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Marco Gross and Javier Población

A false sense of security in applying handpicked equations for stress test purposes

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Abstract

The purpose of this paper is to promote the use of Bayesian model averaging for the design of satellite models that financial institutions employ for stress testing. Banks employing 'handpicked' equations – while meeting standard economic and econometric soundness criteria – risk significantly underestimating the response of risk parameters and therefore overestimating their capital absorption capacity. We present a set of credit risk models for 18 EU countries based both on the model averaging scheme as well as a series of handpicked equations and apply them to a sample of 108 SSM banks. We thereby aim to illustrate that the handpicked equations may indeed imply significantly lower default flow estimates and therefore overoptimistic estimates for the banks' capital absorption capacity. The model averaging scheme that we promote should mitigate that risk and also help establish a level playing field with regard to a common level of conservatism across banks.

Keywords: Stress testing, satellite modeling, model averaging, bank regulation and supervision

JEL classification: C11, C22, C51, E58, G21

Non-technical summary

Stress testing has become a very conventional and increasingly prominent tool for assessing the resilience of financial institutions to hypothetical macro-financial stress scenarios. One significant recent stress test assessment (including as well as an Asset Quality Review) was conducted by the European Central Bank in the course of 2014 for 130 significant European banking groups that are now under the direct supervision of the Single Supervisory Mechanism (SSM).

Our paper aims to address one important element that all stress tests involve — whether conducted by financial institutions themselves (in a bottom-up fashion) or by some central authorities (in a top-down fashion) — which lays in the use of satellite equation systems for translating macro-financial shock scenarios into risk parameters at bank level. The concern that forms the basis for our paper is the fact that virtually all institutions tend to neglect the presence of *model uncertainty*. While the bridge equations for a given risk parameter at bank-level may be sound and look acceptable from an economic and econometric viewpoint, and therefore pass an internal risk management or supervisory sign-off, there is a risk that the chosen specification by the institution would underestimate the risk parameter response and in the sequel overestimate the loss absorption capacity of the bank. The choice of equations that result in overoptimistic scenario conditional forecasts might either be due to explicit incentives for banks to underestimate the cost of risk or be coincidental.

The aim of our paper is to promote the use of a Bayesian model averaging (BMA) methodology to mitigate that risk. The model averaging philosophy is not new and used in other areas by researchers and econometric practitioners. With the BMA-based models and the illustrative stress test simulation results for a sample of 108 SSM banks we are aiming to make a simple point: that the deviation with regard to the banks' projected capital position can be very significant when either employing some overoptimistic handpicked satellite equations or, as we argue, the more robust BMA-based satellite models. Handpicked equations may pass a set of basic criteria for economic and econometric soundness, while implying however unduly benign risk parameter responses to an assumed adverse scenario. They therefore pose a risk for an institution to be significantly under-provisioned.

Supervisors, as well as the institutions that are being supervised, may consider using this approach in order for a risk assessment across portfolios to be more robust, i.e. more likely reflect the relative risks of exposures to different regions and segments. Moreover, it shall help develop a more level playing field also across banks, with portfolios of similar (say equal, hypothetically) risk characteristics more likely resulting in similar capital requirements, if conditioned on the same centrally-defined macro scenario.

1 Introduction

Stress testing has become an increasingly relevant and visible tool over the past decades and is used regularly by financial institutions and those who supervise them, notably by supervisory authorities and central banks to assess the resilience of financial institutions. In the course of 2014, the Comprehensive Assessment (CA) was conducted by the European Central Bank (ECB), in collaboration with the European Banking Authority (EBA) and the European Systemic Risk Board (ESRB), to assess the quality of the balance sheets of 130 significant European banks.[1] One important pillar of the CA was the stress test for the banks and the goal of assessing the resilience of the institutions under a hypothetical adverse scenario over a three-year horizon.

