-1},\ SovSpread_{j,t},\ \Delta STN_{j,t},\ X_{j,t-p},\ \delta^{s}_{i}) \qquad (7)$$

where as earlier i is a bank index, s sector index and j a country index. $STN_{j,t}$ is the reference rate, $SovSpread_{j,t}$ is the difference between 10Y Government bond yields for country j and the German bund at time t, $X_{j,t-p}$ are contemporaneous and lagged macroeconomic variables including GDP growth, residential house price growth, sovereign spread and the credit supply shock defined as in section 4.1.1. δ^{s}_{i} are bank fixed effect. Including the reference rate among the covariates allows the pass-through of the money market rate into bank-level lending rates to differ from one. The equations include up to four lags of dependent variables and are estimates with the Arellano-Bond estimator using robust standard errors.

Empirical models for deposit margins $EIRLiabNew$ follow analogous specification with the breakdown in four segments: sight and term deposits both for households and non-financial corporates.

4.2.2 Data

The interest rate model is based on interest rate information provided in iMIR/iBSI. The data are seasonally and outlier adjusted using the X-12-ARIMA algorithm and complemented with macroeconomic variables from SDW. The dataset results in an unbalanced panel spanning from 2007Q4 to 2017Q4.

4.2.3 Results

	Non-financial corporates		Households mortgage		Households consumption	
Regressor	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
EIRAssetNew $(t-1)$	0.629	0.000	0.824	0.000	0.803	0.000
EIRAssetNew $(t-2)$	0.203	0.000	0.061	0.022		
SovSpread (t)	0.033	0.001	0.019	0.010	0.013	0.297
SovSpread $(t-1)$			-0.014	0.050		
Δ STN (t)	-0.472	0.000	-0.730	0.000	-0.562	0.000
Supplyshock (t)	-0.004	0.650	0.002	0.664	0.029	0.012
GDP growth $(t-2)$	-4.344	0.016				
GDP growth $(t-3)$					-4.067	0.037
Resid.prop.price growth (t)			-1.931	0.028		
Inflation (t)	10.958	0.002	9.099	0.000		
Inflation $(t-2)$					10.531	0.000
Constant	0.341	0.000	0.208	0.011		
Bank fixed effects	Yes		Yes		Yes	
Obs.	1385		1266		1349	

Table 9: Lending margin regressions

Table 9 presents the best-fitting estimation results for lending margins on new loans to the non-financial private sector. During periods of increasing economic activity, as reflected in high output and property price growth, lending margins typically decrease. This is likely to reflect fluctuations in collateral value and banks' risk perception. High price inflation increases lending margins. Sovereign spread increases lending margins (though this effect is insignificant for consumption loans). Finally, the pass-through of reference rates appears strongest for loans to households.

Tables 10 and 11 present the estimation results for term and sight deposit margins, respectively. Both show a positive association with output growth and sovereign spread.

Regressor	Non-financial corporates Term deposits Coefficient	p-value	Households Term deposits Coefficient	p-value
EIRLiabNew $(t-1)$	0.763	0.000	0.811	0.000
EIRLiabNew $(t-2)$	0.150	0.002	0.110	0.000
SovSpread (t)	0.036	0.001	0.034	0.000
Δ STN (t)	-0.678	0.000	-0.704	0.000
GDP growth (t)	1.885	0.004	1.934	0.664
GDP growth $(t-2)$	1.646	0.001		
Inflation (t)	8.947	0.000	6.660	0.000
Inflation $(t-1)$			4.187	0.000
Inflation $(t-2)$	-4.838	0.018		
Constant	-0.084	0.000	-0.068	0.000
Bank fixed effects	Yes		Yes	
Obs.	7894		7879	

Table 10: Term deposit margin regressions

Regressor	Non-financial corporates Sight deposits Coefficient	p-value	Households Sight deposits Coefficient	p-value
EIRLiabNew $(t-1)$	0.920	0.000	0.747	0.000
EIRLiabNew $(t-2)$			0.167	0.000
SovSpread (t)	0.012	0.000	0.005	0.014
Δ STN (t)	-0.528	0.000	-0.721	0.000
GDP growth (t)			1.758	0.016
GDP growth $(t-1)$	2.319	0.000		
Constant	-0.035	0.000	-0.017	0.001
Bank fixed effects	YES		Yes	
Obs.	1427		1318	

Table 11: Sight deposit margin regressions

4.3 Distribution of dividends

Dividend distribution policies are an important channel that impacts bank capital and therefore also their resilience. Dividend pay-outs in the model are governed by the endogenous ratio of dividend pay-outs to the after tax profit and the Maximum Distributable Amount (MDA) restrictions. The latter become binding when banks' own funds drop below their combined buffer requirement.

4.3.1 Methodology

The ratio of dividend pay-outs to the after tax profit is assumed to follow:

$$DivPayoutRatio_{i,t} = \Phi(DivPayoutRatio_{i,t-1},\ CET1REA_{i,t-1},\ NPL_{i,t-1},\ RWAtoTA_{i,t-1},\ CTIR_{i,t-1},\ Loan\,growth_{i,t-1},\ GDP\,growth_{j,t-1},\ \delta_i) \quad (8)$$

where $DivPayoutRatio_{i,t}$ is bank i ratio between dividend payments and profit after tax in time t, $CET1\ ratio_{i,t-1}$ is CET1 capital adequacy ratio, $NPL_{i,t-1}$ is share of non-performing loans, $RWAtoTA_{i,t-1}$ is the ratio between risk weighted assets and total assets, $CTIR_{i,t-1}$ is cost-to-income ratio, $Loan\,growth_{i,t-1}$ is growth of total bank loans, $GDP\,growth_{j,t-1}$ is GDP growth in a country j where bank i is headquartered and δ_i are fixed effects controls described below. $\Phi(.)$ denotes the standard normal cumulative distribution function.

The ratio of the dividend pay-out to the after tax profit is bound between zero and one. Accordingly, we use a fractional response model introduced by Papke and Wooldridge (1996) and Papke and Wooldridge (2008) to estimate equation 8. The time dependency of dividend payments in the non-linear setup presents a challenge. Unlike in linear models, where unobserved effects can be eliminated with certain transformations, there is in general no such transformation for non-linear models. We adopt the methodology proposed by Wooldridge (2005) and include in the regression means and initial values of all right-hand side variables as well as the initial value of the dependent variable. These are fixed-effects controls designed to take away the correlation between the lagged depended variable and the error term.[6]

4.3.2 Data

The data serving the estimation of the dividend pay-out ratio equation stem from Bloomberg and SNL. These datasets allow us to construct time series of dividend pay-out ratios, and right-hand side variables, for a large sample of euro area banks for the period 2005-2017. We set dividend payments to zero in cases, when profit after tax is negative, and set dividend pay-out ratio to one, when banks pay out dividends in excess of profit.

[6]The idea is that instead of eliminating the fixed effects, one should control for them. This largely follows the logic of Chamberlain (1984), who proposes to model conditional expectation of the unobserved effect as a linear function of the exogenous variables.

4.3.3 Results

Table 12 reports the estimated coefficients of the fractional response model. Lagged dividend pay-out ratio, CET1 ratio, the ratio between risk weighted assets and total assets, loan growth and GDP growth have a positive impact on dividend payments, whereas the share of non-performing loans and cost-to-income ratio have a negative effect.

Regressor	Coefficient	p-value
DivPayoutRatio (t-1)	0.315	0.005
CET1REA (t-1)	4.221	0.003
NPL (t-1)	-4.031	0.000
RWA-to-TA ratio (t-1)	1.243	0.019
Cost-to-income ratio (t-1)	-0.755	0.065
Loan growth (t-1)	0.795	0.007
GDP growth (t-1)	1.856	0.076
Constant	-1.242	0.017
Number of observations	554	

Table 12: Estimated coefficients of the dividend distribution model

Final dividend payment $DivPaid$ is defined as the minimum between regression-predicted dividend payments and the MDA:

$$DivPaid_{i,t} = min(DivPayoutRatio_{it} \times ProfBDiv_{it},\ MDA_{it}) \tag{9}$$

where $ProfBDiv$ is profit after tax that is available for profit distribution defined as in Appendix B.5.

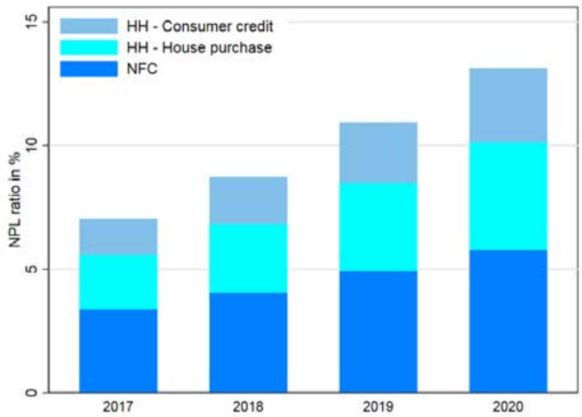
5 Model application in 2018 macroprudential stress test exercise

To illustrate an application of the BEAST we evaluate the performance of the euro area banking sector under the adverse scenario of the 2018 EBA supervisory stress test for 2018 - 2020. The adverse scenario considered a period of prolonged systemic stress, with euro area output contracting by 2.4% in cumulative terms. At the same time the residential house prices were assumed to drop by 16.5% and the euro area unemployment rate reached 10.3% by 2020. The complete description of the analysis can be found in Budnik et al. (2019), while this section emphasises the role of the model's behavioural equations in generating the results.

5.1 Asset quality

Adverse economic conditions are first reflected in the depreciation of asset prices. Movements in market prices translate into imminent losses on financial assets held at fair value in banks' trading books that enter the model as an exogenous variable. Market losses enter either profit and loss or directly reduce banks' own funds via other comprehensive income (see Appendix B.6.1).