Useful entry points to the stress test-related literature from the viewpoint of supervisory institutions and central banks are the following: the Risk Assessment Model for Systemic Institutions (RAMSI) developed by the Bank of England (Alessandri et al. (2009)), the Systemic Risk Monitor (SRM) by the Austrian Central Bank (Boss et al. (2006)), the IMF (Cihak (2007) and Schmieder et al. (2011)) and the macro stress testing framework that was developed by the ECB (Henry and Kok (2013)). These papers have in common that they develop a 'framework' for stress testing, i.e. cover different risk types such as credit risk, interest rate risk, market risk, etc. Foglia (2009) is a useful reference as it provides a comprehensive survey of all stress test-related methodologies that were developed by central banks and supervisors. Borio and Tsatsaronis (2012) is another general discussion paper about macro stress testing and what it can achieve; it emphasizes in particular that macro stress tests are useful for crisis management and resolution (and less so as an early warning device).

The focus of our paper is on one important element that all the existing stress testing frameworks involve: the satellite models that are used to link risk parameters at the bank level with the macro and financial factors to project the evolution of the bank balance sheet conditional on an adverse scenario. There is a rich literature presenting empirical satellite models for various risk types, including in particular credit and interest rate risk.[2]

[1] The Comprehensive Assessment consisted of two pillars, the Asset Quality Review (AQR) and the stress test. The CA started in fall 2013, with the assessment being conducted over the course of 2014 until the results were published in October 2014. See https://www.ecb.europa.eu/ssm/assessment/html/index.en.html for related material.

[2] Risk parameters at the bank level include, prominently, variables such as probabilities of default (PD), loss given default (LGD), loss rates (the product of PD and LGD), and others. These risk parameters drive the profit and loss (P&L) of an institution over time and therefore determine the evolution of its balance sheet structure and size. Concerning credit risk, a useful entry point to the literature are survey papers such as Altman and Saunders (1997), Crouhy et al. (2000) and Gordy (2000).Furthermore, see Schwartz and Torous (1993), Jimenez and Saurina (2006), Demyanyk and Hemert (2011), Ghent and Kudlyak (2011), Pesaran et al. (2006), Duellmann and Erdelmeier (2009), Castren et al. (2010), and Gray et al. (2013).

The starting point of our paper is the observation that financial institutions use single equation satellite models to establish a link between risk parameters at the bank level and macro and financial variables at the country level. We refer to them as 'handpicked' equations which is meant to reflect the fact that institutions pick one equation out of a large pool of possible equation specifications that would fulfill individually a set of economic and econometric criteria, i.e., they would all individually qualify for a bank-internal risk management or supervisory sign-off. Financial institutions have an incentive to choose equations that imply lower provisioning needs and therefore capital requirements conditional on a scenario while conforming to the minimal requirements for economic and statistical soundness. In particular in the course of the 2014 stress test and the quality assurance process led by the ECB, the documentation provided by the participating banks very clearly confirmed that virtually all institutions operate, indeed, with single equation approaches.[3]

Irrespective of whether due to an explicit incentive to choose equations that imply less stress (to minimize the cost of risk) or the choice being coincidental, the risk of using handpicked equations is at least twofold.

First, the use of handpicked equations implies the risk that a specification is chosen that underestimates the response of risk parameters to a prescribed hypothetical adverse scenario. The loss absorption capacity of an institution might as a result be insufficient.

Second, their use may imply a skewed risk assessment across different portfolios (segments and regions) for a given institution, conditional not only on an adverse scenario but also for developing a baseline outlook across portfolios to support business decisions. Similarly, from a macro perspective, for banks with similar risk profiles that use different handpicked equations, scenario-conditional forecasts may suggest very different sensitivities to changing macro conditions although in reality they should not differ significantly (or vice versa: banks with different risk dynamics could happen to choose models that suggest rather similar sensitivities to macro-financial conditions).

These two aspects call for the promotion of satellite model methods that are not based on only one equation but a pool of equations. Specifically, we promote the use of Bayesian Averaging of Classical Estimates (BACE) (Sala-i Martin et al. (2004)) for stress test modeling purposes. In addition to the aforementioned two reasons for the usefulness of model averaging are the following two aspects: First, there is considerable uncertainty regarding the drivers of credit risk dynamics. Being agnostic and employing a model averaging technique

Moreover, see Deng and Gabriel (2006), Deng et al. (2000), Sommar and Shahnazarian (2008), Ferry et al. (2012), Alves and Ribeiro (2011), Salas and Saurina (2002), Jimenez and Saurina (2006), Hoeberichts et al. (2006), Hoggarth et al. (2005), Laeven and Majnoni (2003), and Duffie and Lando (2000)

[3]The Quality Assurance process led by the ECB to challenge and possibly override the banks' assumed risk parameter paths in case that their models did not meet a list of pre-defined soundness criteria is described in http://www.ecb.europa.eu/pub/pdf/other/castmanual201408en.pdf.

is useful for that reason. Second, time series for credit risk measures such as default rates are typically short; thus, one all-encompassing multivariate model including all potential predictors cannot be set up. General-to-specific model structuring methods are therefore likely to be inferior because the general model is bound in its dimension from the beginning and therefore prone as well to suffer from omitted variable bias.

In our paper, we illustrate the use of Bayesian model averaging with an application to credit risk based on a Merton model-type measure of PDs for non-financial corporations for 18 EU countries.[4] We develop scenario-conditional forecasts for the 18 countries from the models that the Bayesian model averaging methodology implies along with a set of handpicked equations. With the models and the illustrative stress test simulation results for a sample of 108 SSM banks, we aim to emphasize how significant the deviation with regard to projected capital measures of the banks can be when employing, in particular, some overoptimistic handpicked satellite equations. The handpicked equations may pass a set of basic criteria for economic and econometric soundness. They may, however, imply unduly benign risk parameter responses to an assumed adverse macroeconomic scenario and therefore the risk for an institution to be under-provisioned.

An additional reference that we shall make is to Hardy and Schmieder (2011). The main message of the authors is that stress testing should involve rules of thumb, which in the context of satellite modeling should mean that equations be simple and for that reason robust. The authors also note that "model uncertainty is an important consideration" and that it is "easy to overlook" (page 4, Hardy and Schmieder (2011)). With the model averaging philosophy that we are aiming to promote we have that same objective, that is, to develop simple and robust models.

It is worthwhile recalling that stress tests conducted by financial institutions are not only 'useful' but in fact required by regulators, as stipulated in the Basel accords.[5] Pillar II, the most relevant in terms of the topic of our paper, stipulates that banks shall use stress testing techniques to assess their ability to withstand hypothetical, severe macroeconomic stress scenarios. Specifically, see Basel Committee on Banking Supervision, BCBS (2006), paragraph 775, for credit risk: "A bank's management should conduct periodic stress tests of its major credit risk concentrations and review the results of those tests to identify and respond to potential changes in market conditions that could adversely impact the bank's performance." In addition, with regard to the results of these stress tests (paragraph 777):

[4] The model averaging approach that we promote should not be seen as being limited to the application to Merton-model-type PDs specifically (observed default rates can be used instead), nor credit risk parameters in general. Pricing parameters, i.e., interest rates for assets and liabilities (interest rates on loans, deposits, wholesale funding, etc.) can be modeled in the same way. The ECB used the Bayesian model averaging approach to develop benchmark models and scenario conditional forecasts for all risk parameters (credit risk related and pricing parameter related) for the 2014 EBA/ECB/SSM stress test.

[5] See Basel Committee on Banking Supervision, BCBS (2006).

"Supervisors should take appropriate actions where the risks arising from a banks credit risk concentrations are not adequately addressed by the bank."

The remainder of the paper is organized as follows. In Section 2 we recall the basic rationale underlying the Bayesian model averaging approach. In Section 3 we present the data and describe the assumptions that are entailed in the stress test simulation that we conduct for the European banks' corporate loan portfolios. In Section 4 we present the main results while in Section 5 we further discuss how the model averaging approach could be operationalized in a supervisory environment. Section 6 concludes.

2 Bayesian model averaging

The Bayesian Model Averaging (BMA) approach entails the assumption that no single model is the only true and it therefore operates with a pool of models to which weights are assigned that reflect the relative performance of each model. The individual models are combined to a posterior model using these weights.