Deteriorating economic conditions lead as well to an increase in credit losses. Loss given default, loss rates and the transition probabilities to stage 2 (assets with deteriorated quality) and stage 3 (non-performing assets) under IRFS 9 go up. The main factors affecting the transition rates are declining GDP and house prices as well as elevated long-term interest rates and unemployment rates (see Appendix A.2). The share of non-performing loans to the non-financial private sector in the banking books starts increasing already in 2018 and by 2020 the share almost doubles compared to 2017 reaching 13% (see Figure 7).

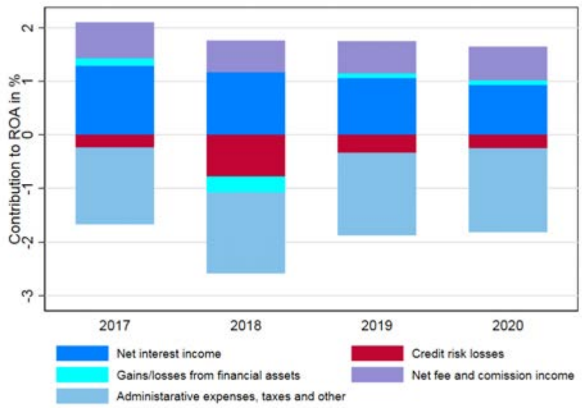


Source: Budnik et al. (2019)

Figure 7: NPL ratio for non-financial private sector

5.2 Profitability and solvency

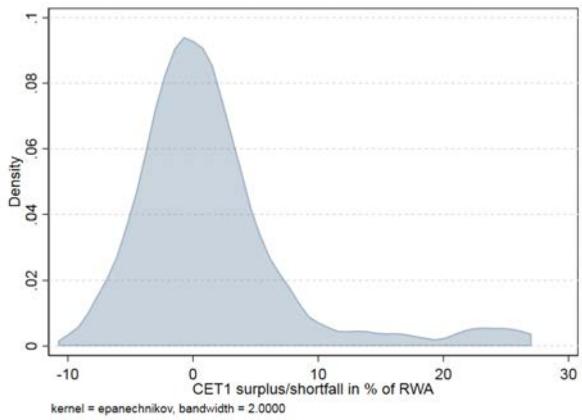
The return-on-assets (ROA) remains negative in every year from 2018 to 2020 (see Figure 8. In 2018 bank profitability is negatively affected by both market and credit risk losses. From 2019 onwards, ROA becomes less negative by around -0.15%, which is mainly due to lower credit risk losses and due to the stabilizing effect of net fee and commission income (NFCI). This reflects the countercyclical nature of NFCI (see Appendix A.1).



Source: Budnik et al. (2019)

Figure 8: ROA decomposition

In line with deteriorating profitability, banks' CET1 ratios fall on average by 3.2 pp relative to 2017. As a consequence, about half of the banks exhibit capital shortfalls, i.e. their CET1 capital ratios fall below their respective regulatory target values (Figure 9).



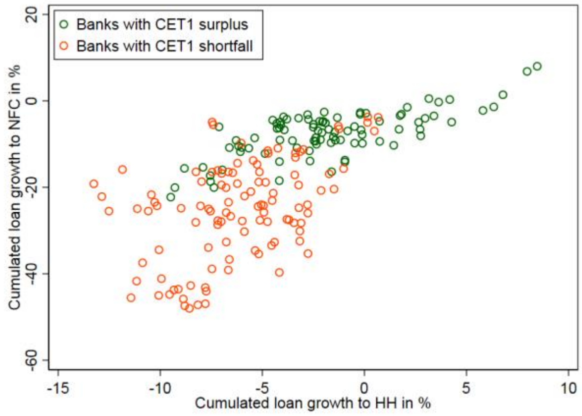
Source: Budnik et al. (2019)

Figure 9: Distribution of CET1 surplus/shortfall in 2020

5.3 Lending

Banks with low profitability and capital shortfalls restrain their dividend pay-outs. Dividends are distributed only when banks generate profit and maintain capitalisation above their MDA trigger point (see Appendix B.5). As many banks experience losses and their CET1 ratios become impaired, their dividend pay-outs remain close to zero.

Another adjustment mechanism preventing further deterioration of CET1 capital ratios is deleveraging. Figure 10 demonstrates that banks with capital shortfall contract lending significantly more compared to banks with capital surplus. As the fraction of banks with capital shortfall increases over the scenario horizon, the deleveraging intensifies in line with the loan supply equations in section 4.1.2.



Source: Budnik et al. (2019)

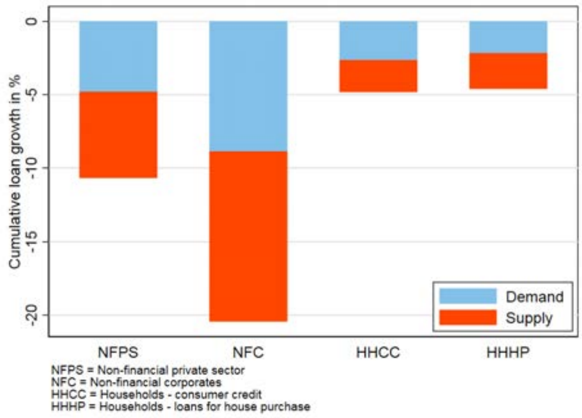
Figure 10: Change in bank lending versus capital shortfall

Weakened loan demand (see section 4.1.1) additionally moderates loan expansion. Figure 11 shows cumulative loan growth across sectors, distinguishing between the impact of supply and demand factors. The lending to non-financial corporates contracts significantly more than to households with the pronounced negative contribution of credit supply factors for the corporate sector (see Table 6).

Beyond, lending evolution differs across domestic and foreign markets. Figure 12 shows that banks deleverage mostly on exposures to foreign markets and less so on domestic assets.

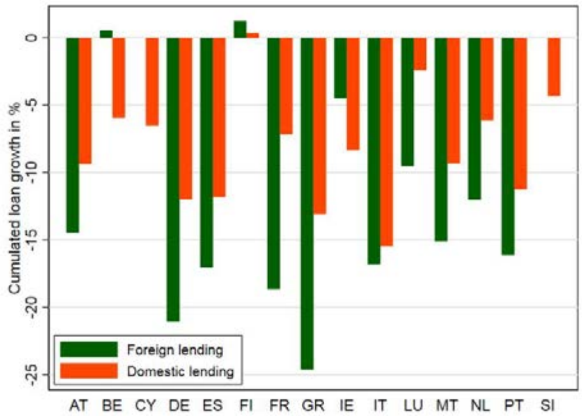
5.4 The role of dynamic balance sheet

A large share of supervisory stress tests, including the bi-annual EBA stress test exercise, assume a constant balance sheet. Under this assumption the size and structure of bank assets and liabilities remains constant. The popularity of the assumption relates to the fact that it ensures larger comparability of the results when a stress test exercise is conducted in a bottom-up fashion



Source: Budnik et al. (2019)

Figure 11: Cumulative loan growth



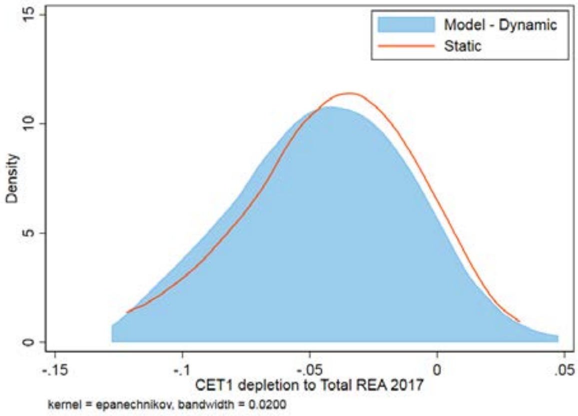
Source: Budnik et al. (2019)

Figure 12: Foreign and domestic lending by geography

(relies on bank own predictions). However, the assumption clearly compromises the realism of stress tests by ignoring banks' most likely reaction to stress conditions.

The dynamic balance sheet assumption ingrained in the BEAST leads to higher capital depletion than the analogous constant balance sheet exercise. Compared to the original EBA stress test results, the BEAST reveals 35 bn EUR higher capital depletion in 2020. This result is illustrated in Figure 13 which contrasts CET1 capital depletion expressed as a share of risk exposure amount at the starting point from a dynamic and constant balance sheet approach.

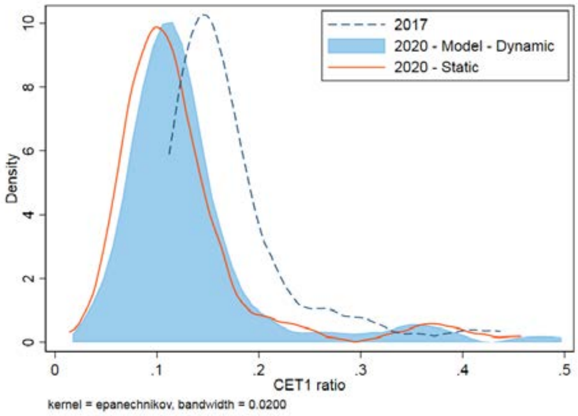
At the same time the end-of-period bank-level CET1 ratios tend to be higher when forecasted with the BEAST as compared to the EBA stress test results. Bank-level CET1 ratios in 2020 are significantly lower on average compared to the 2017 starting values under both approaches.



Source: Budnik et al. (2019)

Figure 13: CET1 capital depletion

However, the capital ratios with a dynamic balance sheet are slightly less adverse compared to those derived under a static balance sheet (Figure 14). This is an outcome of at least two counterbalancing effects. By linking the intensity of deleveraging to banks' solvency, the model introduces a capital ratio restoring mechanism. On the other hand, net interest income is negatively affected by declining asset volumes, especially in combination with a raising share of non-performing assets that bear no or very little interest. For the scenario considered here, the former effect tends to dominate.