Bayesian model averaging is a general model philosophy, while we employ a more specific variant of it, called Bayesian Averaging of Classical Estimates (BACE) (Sala-i Martin et al. (2004)). The BACE approach envisages the use of diffuse priors, which, in case the parameter space is bounded, implies uniform weights for all models (we call them equations in the following) that a model space comprises.[6]

When applying the Bayesian model averaging approach, we may face a constraint: Not all 2^K models that could be set up with K potential predictors can be considered because the higher dimensional models cannot be estimated due to an insufficient number of remaining degrees of freedom (as a result of operating with short time series). For the application at hand, the approach is therefore to truncate the model space by defining a maximum model dimension. All up to the self-defined maximum dimensional models will be considered. For our empirical application the maximum dimension of the models is set to four. The equations in the model space can well all individually be estimated and then be aggregated to a posterior model. No stochastic search techniques will need to be employed.[7]

[6]The weights that are needed to obtain the posterior parameter densities will in our application be computed based on the standard Bayesian information criterion, i.e. it does include a penalty term to down-weigh larger models. The weight function is in this case based on the Bayesian Information Criterion (BIC) (Schwarz (1978)). Other weight functions can be used, which can be based on either in- or out-of-sample predictive performance measures.

[7]The choice of the maximum model dimension does in some cases change the posterior model structures in terms of predictor variables that appear, yet for the stress test simulation results that involve the posterior models' projections of PDs we obtain similar results when choosing for instance a maximum of three instead

As a basis for forming the model space we use an Autoregressive Distributed Lag (ADL) model structure. The dependent variable Y_t is allowed to be a function of its own lags as well as contemporaneous and possibly further lags of a set of predictor variables.

$$Y_t = \alpha + \rho_1 Y_{t-1} + ... + \rho_p Y_{t-p} + \sum_{k=1}^{k_i} (\beta_0^k X_t^k + ... + \beta_{q^k}^k X_{t-q^k}^k) + \varepsilon_t \quad (1)$$

Y_t will be the level Distance-to-Default (DD) measure. It will be translated into a PD measure based on a power function.[8] The model and simulation results that we present are not sensitive to the choice of level or first differences of the DD measure.

The model space will be constructed by considering all conceivable combinations of predictors from a pool of K variables, with the dimension of the models set to the self-defined limit L.[9] For each model equation i with its predetermined set of predictor variables, the lag structures for autoregressive and distributed exogenous terms, p and q^k, are chosen optimally by estimating all possible combinations of lag structures up to a limit G (which will be set to two). The specification for which the BIC is minimal will be chosen. In the course of the additional search for the optimal lags, the lag structures for the autoregressive part and for lags of exogenous predictors are forced to be 'closed' (without gaps). Every single equation in the model space is expected therefore to be well behaved with regard to residual statistics.

An object of interest, besides the posterior model's parameters, is the probability for a particular predictor to be included in the model space, the *posterior inclusion probability*. It is computed as the sum of the posterior model probabilities that contain the particular predictor. It shall be noted that a predictor variable will be said to be significant in the posterior model if the corresponding posterior inclusion probability exceeds the prior inclusion probability.[10]

We compute the posterior inclusion probability for the combined inclusion of the contemporaneous and, if present, lagged term of a predictor variable. Moreover, we present the model structure in terms of long-run multipliers (henceforth LRM) with respect to a predictor variable X^k from a model i in the model space. The LRM is defined as follows.

of four predictors.

[8]Alternative PD transformations could have been used instead, for instance, a logit transform of a PD, a probit, or an inverse Normal.

[9]When all combinations of variables in models with $(1, 2, ..., L)$ predictors are considered, the number of models I can be computed as $I = \sum_{l=1}^{L} \frac{K!}{l!(K-l)!}$.

[10]For the formulas for the prior and posterior inclusion probabilities, see Sala-i Martin et al. (2004).

$$\sum_{l=0}^{\infty} \partial E(Y_{t+l})/\partial X_t^k = (\beta_0^k + ... + \beta_q^k)/(1 - \rho_1 - ... - \rho_p) \equiv \Theta^k \tag{2}$$

The LRM will, moreover, be *normalized*. The normalization is accomplished by basing the LRM on normalized posterior model coefficients. A coefficient is normalised by multiplying the initial coefficient estimate by the ratio of the standard deviations of a predictor and the dependent variable. Normalized multipliers can be compared across predictor variables within a model as well as across models (countries).

The imposition of *sign constraints*, as proposed in this paper, is meant to exclude equations from the model space that do not meet some predefined criteria. We define the sign constraints on the basis of the long-run multipliers. For instance, the long-run multiplier on real activity variables such as real GDP or components of it (e.g., private consumption, investment) should have a negative sign in a PD equation (a positive sign in a DD equation) to be conform with theory that suggests that if economic activity slows down, the distance to default for a company shall decrease.