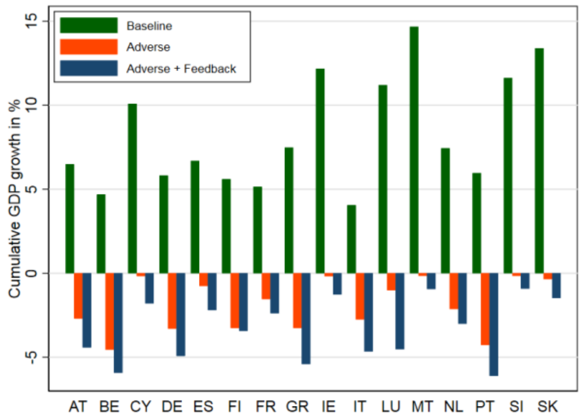


Source: ECB calculations in MST 2018 exercise.

Figure 14: CET1 ratio

5.5 The role of the financial sector-real economy feedback loop

Next to the dynamic balance sheet property, the model can serve the description of the financial sector-real economy feedback loop. To this end, we assume that the original adverse scenario does not yet reflect the impact of excessive banks' deleveraging in adverse economic conditions. More precisely, we assume that changes in bank lending that can be attributed to credit demand factors, deterioration in profits, or linear effects of asset quality and capitalisation are accommodated in the original scenario. However, the non-linear part of the lending equations involving capital shortfall and the share of non-performing loans, represents banks' excessive delevaraging and can be added to the original scenario after being translated in country-level structural credit supply shocks.



Source: Budnik et al. (2019)

Figure 15: GDP in the adverse scenario with and without the feedback loop

Emphasising the feedback between the banking sector and the real economy increases the severity of the adverse scenario. In aggregate, the euro area output contracts about 1.6 pp more by 2020 in addition to the cumulative contraction of 2.4% GDP in the original adverse scenario. In the cross-country perspective, GDP contracts by additional 0.2 pp to 3.5 pp depending on the jurisdiction.

6 Conclusions

The primary objective of macroprudential stress testing is measuring, monitoring and understanding of systemic risk. To deliver upon this mandate, the paper presents a new Banking Euro Area Stress Test (BEAST) model for assessing system-wide resilience while accounting for interactions between the financial sector and the real economy. The model links macro and bank level information and describes in detail propagation of macroeconomic conditions into bank balance sheets and the real economy-financial sector feedback loop. Thanks to its semi-structural design the model can provide a comprehensive narrative for some of the transmission channels of systemic risk.

A big strength of the model is that it captures many aspects of bank heterogeneity. This includes different structures of bank balance sheets but also their diverse reactions to economic conditions depending on their individual solvency situation, asset quality and profitability performance. As such the model can be prospectively used not only for stress testing but also to track the heterogeneous impact of regulatory or macroprudential policies on banks.

However, there are also numerous limitations of the described model version. Due to data challenges, most of the bank reaction functions are estimated within panel specifications and represent the average rather than individual decisions by banks. Furthermore, we estimate separately bank responses for volume, price or dividend adjustments rather than a full system of equations representing the joint optimization problem of banks. In the current model version, bank liabilities follow simplified dynamics and funding costs are largely exogenous. There is also a scope for including an additional layer of endogenous propagation of systemic risk, such as interbank lending with fire sales or interbank contagion risk.

Hence, many challenges remain and our future work will aim to improve the existing framework, both in terms of the identification of bank response functions as well as extending endogenous mechanisms in the model. This work will focus on improving the identification of loan supply and demand drivers, on modelling banks funding costs and liability structure. The latter elements could then be used to introduce the solvency-funding cost feedback loop mechanism.

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A Estimated bank sensitivities

The Appendix includes the description of two models used to map macroeconomic scenarios into bank balance sheets and profit and loss statements. In contrast to equations discussed in the main text, these empirical models reflect banks' sensitivity to a scenario rather than their reactions. This model version includes only a relatively narrow subset of endogenous sensitivity equations, the net-fee-commission income, and transition rates between IRFS9 states.

A.1 Net fee and commission income

Net fee and commission income together with interest and trading income constitute the three most important sources of income for most euro area banks. Furthermore, Kok, Mirza and Pancaro (2019) document that fee and commission income is substantially varying with changes in macroeconomic and financial variables such as short-term interest rate, stock market returns and real GDP growth.

A.1.1 Data and methodology

Net fee and commission income is given by:

$$\mathrm{NFCI}_{i,t} = \mathrm{FCI}_{i,t} + \mathrm{FCE}_{i,t} \tag{10}$$

Following Kok et al. (2019) fee and commission income FCI is projected using a dynamic panel regression model. The dependent variable is the ratio of bank i's fee and commission income $\mathrm{FCI}_{i,t}$ to total assets $\mathrm{TA}_{i,t}$.

$$\mathrm{FCI/TA}_{i,t} = f(\mathrm{FCI/TA}_{i,t-1}, \Delta\mathrm{STN}_{j,t-1}, \Delta\mathrm{LTN}_{j,t-1}, X_{j,t}, \mathrm{LOAN\_ASSET}_{i,t}, \delta_i)$$

where $\Delta\mathrm{STN}_j$ stands for the change in short term interest rate (EURIBOR) in the domestic country j of bank i, $\Delta\mathrm{LTN}_j$ respectively for the change in the long-term interest rate. $X_{j,t}$ contains additional macro factors such as real GDP growth, stock market growth, inflation and residential property price growth of country j. $\mathrm{LOAN\_ASSET}_i$ corresponds to the loan-to-asset ratio of bank i and δ_i are bank fixed effects. The income model's variable selection is based on a variable selection procedure using the LARS algorithm. The final model is estimated using the dynamic panel bias correction introduced by Blundell and Bond (1998) where the estimates can be found in Table 13.

Since coverage of fee and commission expense data in public sources is scarce, the change in expenses FCE of net fee and commission income is estimated using an implied elasticity $\sigma = 0.867$ based on supervisory reporting information:

$$\Delta \mathrm{FCE}_{i,t} = \sigma \Delta \mathrm{FCI}_{i,t} \tag{11}$$

A.1.2 Data

The income model is estimated on a public dataset from Bloomberg covering annual information from 1995 until 2017 for 98 banks. Based on FINREP information we estimate the implied elasticity for FCE.

A.1.3 Results

The estimated coefficients in the selected specification indicate a relatively high inertia in fee- and commission income. The selected explanatory variables to explain the remaining dynamics in FCE are given by GDP growth, short-term and long-term rates, stock market and property price growth as well as loan-to-asset ratio as indicator for banks business model.

Regressor	Coefficient	p-value
$\mathrm{FCI/TA}(t-1)$	0.7918	0.000
GDP growth (t)	0.0048	0.006
Inflation (t)	-0.0043	0.085
Δ STN $(t-1)$	-0.0032	0.332
Δ LTN (t)	0.0031	0.140
Δ LTN $(t-1)$	0.0013	0.517
Stock market growth (t)	0.0006	0.002
Prop. price growth (t)	-0.0011	0.195
Loan-to-asset ratio (t)	0.0027	0.000
Bank fixed effects	YES	
Number of observations	1062	
Number of banks	98	
R^2 (within)	0.524	

Table 13: Fee- and comission income over total assets model, Dynamic panel (LSDV) estimator

A.2 Transition rates

According to IFRS9, assets are classified into three stages. Performing exposures are divided into Stage 1 (S1) exposures with stable risk profile, and Stage 2 (S2) exposures with significant increase in credit risk, Stage 3 (S3) includes non-performing exposures. The IFRS9 became effective in 2018 and at the moment of estimation of the model the historical data on classification of assets to three stages were not available. We had also no access to detailed credit register data that could be, under certain assumptions, used to reconstruct the historical series. Accordingly, the methodology of estimating transition rates between the three states rests fully on the data submitted by banks in the EBA stress test exercise in 2018.

A.2.1 Transition rates TR12, TR13, TR21 and TR23

A.2.1.1 Methodology

Following Niepmann and Stebunovs (2018) we focus on transition rates projected by banks conditional on the baseline and adverse stress test scenarios. A possible limitation of this approach is that banks' projected transition rates might not represent the true sensitivity of the riskiness in banks' portfolio to both scenarios. However, by using the data from the last submission cycle, we expect that this bias was addressed in the quality assurance process.

Our general model specification is the following:

$$\mathrm{TR}^{s,C}_{i,t} = f(\mathrm{TR}^{s,C}_{S1,S2,i,t-1,}, \mathrm{TR}^{s,C}_{S1,S3,i,t-1}, \mathrm{TR}^{s,C}_{S2,S1,i,t-1}, \mathrm{TR}^{s,C}_{S2,S3,i,t-1}, X^{C}_{t-p}) \tag{12}$$

where $\mathrm{TR}^{S,C,P}_{Y,i,t}$ is the projected transition rate ($\mathrm{TR}^{s,C}_{S1,S2,i,t,}$, $\mathrm{TR}^{s,C}_{S1,S3,i,t}$, $\mathrm{TR}^{s,C}_{S2,S1,i,t}$ or $\mathrm{TR}^{s,C}_{S2,S3,i,t}$) by bank i for sector s in country C. Transition rates are modelled as logit transformed variables, t refers to quarter. Each transition rate is a function of lags of all the transition rates and a set of macro variables X^{C}_{t-p}. A set of macro variables allows the identification of the sensitivity of transition rates to macroeconomic conditions containing GDP growth rate, house price growth , long-term interest rates and level of unemployment.

The four transition rates are estimated jointly as a system of equations following the seemingly unrelated regression (SUR) methodology. The SUR methodology recognises that the error terms of the four transition rates can be correlated. The system of equations is estimated for five sectors separately: non-financial corporates, households - loans for house purchase, households

- consumer credit, financial institutions and sovereign exposures.

A.2.1.2 Data

The EBA stress test methodology requires from banks to provide for each scenario the projections for four transition rates: transition rate from S1 to S2 ($TR_{S1,S2}$), transition rate from S1 to S3 ($TR_{S1,S3}$), transition rate from S2 to S1 ($TR_{S2,S1}$) and transition rate from S2 to S3 ($TR_{S2,S3}$). Whereas banks' projections are annual, we quarterly interpolate them. In all the cases the data for baseline and adverse scenario are pooled together.