Each equation in the model space will be subject to the set of sign constraints. Should an equation not meet at least one constraint it will be assigned a zero posterior model weight, i.e. not have any bearing on the posterior model's structure and coefficient estimates. By imposing sign constraints on the individual equations it is guaranteed that all signs on the LRMs of predictors in the posterior model will be in line with the restrictions.

The rationale behind the imposition of sign constraints is to mimic the modeling process that an econometrician would pursue if working with a single (handpicked) equation approach. That is, the econometrician would search for a specification that has the 'right signs' and not accept a model with the wrong signs, as it would not result in stress in a stress scenario.[11]

[11] The imposition of sign constraints is not a necessary component of the model averaging approach. An empirical application of the BMA to, say, a PD measure, can result in a meaningful model also without the prior imposition of sign constraints. However, some of the individual equations in the model space may (quite likely) have the incorrect signs and therefore influence the posterior multipliers on a predictor in a way that would be against theory. The sign of the posterior coefficient then depends on how strong the posterior equation weight is on the equations that had the correct and the incorrect signs. The choice as to whether sign constraints are to be imposed depends on how strong the modeler's prior beliefs and confidence in some underlying theory (implying the signs of the predictor variables) are. The number of equations that are assigned a zero posterior weight due to a violation of some sign constraint can in itself be an interesting measure. If a large portion, say 80% or more, of the equations in the model space get rejected on the basis of the sign constraints, one can interpret this as being strong evidence against some underlying theory. When operating with short time series, one should not draw too strong conclusions though in that respect, as the underlying sample may rather by chance imply relationships that appear to speak against theory.

3 A stress test simulation for European banks' corporate loan portfolios

The objective is now to apply the Bayesian model method to develop a system of satellite equations for a sample of EU countries. The satellite equation system will be used to conduct a stress test for the corporate loan portfolios of 108 European banks to then make a simple point: that it can make a material difference for the projected capital position of the banks when using either some selected handpicked equations that meet some predefined economic and econometric criteria or the posterior model structure resulting from the BMA approach.

3.1 Data

The data involved in the modelling exercise includes: i) the Merton-model-based DD measure for 18 EU countries, ii) bank-level data for 108 SSM banks and iii) macro and financial data for the 18 EU countries.

The dependent variable is a Contingent Claims Analysis (CCA)-based measure of Distance-to-Default (DD) for nonfinancial corporations in the 18 EU countries.[12] The DD and corresponding PD data are sourced from Credit Edge/Moody's KMV'[13]

Bank-level data is sourced from the EBA/SSM/ECB stress test templates that were published in October 2014 by the EBA and the ECB.[14] The bank sample contains 108 banks, i.e. the subset of the 130 banks from the ECB Comprehensive Assessment that are located in the 18 EU countries for which we develop models.[15] Bank-individual information, both with regard to the raw input data and model outputs, will be presented at the aggregate country-level.

The information that is employed includes exposures at default (EAD) for the corporate

[12]Three useful references for an exposition of the conceptual basis for the DD measure and how it relates to the probability of default can be found in Crosbie and Bohn (2003), Sun et al. (2012) and Ferry et al. (2012).

[13]The DD measure can be translated into a PD empirically by means of a power equation that we base on Moody's PD and DD data. The simple bivariate equations are meant to mimic the more advanced (and proprietary) model that Moody's KMV developed to map DDs into PDs (see Crosbie and Bohn (2003)). We use the DD data for 18 EU countries at a quarterly frequency, spanning for the majority of countries the period from 1999 to 2013 (for all countries the time series end in 2013Q4).

[14]See https://www.ecb.europa.eu/ssm/assessment/html/index.en.html.