A.2.2 Cure rates

Unlike the EBA methodology that assumes zero cure rate (no transition from S3 to either S2 or S1), our approach accounts for the possibility that assets cure and become performing in the baseline scenario. These are calculated on the basis of the information reported by banks in the EBA stress test in line with their LGD calculation.

A.2.2.1 Approach and data

For the purpose of LGD calculation banks are required to provide the proportion of S3 exposures that cure through repayments and with zero losses in all years until maturity. We then adjust these reported bank-specific life-time cure rates by their average portfolio maturity as reported in EBA net-interest income template. The maturity structure was cross-checked with average maturity of defaulted exposures as reported in COREP to rule out that non-performing and performing maturity substantially differs for some banks.

Last but not least, to remove outliers and confounding bank heterogeneity in the resulting quarterly rates, individual bank-level cure rates are transformed to sector-country level average parameters weighted by loan exposures and kept constant for the projection horizon. In the adverse scenario, cure rates are assumed to be zero for all portfolios.

B Structural and accounting identities

B.1 Assets volumes

Assets held by banks are grouped into eight categories referred to as *sectors* in what follows. Table 14 presents the mapping from the categories used in the EBA submissions (which are further split according to the credit risk regulatory approaches, i.e. internal rating based (IRB) and standardised (STA) approach) into the BEAST sectors.

Consistently with the euro area focus we treat banks' exposures to the non-financial private sectors in 19 euro area countries individually, whereas the analogous exposures to other jurisdictions are grouped into the "rest of the world" category. The remaining banks' exposures are tracked on a sector level only. The evolution of asset quality and volumes as described below refers to all sectors but equities, securities and other, which remain exogenous in all model blocks.

Assets are classified according to IRFS9 stages: 1 – performing (S1), 2 – at risk (S2), 3 – non-performing (S3). The exposures of bank i at time t to sector s in country C are denoted by $\mathrm{NonDefExp}^{s,C}_{S1,i,t}$, $\mathrm{NonDefExp}^{s,C}_{S2,i,t}$, and $\mathrm{DefExp}^{s,C}_{i,t}$ for Stage 1, 2 and 3 assets, respectively.

It is assumed that within each IFRS9 stage bank portfolios are infinitely divisible and homogeneous. There are no write-offs of non-performing exposures. The evolution of the distribution of assets across stages from one quarter to the next can thus be described by the sector and-country pair-specific transition probability matrix:

$$\begin{bmatrix} \mathrm{TR}^{s,C}_{S1,S1,i,t} & \mathrm{TR}^{s,C}_{S1,S2,i,t} & \mathrm{TR}^{s,C}_{S1,S3,i,t} \\ \mathrm{TR}^{s,C}_{S2,S1,i,t} & \mathrm{TR}^{s,C}_{S2,S2,i,t} & \mathrm{TR}^{s,C}_{S2,S3,i,t} \\ \mathrm{TR}^{s,C}_{S3,S1,i,t} & \mathrm{TR}^{s,C}_{S3,S2,i,t} & \mathrm{TR}^{s,C}_{S3,S3,i,t} \end{bmatrix} \tag{13}$$

where

$$\mathrm{TR}_{S_j,S_k,i,t} = \Pr\{\text{asset in stage } S_k \text{ in } t+1 | \text{asset in stage } S_j \text{ in } t\} \tag{14}$$

It is further assumed that asset quality changes at the very beginning of a period. For each bank portfolio we define asset flows by:

$$\mathrm{Flow}^{s,C}_{S1,S3,i,t} = \mathrm{TR}^{s,C}_{S1,S3,i,t} \times \mathrm{NonDefExp}^{s,C}_{S1,i,t-1} \tag{15}$$

$$\mathrm{Flow}^{s,C}_{S2,S3,i,t} = \mathrm{TR}^{s,C}_{S2,S3,i,t} \times \mathrm{NonDefExp}^{s,C}_{S2,i,t-1} \tag{16}$$

BEAST CR asset sector	EBA asset category - IRB approach	EBA asset category - STA approach
SOV - Central banks and governments	Central banks and governments	Central banks and governments Regional governments or local authorities Public sector entities Multilateral development banks International organisations
FIN - Financials	Institutions	Institutions
NFC - Corporates	Specialised lending secured by real estate property SME secured by real estate property Other secured by real estate property Specialised lending not secured by real estate property SME not secured by real estate property Other not secured by real estate property	Secured by mortgages on immovable property SME Corporates
HHHP - Household backed by real estate	Secured by real estate property	Secured by mortgages on immovable property
HHHC - Households not backed by real estate	Qualifying revolving Other	Retail
EQ - Equity	Equity	Equity
SEC - Securitisation	Securitisation	Securitisation
OTHER - Other	Other non-credit obligation assets	Assets - other assets Assets - derivatives - hedge accounting - cash flow hedge Assets - derivatives - hedge accounting - fair value hedge Assets - derivatives - hedge accounting - net investment hedge Assets - derivatives - not used for hedge accounting

Table 14: Mapping of EBA sector asset categories to calculate credit risk exposures in the model

$$\mathrm{Flow}^{s,C}_{S1,S2,i,t} = \mathrm{TR}^{s,C}_{S1,S2,i,t} \times \mathrm{NonDefExp}^{s,C}_{S1,i,t-1} \tag{17}$$

$$\text{Flow}^{s,C}_{S2,S1,i,t} = \text{TR}^{s,C}_{S2,S1,i,t} \times \text{NonDefExp}^{s,C}_{S2,i,t-1} \tag{18}$$

$$\text{Flow}^{s,C}_{S3,S1,i,t} = \text{TR}^{s,C}_{S3,S1,i,t} \times \text{DefExp}^{s,C}_{i,t-1} \tag{19}$$

$$\text{Flow}^{s,C}_{S3,S2,i,t} = \text{TR}^{s,C}_{S3,S2,i,t} \times \text{DefExp}^{s,C}_{i,t-1} \tag{20}$$

Since there are no write-offs, the defaulted (S3) exposures evolve according to

$$\text{DefExp}^{s,C}_{i,t} = \text{DefExp}^{s,C}_{i,t-1} + \text{Flow}^{s,C}_{S1,S3,i,t} + \text{Flow}^{s,C}_{S2,S3,i,t} - \text{Flow}^{s,C}_{S3,S1,i,t} - \text{Flow}^{s,C}_{S3,S2,i,t} \tag{21}$$

In every period, a share of non-defaulted loans will mature and new loans (assumed to be performing at the moment of issuance i.e. be in stage 1) will be issued. The share of maturing exposures is assumed to be inversely proportional to the average maturity of assets $\text{AvgMat}^{s,C}_{i}$, which is constant over time. At the end of the period, we have:

$$\begin{aligned} \text{NonDefExp}^{s,C}_{S1,i,t} = {} & \text{NewLoans}^{s,C}_{i,t} + (1 - (\text{AvgMat}^{s,C}_{i})^{-1}) \\ & \times (\text{NonDefExp}^{s,C}_{S1,i,t-1} - \text{Flow}^{s,C}_{S1,S2,i,t} - \text{Flow}^{s,C}_{S1,S3,i,t} + \text{Flow}^{s,C}_{S2,S1,i,t} + \text{Flow}^{s,C}_{S3,S1,i,t}) \end{aligned} \tag{22}$$

$$\begin{aligned} \text{NonDefExp}^{s,C}_{S2,i,t} = (1 - (\text{AvgMat}^{s,C}_{i})^{-1}) \times (\text{NonDefExp}^{s,C}_{S2,i,t-1} - \text{Flow}^{s,C}_{iS2,S1,i,t} - \text{Flow}^{s,C}_{S2,S3,i,t} \\ + \text{Flow}^{s,C}_{S1,S2,i,t} + \text{Flow}^{s,C}_{i,S3,S2,i,t}) \end{aligned} \tag{23}$$

The volumes of assets that mature within a period:

$$\begin{aligned} \text{Outflows}^{s,C}_{i,t} = (\text{AvgMat}^{s,C}_{i})^{-1}) \times (\text{NonDefExp}^{s,C}_{S1,i,t-1} - \text{Flow}^{s,C}_{S1,S2,i,t} \\ - \text{Flow}^{s,C}_{S1,S3,i,t} + \text{Flow}^{s,C}_{S2,S1,i,t} + \text{Flow}^{s,C}_{i,S3,S1,i,t}) \\ + (\text{AVGMAT}^{s,C}_{i})^{-1}) \times (\text{NonDefExp}^{s,C}_{S2,i,t-1} - \text{Flow}^{s,C}_{S2,S1,i,t} - \\ \text{Flow}^{s,C}_{S2,S3,i,t} + \text{Flow}^{s,C}_{S1,S2,i,t} + \text{Flow}^{s,C}_{i,S3,S2,i,t}) \end{aligned} \tag{24}$$

Finally, the total exposures equal:

$$\text{TotalLoans}^{s,C}_{i,t} = \text{NonDefExp}^{s,C}_{S1,i,t} + \text{NonDefExp}^{s,C}_{S2,i,t} + \text{DefExp}^{s,C}_{i,t} \tag{25}$$

Assets evolve along with the behavioural equations 4, which determine the growth rate of $\text{TotalLoans\_gr}^{\text{S,C}}_{\text{i,t}}$. New loans can be worked out as:

$$\text{NewLoans}^{\text{s,C}}_{\text{i,t}} = \text{TotalLoans}^{\text{s,C}}_{\text{i,t}-1}\text{TotalLoans\_gr}^{\text{s,C}}_{\text{i,t}} + \text{Outflows}^{\text{s,C}}_{\text{i,t}} \tag{26}$$

B.2 Loan-loss provisioning

B.2.1 Impairment losses on Stage 1 assets

The impairments flow for S1 exposures are given by: $\text{ImpGross}^{\text{s,C}}_{\text{S2,S1,i,t}}$).