[15]DD data at the country level were missing or of insufficient quality or time series length for Cyprus, Estonia, Lithuania, Latvia, Malta, and Slovakia. The banks from these countries could have been included in the stress test simulation but would have been shocked only with regard to their foreign exposures as we would not have had a domestic DD model for them (the impact estimates for them would have been rather limited by design in this case).

exposure (because the DD models are developed for the nonfinancial corporate segment), Common Equity Tier 1 (CET1) capital, and Risk Weighted Assets (RWA); all as of 2013. In addition, risk parameter starting points as of 2013 are involved, i.e., the PD and LGD starting points for the corporate portfolios. PDs are either the bank regulatory model-based point-in-time parameters or, in case the PDs are not available, the realized default rates for 2013 (default flow 2013 over EAD beginning of 2013).[16] In Table 1 we summarize the list of banks that is involved in the modeling exercise, including some basic information about the CET1 and RWA starting point for all banks.

The macroeconomic and financial variables involved in the models are sourced from the ECB statistical data warehouse which partly mirror the information provided by other data vendors (e.g. Eurostat for macro data as well as Bloomberg and Datastream for financial data). The eleven variables that are involved in the modelling exercise are: real GDP YoY growth (GDP), real investment growth YoY (ITR), real export growth YoY (XTR), the unemployment rate (URX), the year-on-year absolute change in URX (Δ4URX), consumer price inflation YoY (INF), residential property prices (YoY, over-2-years, over-3-years, denoted respectively as HP, HP2y and HP3y), 10-year benchmark government bond yields as a spread to the German bond yield (LTN), and a 3-month money market rate (Euribor or national equivalent for non-euro area countries, as a spread to ECB or national central bank policy rates, denoted as STN).

3.2 Stress test setting and assumptions

The stress test simulation that we conduct focuses on credit risk in the nonfinancial corporate portfolio of the banks. Our settings follow relatively closely the methodological assumptions that were involved in the 2014 ECB/SSM/EBA stress test.[17] The stress test horizon is set to 3 years (2014 to 2016) and we focus on only the adverse scenario (neglecting the baseline scenario).

The NPL formation at bank-level should be defined. It is a function of the expected default rate, i.e. the PD, and write-off rates w.

$$NPL_t = NPL_{t-1}(1 - w_t) + PD_t(L_{t-1} - NPL_{t-1}) \tag{3}$$

where L_t are gross loans and $L_t - NPL_t$ is assumed to equal EAD_t. In conjunction with an assumed path for LGDs, the expected loss will be the product of PD and LGD.

[16] PD and LGD starting points can be obtained for instance from the following source: https://www.eba.europa.eu/documents/10180/679742/Risk+parameters+disclosure+of+EU+banks+%28pdf%29.

[17] See EBA (2014a).

$$EL_t = PD_t \times LGD_t \times EAD_{t-1} \tag{4}$$

where EAD_{t-1} is the exposure at default at the end of period $t-1$ (the beginning of period t).

Concerning LGDs, the corporate loan stock of each bank (and country) is divided into corporate exposures that are collateralized by real estate and other. For the real estate (RE)-related exposures, the LGD^corpRE will be parameterized as a mechanical function of Commercial Property Prices (CPP) in the scenario according to the following equation.

$$LGD_{2013+h}^{corpRE} = 1 - \frac{(1 - LGD_{2013}^{corpRE})CPP_{2013+h}}{CPP_2013} \tag{5}$$

For the part of the corporate portfolio backed by collateral other than real estate, the LGD will be held constant by assumption. Moreover, for the sake of simplicity, the LGD parameters for the already defaulted assets, i.e., the NPL stock, are assumed to not be further affected along the scenario horizon.[18]

The provision stock of the institutions will be assumed to evolve in a way to reflect the projected evolution of LGDs, i.e., the coverage ratio (provision stock over NPL stock) is therefore assumed to be proxied by LGDs.

The balance sheets of all banks are assumed to be static, i.e., gross loan amounts (performing plus nonperforming stocks) are constant over the 3-year simulation horizon (i.e., L_{t-1} in equation (3) does not actually need a time subscript as it is constant by assumption). Write-offs of nonperforming assets or sales of performing assets are therefore not allowed (i.e., w_t in equation (3) is assumed to equal zero). Loans that would mature during the simulation horizon are assumed, implicitly, to be replaced by new business that has identical risk and maturity characteristics. The only effect that is being simulated is therefore the migration of loans from performing to nonperforming status. Cures (i.e., the migration of NPLs back to performing status) will be ruled out by assumption.