$$\text{ImpGross}^{\text{s,C}}_{\text{S1,S1,i,t}} = \text{NonDefExp}^{\text{s,C}}_{\text{S1,i,t}-1} \times (1 - \text{TR}^{\text{s,C}}_{\text{S1,S2,i,t}} - \text{TR}^{\text{s,C}}_{\text{S1,S3,i,t}}) \times \text{TRLT}^{\text{s,C}}_{\text{S1,S3,i,t}} \times \text{LGDLT}^{\text{s,C}}_{\text{S1,S3,i,t}} \tag{27}$$

$$\text{ImpGross}^{\text{s,C}}_{\text{S2,S1,i,t}} = \text{Flow}^{\text{s,C}}_{\text{S2,S1,t}} \times \text{TRLT}^{\text{s,C}}_{\text{S1,S3,i,t}} \times \text{LGDLT}^{\text{s,C}}_{\text{S1,S3,i,t}} \tag{28}$$

$$\text{ImpGross}^{\text{s,C}}_{\text{S3,S1,i,t}} = \text{Flow}^{\text{s,C}}_{\text{S3,S1,t}} \times \text{TRLT}^{\text{s,C}}_{\text{S1,S3,i,t}} \times \text{LGDLT}^{\text{s,C}}_{\text{S1,S3,i,t}} \tag{29}$$

where $\text{TRLT}^{\text{s,C}}_{\text{S1,S3,i,t}}$ is sector and country dependent lifetime transition rate from S1 to S3, and $\text{LGDLT}^{\text{s,C}}_{\text{S1,S3,i,t}}$ is the expected loss rate for exposures that transition from S1 to S3 in the horizon of 12 months.

The stock of loan-loss provisions for stage 1 assets is derived by deducting the release of provisions of exposures which begin the period in S1 and transition to S2 or to S3:

$$\begin{aligned}\text{ProvStockNonDef}^{\text{s,C}}_{\text{S1,i,t}} = {} & \text{ImpGross}^{\text{s,C}}_{\text{S1,S1,i,t}} + \text{ImpGross}^{\text{s,C}}_{\text{S2,S1,i,t}} + \text{ImpGross}^{\text{s,C}}_{\text{S3,S1,i,t}} \\ & - \text{ProvStockNonDef}^{\text{s,C}}_{\text{S1,i,t}-1} \times (\text{TR}^{\text{s,C}}_{\text{S1,S2,i,t}} + \text{TR}^{\text{s,C}}_{\text{S1,S3,i,t}})\end{aligned} \tag{30}$$

B.2.2 Impairment losses on Stage 2 assets

Analogously as for stage 1 assets:

$$\text{ImpGross}^{\text{s,C}}_{\text{S2,S2,i,t}} = \text{NonDefExp}^{\text{s,C}}_{\text{S2,i,t}-1} \times (1 - \text{TR}^{\text{s,C}}_{\text{S2,S1,i,t}} - \text{TR}^{\text{s,C}}_{\text{S2,S3,i,t}}) \times \text{LR}^{\text{s,C}}_{\text{2X,i,t}} \tag{31}$$

where $\text{LR}^{\text{C,S}}_{\text{2X,i,t}}$ is lifetime expected loss rate for all exposures that start the year in S2 regardless of when and where they transition.

$$\mathrm{ImpGross}^{s,C}_{S1,S2,i,t} = \mathrm{Flow}^{s,C}_{S1,S2,t} \times \mathrm{LR}^{s,C}_{S1,S2,i,t} \tag{32}$$

And $\mathrm{LR}^{C,S}_{S1,S2,i,t}$ being the lifetime expected loss rate of exposures that move from S1 to S2.

$$\mathrm{ImpGross}^{s,C}_{S3,S2,i,t} = \mathrm{Flow}^{s,C}_{S3,S2,t} \times \mathrm{LR}^{s,C}_{S1,S2,i,t} \tag{33}$$

And we have:

$$\begin{aligned}\mathrm{ProvStockNonDef}^{s,C}_{S2,i,t} &= \mathrm{ImpGross}^{s,C}_{S2,S2,i,t} + \mathrm{ImpGross}^{s,C}_{S1,S2,i,t} + \mathrm{ImpGross}^{s,C}_{S3,S2,i,t} \\ &- \mathrm{ProvStockNonDef}^{s,C}_{S2,i,t-1} \times (\mathrm{TR}^{s,C}_{S2,S1,i,t} + \mathrm{TR}^{s,C}_{S2,S3,i,t})\end{aligned} \tag{34}$$

B.2.3 Impairment losses on Stage 3 assets

$$\begin{aligned}\mathrm{ImpGross}^{s,C}_{S3,S3,i,t} &= \mathrm{DefExp}^{s,C}_{i,t-1} \times (1 - \mathrm{TR}^{s,C}_{S3,S1,i,t} - \mathrm{TR}^{s,C}_{S3,S2,i,t}) \times \mathrm{LR}^{s,C}_{S3,S3,i,t} \\ &+ (\mathrm{ProvStockDef}^{s,C}_{i,t-1} - \mathrm{DefExp}^{s,C}_{i,t-1}\mathrm{LR}^{s,C}_{S3,S3,i,t}) \times \mathrm{I}(\mathrm{ProvStockDef}^{s,C}_{i,t-1} \\ &> \mathrm{DefExp}^{s,C}_{i,t-1}\mathrm{LR}^{s,C}_{S3,S3,i,t})\end{aligned} \tag{35}$$

where $\mathrm{LR}^{s,C}_{S3,S3,i,t}$ is the lifetime expected loss associated with non-performing exposures.

$$\mathrm{ImpGross}^{s,C}_{S1,S3,i,t} = \mathrm{Flow}^{s,C}_{S1,S3,t} \times \mathrm{LGD}^{s,C}_{S1,S3,i,t} \tag{36}$$

$$\mathrm{ImpGross}^{s,C}_{S2,S3,i,t} = \mathrm{Flow}^{S,C}_{S2,S3,t} \times \mathrm{LGD}^{s,C}_{S2,S3,i,t} \tag{37}$$

where $\mathrm{LGD}^{s,C}_{S1,S3,i,t}$ is the expected loss rate for exposures that transition from S1 to S3 and $\mathrm{LGD}^{s,C}_{S2,S3,i,t}$ is the expected loss rate for exposures that transition from S2 to S3.

The stock of provisions for non-performing assets is:

$$\begin{aligned}\mathrm{ProvStockDef}^{s,C}_{i,t} &= \mathrm{ImpGross}^{s,C}_{S1,S3,i,t} + \mathrm{ImpGross}^{s,C}_{S2,S3,i,t} + \mathrm{ImpGross}^{s,C}_{S3,S3,i,t} \\ &- \mathrm{ProvStockDef}^{s,C}_{S2,i,t-1} \times (\mathrm{TR}^{s,C}_{S3,S1,i,t} + \mathrm{TR}^{s,C}_{S3,S2,i,t})\end{aligned} \tag{38}$$

B.2.4 Evolution of the stock of provisions

For each sector the stock of provisions sums provisions for non-defaulted ProvStockNonDef and for defaulted ProvStockDef exposures:

$$\mathrm{ProvStock}_{i,t}^{s,C} = \mathrm{ProvStockNonDef}_{i,S1,t}^{s,C} + \mathrm{ProvStockNonDef}_{i,S2,t}^{s,C} + \mathrm{ProvStockDef}_{i,t}^{s,C} \tag{39}$$

ProvStock is the aggregate amount of provisions:

$$\mathrm{ProvStock}_{i,t} = \sum_{s,C} \mathrm{ProvStock}_{i,t}^{s,C} + \mathrm{ProvStock}_{i,t}^{\mathrm{Other}} + \mathrm{ProvStock}_{i,t}^{\mathrm{Eq}}$$

B.2.5 Total impairment losses and profit and loss impact

Total impairment losses equal:

$$\mathrm{TotalImpLosses}_{i,t} = \mathrm{ProvStock}_{i,t} - \mathrm{ProvStock}_{i,t-1}$$

Credit risk impacts profit and loss via impairment (or reversal of impairment) on financial assets not measured at fair value through profit and loss, i.e. financial assets at amortised costs, $\mathrm{Impfa}_{i,t}$:

$$\mathrm{Impfa}_{i,t} = \mathrm{TotalImpLosses}_{i,t} + \mathrm{TotalImpLosses}_{i,t}^{\mathrm{sec}}$$

where $\mathrm{TotalImpLosses}_{i,t}^{\mathrm{sec}}$ are the exogenous total impairments for securitisation exposures that are not subject to mark-to-market valuation.

B.3 Interest income

Assets categories for the calculation of interest income are summarised in Table 15 jointly with asset categories in the banking book.[7]

B.3.1 Evolution of the end of period asset volumes

The end of period volumes of interest bearing assets $\mathrm{VolAssetTotal}_{i,t}^{s,C}$ are linked to the end of period $\mathrm{TotalLoans}_{i,t}^{s,C}$ via:

$$\mathrm{VolAssetTotal}_{i,t}^{s,C} = \mathrm{VolAssetTotal}_{i,t-1}^{s,C} \times \frac{\mathrm{TotalLoans}_{i,t}^{s,C}}{\mathrm{TotalLoans}_{i,t-1}^{s,C}} \tag{40}$$

[7] A different categorisation of banking book and interest bearing assets in the model is inherited form the EBA stress test templates.

Asset sector for interest income accounting	EBA asset category	Asset sector for calculating REA
Loans to central banks and governments	Central banks and governments	Central banks and governments
Loans to financials	Credit institutions and other financial corporations	Institutions
Loans to corporates	Non-financial corporations - small and medium-sized enterprises and non-financial corporations - other	Corporate backed by real estate Corporate not backed by real estate
Loans to households backed by real estate	Residential mortgage loans	Households not backed by real estate
Loans to households other	Households - credit for consumption Households - other	Households not backed by real estate
Securities central banks and governments	Securities central banks and governments	
Securities financials	Securities financials	
Securities corporates	Securities corporates	
Other	Derivatives - hedge accounting - cash flow hedge Derivatives - hedge accounting - fair value hedge Derivatives - hedge accounting - net investment hedge Derivatives - not used for hedge accounting Assets - other assets	

Table 15: Mapping of sectors for credit risk calculation purposes into corresponding categories for interest income accounting

For interest bearing asset categories from Table 15 for which no mapping with corresponding banking book assets exists (empty last column), we assume their exogeneity with the corresponding volumes remaining constant over time.

The volumes of non-performing loans for interest income calculations VolNPE are next derived under the assumption that the share of non-performing assets evolves along with the same dynamics in net interest income and credit risk module. Along with the earlier assumption that asset quality changes at the beginning of each period it boils down to the following formulas:

$$\frac{\mathrm{VolNPE}^{s,C}_{i,t}}{\mathrm{VolAssetTotal}^{s,C}_{i,t-1}} = \frac{\mathrm{VolNPE}^{s,C}_{i,t-1}}{\mathrm{VolAssetTotal}^{s,C}_{i,t-2}} + \left(\frac{\mathrm{DefExp}^{s,C}_{i,t}}{\mathrm{TotalLoans}^{s,C}_{i,t}} - \frac{\mathrm{DefExp}^{s,C}_{i,t-1}}{\mathrm{TotalLoans}^{s,C}_{i,t-1}}\right) \tag{41}$$

And finally, the volumes of provisions for non-performing loans are derived under the same set of assumptions:

$$\frac{\text{VolProvNPE}^{s,C}_{i,t}}{\text{VolNPE}^{s,C}_{i,t-1}} = \frac{\text{VolProvNPE}^{s,C}_{i,t-1}}{\text{VolNPE}^{s,C}_{i,t-2}} + \left(\frac{\text{ProvStockDef}^{s,C}_{i,t}}{\text{DefExp}^{s,C}_{i,t}} - \frac{\text{ProvStockDefs, C}_{i,t-1}}{\text{DefExp}^{s,C}_{i,t-1}}\right) \tag{42}$$

B.3.2 Evolution of the period average asset volumes

In contrast to end of period values in the banking (and trading) books, the interest income calculations are based on period-average values of asset volumes and interest rates. Let us first clarify the evolution of average interest bearing asset volumes. For each portfolio, the performing volumes are further subdivided into existing $\text{VolAssetExist}^{s,C}_{i,t}$, maturing $\text{VolAssetMat}^{s,C}_{i,t}$, and new $\text{VolAssetNew}^{s,C}_{i,t}$ asset volumes, where only performing assets are assumed to mature and new volumes are not allowed to become non-performing within the period when they are issued.

The laws of motion of these categories are:

$$\begin{aligned} \text{VolAssetMat}^{s,C}_{i,t} = \text{PomAsset}^{s,C}_{i} \times (\text{AvgMat}^{s,C}_{i})^{-1} \times \\ (\text{VolAssetTotal}^{s,C}_{i,t-1} - \text{VolNPE}^{s,C}_{i,t}) \end{aligned} \tag{43}$$

The parameter $\text{PomAsset}^{s,C}_{i}$ stands for the point of maturity of the assets, which is defined as the average fraction of a year at which the maturing positions would in fact mature. It can be thought of as the proportion of maturing assets within a certain period and thus a measure of asset turnover.

$$\begin{aligned} \text{VolAssetExist}^{s,C}_{i,t} = (1 - (\text{AvgMat}^{s,c}_{i})^{-1}) \times (\text{VolAssetTotal}^{s,C}_{i,t-1} - \\ \text{VolNPE}^{s,C}_{i,t}) \end{aligned} \tag{44}$$

$$\begin{aligned} \text{VolAssetNew}^{s,C}_{i,t} = (1 - \text{PomAsset}^{s,C}_{i}) \times (\text{VolAssetTotal}^{s,C}_{i,t} - \\ \text{VolAssetTotal}^{s,C}_{i,t-1}) + (\text{PomAsset}^{s,C}_{i})^{-1} \times \text{VolAssetMat} \end{aligned} \tag{45}$$

B.3.3 Interest rates

Interest rates on new loans are governed by the set of behavioural equations reported in the main text in section 4.2. The reference rate on the existing business in period t is derived from an

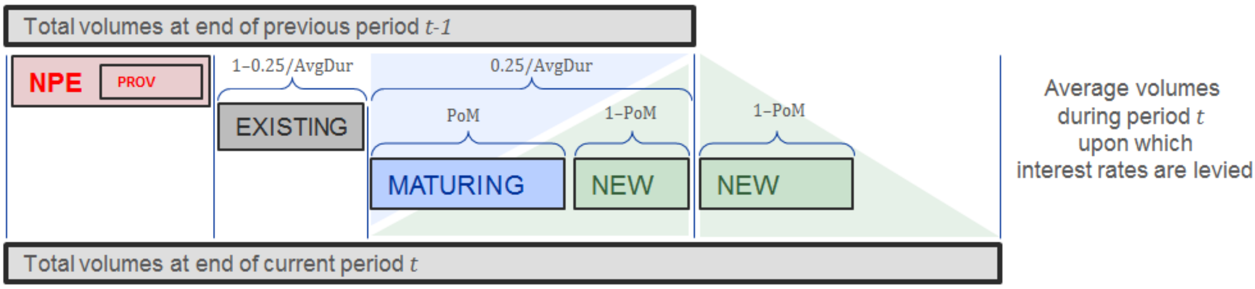

Figure 16: Schematic representation of average interest bearing asset volumes

intertemporal consistency relationship with the interest rates on existing and new volumes, for which it is adjusted. In the formula below, $\text{ShareFloat}_{i}^{s,C}$ refers to the share of floating positions, in other words assets whose income is based on a floating rate instrument. We assume that floating positions have a floating and a fixed leg. The floating part of the position depends on an interest margin charged by the bank, whereas the fixed part is contractually linked to a reference index rate. The reference rate $\text{RefRate}_{i,t}^{s,C}$, which is supposed to capture the general risk-free conditions relevant for the given instrument, is in turn linked to the Euribor 3-month rate (STN) from the macroeconomic block. $\text{RefDuration}_{i}^{s,C}$ simply refers to the average time duration (in quarters) for which the corresponding reference rate stays unchanged for an instrument before it is repriced. Effective interest rates on existing assets are adjusted with the aforementioned parameters in the following way:

$$\begin{aligned} \text{EIRAssetExist}_{i,t}^{s,C} = (&\text{EIRAssetNew}_{i,t-1}^{s,C} \times \text{VolAssetNew}_{i,t-1}^{s,C} + \\ &\text{EIRAssetExist}_{i,t-1}^{s,C} \times \text{VolAssetExist}_{i,t-1}^{s,C})/ \\ &(\text{VolAssetNew}_{i,t-1}^{s,C} + \text{VolAssetExist}_{i,t-1}^{s,C}) \\ +&(\text{RefDuration}_{i}^{s,C})^{-1}\text{ShareFloat}_{i}^{s,C}(\text{RefRate}_{t}^{s,C} - \text{RefRate}_{t-1}^{s,C}) \end{aligned} \tag{46}$$

We assume that the assets mature uniformly across the (unobserved) distribution of portfolio rates, so the interest rates on maturing assets co-move with the average portfolio rates, adjusted for the rate difference on the previous stock of maturing loans.

$$\begin{aligned}\mathrm{EIRAssetMat}_{i,t}^{s,C} = \mathrm{EIRAssetMat}_{i,t-1}^{s,C} + (\mathrm{EIRAssetExist}_{i,t}^{s,C} - \\ \mathrm{EIRAssetExist}_{i,t-1}^{s,C}) - (\mathrm{AvgMat}_{i}^{s,C})^{-1}) \times (\mathrm{EIRAssetMat}_{i,t-1}^{s,C} \\ - \mathrm{EIRAssetExist}_{i,t-1}^{s,C})\end{aligned} \tag{47}$$

B.3.4 Interest income

Interest income is calculated as follows:

$$\mathrm{TotalIntInc}_{i,t} = \sum_{s,C} (\mathrm{IntIncPE}_{i,t}^{s,C} + \mathrm{IntIncNPE}_{i,t}^{s,C}) \tag{48}$$

$\mathrm{IntIncPE}_{i,t}^{s,c}$ is an income from performing loans:

$$\begin{aligned}\mathrm{IntIncPE}_{i,t}^{s,C} = \mathrm{VolAssetMat}_{i,t}^{s,C} \times \mathrm{EIRAssetMat}_{i,t}^{s,C} + \mathrm{VolAssetExist}_{i,t}^{s,C} \times \mathrm{EIRAssetExists}, C_{i,t} + \\ + \mathrm{VolAssetNew}_{i,t}^{s,C} \times \mathrm{EIRAssetNews}, C_{i,t}\end{aligned} \tag{49}$$

$\mathrm{IntIncNPE}_{i,t}^{s,c}$ are the projections of income on non-performing exposure on a net basis, i.e net of provisions:

$$\mathrm{IntIncNPE}_{i,t}^{s,C} = \mathrm{EIRNPE}_{i,t}^{s,C} \times (\mathrm{VolNPE}_{i,t}^{s,C} - \mathrm{VolProvNPE}_{i,t}^{s,C}) \tag{50}$$

B.4 Bank funding

The basic structure of liabilities is outlined in Table 16 where all the sight deposits (sight - regulated, sight - non regulated, zero IR and sight - other) are aggregated together and complemented with their term deposit classes:

We aggregate fixed and floating rate portfolios.

B.4.1 Evolution of the end of period liability volumes

The end of period total volumes are updated following the rule:

BEAST liability sectors	EBA liability class
Deposits - central banks	ELA Other central bank liabilities
Deposits - general governments	General governments - sight General governments - term
Deposits- financials	Deposits (excl. repo) - credit Institutions and other financial corporations - sight Deposits (excl. repo) - credit Institutions and other financial corporations - term
NFC sight deposits	Deposits (excl. repo) - non-financial corporations - sight
NFC term deposits	Deposits (excl. repo) - non-financial corporations - term Deposits - repo
HH sight deposits	Deposits (excl. repo) - households - sight
HH term deposits	Deposits (excl. repo) - households - term
Debt securities	Asset-backed securities Covered bonds Hybrid contracts Other debt securities issued - Convertible compound financial instruments Other debt securities issued - non-convertible
Other	Derivatives - hedge accounting - cash flow hedge Derivatives - hedge accounting - fair value hedge Derivatives - hedge accounting - net investment hedge Derivatives - not used for hedge accounting Other liabilities

Table 16: Mapping of EBA liability categories to sectors for interest expenditure accounting

$$\mathrm{VolLiabTotal}_{i,t}^{s,C} = \mathrm{VolLiabTotal}_{i,t-1}^{s,C} \times (1 + \mathrm{VolLiabTotal\_gr}_{i,t}^{s,C}) \tag{51}$$

where $\mathrm{VolLiabTotal\_gr}_{i,t}^{s,C}$ is for each segment equal to the growth rate of total assets excluding securities and other assets.

B.4.2 Evolution of period average liability volumes

Further, for each portfolio we distinguish between existing $\mathrm{VolLiabExist}_{i,t}^{s,C}$ asset values, maturing $\mathrm{VolLiabMat}_{i,t}^{s,C}$ and new $\mathrm{VolLiabNew}_{i,t}^{s,C}$ liability volumes. Segment and country specific parameter $\mathrm{PomLiab}_{i}^{s,C}$ stands for point-of-maturity and $\mathrm{AvgDurationLiab}_{i}^{s,C}$ denotes the total time (in quarters) between liability time of origination and the maturity date, which suggests how long it is expected for the respective liability to stay on the banks' books. The laws of motion of these liability volumes are:

$$\mathrm{VolLiabMat}_{i,t}^{s,C} = \mathrm{PomLiab}_{i}^{s,c} \times (\mathrm{AvgDurationLiab}_{i}^{s,C})^{-1} \mathrm{VolLiabTotal}_{i,t-1}^{s,C} \tag{52}$$

$$\mathrm{VolLiabExist}_{i,t}^{s,C} = (1 - (\mathrm{AvgDurationLiab}_{i}^{s,C})^{-1}) \times \mathrm{VolLiabTotal}_{i,t-1}^{s,C} \tag{53}$$

$$\begin{aligned} \mathrm{VolLiabNew}_{i,t}^{s,C} = (1 - \mathrm{PomLiab}_{i}^{s,C}) \times (\mathrm{VolLiabTotal}_{i,t}^{s,C} - \mathrm{VolLiabTotal}_{i,t-1}^{s,C}) + \\ + (\mathrm{PomLiab}_{i}^{s,C})^{-1} \times \mathrm{VolLiabMat} \end{aligned} \tag{54}$$

B.4.3 Interest rates

Interest rates on new deposits are governed by the set of behavioural equations reported in the main text in section 4.2. As for interest bearing assets the reference rate $\mathrm{RefRate}_{i,t}^{s,C}$ will be linked to the short-term interest rate in the macro block (STN). The interest rate on existing liabilities equals:

$$\text{EIRLiabExist}^{s,C}_{i,t} = (\text{EIRLiabNew}^{s,C}_{i,t-1} \times \text{VolLiabNew}^{s,C}_{i,t-1} +$$
$$\text{EIRLiabExist}^{s,C}_{i,t-1} \times \text{VolLiabExist}^{s,C}_{i,t-1})/(\text{VolLiabNew}^{s,C}_{i,t-1} + \text{VolLiabExist}^{s,C}_{i,t-1}) \tag{55}$$
$$+(\text{RefDurationLiab}^{s,C}_{i})^{-1} \times \text{ShareFloatLiab}^{s,C}_{i} \times (\text{RefRate}^{s,C}_{t} - \text{RefRate}^{s,C}_{t-1})$$

We assume that the liabilities are retired uniformly across the (unobserved) distribution of funding costs. Hence the interest rates on maturing liabilities follow an error-correction relationship, reflecting the funding portfolio turnover rate:

$$\begin{aligned}\text{EIRLiabMat}^{s,C}_{i,t} &= \text{EIRLiabMat}^{s,C}_{i,t-1} + (\text{EIRLiabExist}^{s,C}_{i,t} - \text{EIRLiabExist}^{s,C}_{i,t-1}) + \\ &+(\text{AvgDurationLiab})^{-1} \times (\text{EIRLiabMat}^{s,C}_{i,t-1} - \text{EIRLiabEXIST}^{s,C}_{i,t-1})\end{aligned} \tag{56}$$

B.4.4 Interest expenses

Interest expenses on segment s in $\{\text{Liabilities}\}$ are summed up across sector and countries:

$$\text{TotalIntExp}_{i,t} = -\sum_{s,c} \text{IntExp}^{s,c}_{i,t} \tag{57}$$

Interest expenses on a portfolio level are equal:

$$\begin{aligned}\text{IntExp}^{s,C}_{i,t} &= \text{VolLiabExist}^{s,C}_{i,t} \times \text{EIRLiabExist}^{s,C}_{i,t} \\ +\text{VolLiabMat}^{s,C}_{i,t} &\times \text{EIRLiabMat}^{s,C}_{i,t} + \text{VolLiabNew}^{s,C}_{i,t} \times \text{EIRLliabNew}^{s,C}_{i,t}\end{aligned} \tag{58}$$

B.5 Profit and loss

The profit and loss module summarises the interest income and expenses as outlined in Appendix B.3 and B.4 and the impairment losses arising from credit risk as in Appendix ??. The remaining profit and loss components, therein those related to trading book income and losses.

B.5.1 Total operating income and profit and loss

The dynamics of total operating income (net) TotOpInc is driven mostly by net interest income NII and net fee and commission income NFCI, both modelled endogenously in the model. Other components of the total operating income are GainsHFT, gains or losses on financial assets and liabilities held for trading, GainsOnTR gains or losses on non-trading financial assets mandatorily at fair value through profit or loss, GainsFAFV gains or losses on financial assets and liabilities designated at fair value through profit or loss and GainsHA corresponding to gains or losses from hedge accounting (net). All the latter are either exogenised or follow a simplified updating rule.

$$\begin{aligned}\mathrm{TotOpInc}_{i,t} =& \mathrm{NII}_{i,t} + \mathrm{NFCI}_{i,t} + \mathrm{GainsHFT}_{i,t} + \mathrm{GainsOnTR}_{i,t} + \\ & \mathrm{GainsHA}_{i,t} + \mathrm{GainsFAFV}_{i,t} + \mathrm{OthTotOpInc}_{i,t}\end{aligned} \tag{59}$$

OthTotOpInc in the formula above defines the exogenous residual term that includes expenses on share capital repayable on demand, dividend income, exchange differences (gain or loss), other operating expenses, gains or losses from the derecognition of non-financial assets and financial assets and liabilities not measured at fair value through profit and loss, and from non-financial and other operating income.

Profit or loss before tax from continuing operations ProfBTCO includes total operating income TotOpInc and credit risk impairment losses IMPFA:

$$\begin{aligned}\mathrm{ProfBTCO}_{i,t} =& \mathrm{TotOpInc}_{i,t} + \mathrm{IMPFA}_{i,t} + \mathrm{Prov}_{i,t} + \mathrm{IMPFACCR}_{i,t} + \\ & \mathrm{GainsOpR}_{i,t} + \mathrm{OthProfBTCO}_{i,t} + \mathrm{PrAdjPreTax}_{i,t}\end{aligned} \tag{60}$$

The remaining parts of the bank profitability remain exogenous in the model. This concerns Prov, sum of provisions or reversal of operational provisions, IMPFACCR, impairment of financial assets (CCR losses), gains or losses arising from operational risk GainsOpR, pre-tax MDA adjustments PrAdjPreTax and the remaining residual components OthProfBTCO[8].

The model's main profitability variable is given by ProfATCO, profits after tax from continuing operations, which is composed of ProfBTCO, profit or loss before tax from continuing operations, and the resulting tax expenses Tax:

[8]OthProfBTCO includes items such as administrative expenses, depreciation, other income and expenses from continuing operations, impairment or reversal of impairment on non-financial assets, negative goodwill recognised in profit or loss, share of the profit or (-) loss of investments in subsidiaries, joint ventures and associates accounted for using the equity method.

$$\mathrm{ProfATCO_{i,t} = ProfBTCO_{i,t} + Tax_{i,t}} \tag{61}$$

where we assume a flat tax rate of 30%:

$$\mathrm{Tax_{i,t}} = -0.3 \times \mathrm{ProfBTCO_{i,t}} \times \mathrm{I}(\mathrm{ProfBTCO_{i,t}} >= 0) \tag{62}$$

B.5.2 Retained earnings

The current period retained earnings flow ProfOwnDiv amounts to the profit or loss after tax from continuing operations ProfATCO after deducting the exogenous minority interest ATTR2MinInt and dividend payments DivPaid:

$$\mathrm{ProfOwnDiv_{i,t} = ProfATCO_{i,t} - ATTR2MinInt_{i,t} - DivPaid_{i,t}} \tag{63}$$

Dividend payments DivPaid are governed by equation (9) in section 4.3 and profit after tax that is available for profit distribution after regulatory MDA adjustments ProfBDiv :

$$\mathrm{ProfBDiv_{i,t} = ProfATCO_{i,t} - ATTR2MinInt_{i,t} - PRAdjPostTax_{i,t}} \tag{64}$$

where PRAdjPostTax is projected adjustments to post-tax distributions as in CRD-IV (MDA).

B.5.3 Maximum Distributable Amount (MDA)

Projected adjustments to post-tax distributions related to MDA are given by:

$$\mathrm{PRAdjPostTax_{i,t}} = \mathrm{ProfATCO_{i,t}} \times (1 - \mathrm{MDA\_Factor_{i,t-1}}) \times \mathrm{I}(\mathrm{ProfATCO_{i,t}} \geq 0) \tag{65}$$

where the determination of the maximum distributable amount follows CRR Article 92 and CRD Article 104, 141. The MDA adjustments can take place before the determination of pre-tax profits via cost reductions or as an adjustment to post-tax distribution (CRD 141) via reduced pay-outs. For simplicity, we assume that banks always adjust their post-tax profit distribution via reduction in dividend pay-outs. Accordingly, the MDA_Factor is retrieved via the following equation:

$$\mathrm{MDA\_Factor}_{i,t} = \begin{cases} 0\% & \text{if} \quad \mathrm{CET1\_NUseR}_{i,t} < 1\mathrm{quart}_{i,t} \\ 20\% & \text{if} \quad 1\mathrm{quart}_{i,t} < \mathrm{CET1\_NUseR}_{i,t} < 2\mathrm{quart}_{i,t} \\ 40\% & \text{if} \quad 2\mathrm{quart}_{i,t} < \mathrm{CET1\_NUseR}_{i,t} < 3\mathrm{quart}_{i,t} \\ 60\% & \text{if} \quad 3\mathrm{quart}_{i,t} < \mathrm{CET1\_NUseR}_{i,t} < 4\mathrm{quart}_{i,t} \\ 100\% & \text{else} \end{cases} \tag{66}$$

The MDA buckets are defined by quartiles of the combined buffer requirement ComB:

$$1\mathrm{quart}_{i,t} = (\mathrm{ComB}_{i,t}/4) * 1 \tag{67}$$

$$2\mathrm{quart}_{i,t} = (\mathrm{ComB}_{i,t}/4) * 2 \tag{68}$$

$$3\mathrm{quart}_{i,t} = (\mathrm{ComB}_{i,t}/4) * 3 \tag{69}$$

$$4\mathrm{quart}_{i,t} = (\mathrm{ComB}_{i,t}/4) * 4 \tag{70}$$

CET1_NUseR stands for the CET1 capital ratio maintained by the institutions which is not used to meet own funds requirements:

$$\mathrm{CET1\_NUseR}_{i,t} = \mathrm{CET1\_NUse}_{i,t}/\mathrm{TotREA}_{i,t} \tag{71}$$

$$\mathrm{CET1\_NUse}_{i,t} = \mathrm{CET1TR}_{i,t} - (\mathrm{P2CR}_{i,t} + \mathrm{AT1T2\_SHORT\_P1R}_{i,t}) * \mathrm{TOTREA}_{i,t} \tag{72}$$

In the above CET1_NUse is defined as the surplus of transitional capital stock with respect to total SREP capital requirements P2CR and AT1/T2 shortages of Pillar 1 requirements AT1T2_Short_P1R. The latter equals::

$$\mathrm{AT1T2\_Short\_P1R}_{i,t} = \max\left(0, 0.035 - (\mathrm{T1CRTA}_{i,t} - \mathrm{CET1TR}_{i,t}) - \min(0.02, (\mathrm{OFRTA}_{i,t} - \mathrm{T1CRTA}_{i,t}))\right) \tag{73}$$

T1CRTA is Tier1 transitional capital ratio and CET1TR respectively for CET1 and OFRTA is the own funds capital ratio.

B.6 Capital

The capital block summarizes the relevant items for the determination of the nominator of bank solvency ratios and closes the model.

B.6.1 Common Equity Tier 1 capital (net of deductions and after transitional adjustments)

The Common Equity Tier 1 definition in the model relates to CET1 net of deductions and after transitional adjustments $\mathsf{CET1TR}$:

$$\mathsf{CET1TR}_{i,t} = \mathsf{CICET}_{i,t} + \mathsf{RetEarn}_{i,t} + \mathsf{AOCI}_{i,t} + \mathsf{DTA}_{i,t} + \mathsf{IRBSF}_{i,t} + \mathsf{DBPFA}_{i,t} + \mathsf{CET1Oth}_{i,t} \quad (74)$$

where CICET are capital instruments eligible as CET1 capital (including share premium and net own capital instruments), $\mathsf{RetEarn}$ are retained earnings, AOCI is accumulated other comprehensive income, DTA stand for deferred tax amounts , IRBSF is IRB shortfall of credit risk adjustments to expected losses, DBPFA corresponds to defined benefit pension fund assets. Finally, $\mathsf{CET1Oth}$ summarises all other components of CET1 capital such as other reserves, funds for general banking risks or transitional adjustments. Aside of retained earnings and accumulated other comprehensive income all other components of CET1 capital remain exogenous in the model.

The capital block is directly interlinked with the profit and loss statement via $\mathsf{RetEarn}_t$ and the current period earning flow $\mathsf{ProfOwnDiv}$ as defined in equation63:

$$\mathsf{RetEarn}_{i,t} = \mathsf{RetEarn}_{i,t-1} + \mathsf{ProfOwnDiv}_{i,t} \quad (75)$$

Accumulated other comprehensive income includes gains/losses from revaluation $\mathsf{AOCIRev}$, the impact of defined benefit pension plans DBOCI and the AOCI balancing term AOCIOC:

$$\mathsf{AOCI}_{i,t} = \mathsf{AOCIRev}_{i,t} + \mathsf{DBOCI}_{i,t} + \mathsf{AOCIOC}_{i,t} \quad (76)$$

All of which are exogenous.

B.6.2 Tier 1 capital (net of deductions and after transitional adjustments)

Tier 1 capital is derived as:

$$\mathsf{T1CAP}_{i,t} = \mathsf{CET1FL}_{i,t} + \mathsf{AT1CAP}_{i,t} \tag{77}$$

Where $\mathsf{CET1FL}_{i,t}$ is a fully loaded CET1 capital stock (derived from transitional CET1 where transitional adjustments are replaced by fully loaded adjustments) and $\mathsf{AT1CAP}_{i,t}$ is an additional Tier 1 capital stock.

B.6.3 Capital ratios

The transitional Common Equity Tier 1 capital ratio equals:

$$\mathsf{CET1REA}_{i,t} = \mathsf{CET1TR}_{i,t}/(\mathsf{TotREA}_{i,t} + \mathsf{TAIFRSREA}_{i,t}) \tag{78}$$

and $\mathsf{TAIFRSREA}$ are adjustments due to IFRS9 transitional arrangements. Further, the transitional Tier 1 capital ratio is derived as:

$$\mathsf{T1CRTA}_{i,t} = (\mathsf{T1CAP}_{i,t}/(\mathsf{TotREA}_{i,t} + \mathsf{TAIFRSREA}_{i,t}) \tag{79}$$

And own funds transitional ratio is given by:

$$\mathsf{OFRTA}_{i,t} = (\mathsf{T1CAP}_{i,t} + \mathsf{T2CAP}_{i,t})/(\mathsf{TotREA}_{i,t} + \mathsf{TAIFRSREA}_{i,t}) \tag{80}$$

B.7 Risk Exposure Amounts

B.7.1 Total Risk Exposure Amount

The denominator of the capital ratios is given by the (adjusted) amount of total risk-weighted assets defined by TotREA in the following:

$$\mathsf{TotREA}_{i,t} = \mathsf{CRREA}_{i,t} + \mathsf{MRREA}_{i,t} + \mathsf{OPREA}_{i,t} + \mathsf{OTHERREA}_{i,t} \tag{81}$$

where CRREA is the credit risk-weighted banking book and is detailed hereafter. Market risk-weighted assets MRREA, risk-weighted assets by operational risk OPREA and other risk exposure amount $\mathsf{OTHERREA}$ enter the model exogenously.

B.7.2 Credit Risk Exposure Amounts

CRREA can be decomposed into:

$$\mathrm{CRREA}_{i,t} = \sum_{s,C} \mathrm{CRREA}_{i,t}^{s,C} + \mathrm{CRREA}_{i,t}^{CCP} \tag{82}$$

where the sector subscript s is defined as in Table 14. Credit-risk weighted amounts for equity, securitisations and other assets as well as the contributions to the default fund of a credit counter-party CRREA^{CCP} are exogenous. The risk-weighted amounts corresponding with remaining banking book assets are further divided into risk-weighted amounts for non-defaulted and defaulted exposures:

$$\mathrm{CRREA}_{i,t}^{s,C} = \mathrm{CRREA}_{i,t}^{s,C,NonDef} + \mathrm{CRREA}_{i,t}^{s,C,Def} \tag{83}$$

Both are computed as the outstanding exposures times the corresponding risk weights CRRW:

$$\mathrm{CRREA}_{i,t}^{s,C,Def} = \mathrm{CRRW}_{i,t}^{s,C,Def} \times \mathrm{DefExp}_{i,t}^{s,C} \tag{84}$$

$$\mathrm{CRREA}_{i,t}^{s,C,NonDef} = \mathrm{CRRW}_{i,t}^{s,C,NonDef} \times \mathrm{NonDefExp}_{i,t}^{s,C} \tag{85}$$

Risk weights $\mathrm{CRRW}_{i,t}^{s,C,NonDef}$ and $\mathrm{CRRW}_{i,t}^{s,C,Def}$ are calculated as effective risk weights assuming constant proportions $\theta_i^{M,s,C}$ of assets risk-weighted along with each methodology $\mathrm{M} \in (\mathrm{AIRB}, \mathrm{FIRB}, \mathrm{STA})$ i.e:

$$\mathrm{CRRW}_{i,t}^{s,C,NonDef} = \sum_{M} \theta_i^{M,s,C} \times \mathrm{CRRW}_{i,t}^{M,s,C,NonDef} \tag{86}$$

$$\mathrm{CRRW}_{i,t}^{S,C,Def} = \sum_{M} \theta_i^{M,s,C} \times \mathrm{CRRW}_{i,t}^{M,s,C,Def} \tag{87}$$

where $\sum_M \theta_i^{M,s,C} = 1$. For the standardised approach the risk weights are assumed to remain constant, while for IRB methodologies the calculation of risk weights follows the CRR formulas.

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