Profit and loss components other than loan loss provisions are assumed to equal zero along the scenario horizon. This assumption is not entirely realistic of course, nor would it be stipulated in regular stress test exercises. However, it is in that sense that our simulation exercise is indeed to be seen as purely illustrative with regard to the partial effect of only loan loss provision buildup and the implied impact on the capital position of the banks as

[18] We shall note that the assumption for the evolution of LGDs is not very influential for what concerns the results, as we will present them later on (namely, as CET1 ratio differentials between handpicked and posterior models).

implied by either handpicked equations or a posterior model following the model averaging methodology. The focus lies on illustrating the impact of choosing handpicked versus posterior model averages for the provisioning needs of the banks in the form of CET1 ratio differences. As the focus lies on capital ratio differences, the assumption of zero P&L for items other than loan losses is not very relevant.

While the simulation is simplistic with regard to all remaining P&L components, we do account for two additional effects that the default flow implies.

First, the impact on risk weights is accounted for by employing the Basel formula for the corporate segment, which translates PD, LGD and EAD parameters into RWA.[19] We compute an RWA amount for the corporate segment as of end-year 2013 (denoted as $RWA_{2013}^{aggr,corp}$) and then for the scenario-conditional paths from the different handpicked and posterior models ($RWA_{2013+h}^{aggr,corp}$). The absolute difference between these self-computed forward paths of the corporate RWA and the self-computed 2013 starting point is then applied to the 2013 RWA as observed at the bank-level (denoted as $RWA_{2013}^{bank,total}$).[20] Equation (6) indicates how the RWA forward paths are computed.

$$RWA_{2013+h}^{bank,total} = RWA_{2013}^{bank,total} + max(RWA_{2013+h}^{aggr,corp} - RWA_{2013}^{aggr,corp}, 0) \tag{6}$$

As can be seen in the formula, we introduce a floor for the RWA at the 2013 starting value for each bank so that RWAs cannot fall below the 2013 starting point.

Second, we account for forgone interest income that the simulated default flows imply. To that end, an effective interest rate is computed at bank level for the 2013 starting point, which is then held constant by assumption throughout the simulation horizon.[21] The loan interest rate proxy is then multiplied by the default flows that are being simulated from the various satellite models and the resulting forgone interest amounts subtracted from capital for the respective years along the scenario horizon.

In line with the structure of the EBA/ECB disclosure, the ten largest country exposures of each bank are used at the granular level. That is, the PD, LGD and EAD parameters are steered by means of the satellite equations from the respective countries. If, for instance, an Austrian bank has some corporate loan exposure in Germany, it will be the German satellite

[19]See CRR (2013), Article 153 point 1 (iii) (pg. 97).

[20]The reason for computing a 2013 starting point ourselves and then attaching the absolute changes to the 2013 bank starting point is that the RWA formula is not expected to exactly replicate the RWA reported by a bank due to the nonlinear nature of the RWA formula. When being applied at different levels of granularity, the formula gives slightly different estimates of RWA total for a portfolio (the formula is applied at the exposure level in the institution as opposed to the portfolio level in this paper).

[21]The interest rate is computed as the ratio of interest income over interest bearing assets.

model that is used to project the DD, and therefore the PD, for the Austrian bank's exposure in Germany. The NPL formation and corresponding provision flow will therefore be country specific for each bank in the sample. The starting point PDs at bank level are translated into DD starting points by means of the same power functions (their inverse) that are used to map the Merton model PDs and DDs. Note that the aforementioned RWA formula for the corporate segment is applied at country exposure level for every single bank (just as in all default and impairment flow calculations).

The underlying macro-financial scenario that is translated by means of the DD equation system is the one that was used as a basis for the 2014 EBA/SSM/ECB stress test.[22]

4 Results and application

4.1 Stress test model and simulation results

All predictor variables that relate to economic activity (GDP, investment, exports) were assigned a positive sign constraint on their LRM, to reflect that an economic downturn should induce DDs to decrease (PD increase). Consumer price and residential property price inflation were assigned a positive constraint, too. The LRMs on short- and long-term interest rates are expected to have a negative sign because the ability of debtors to repay their debt should, ceteris paribus, worsen in case the cost of credit increases. For jurisdictions in which loan contracts are predominantly 'variable rate', the sensitivity of DDs/PDs is expected to be more pronounced than in fixed rate regimes. Finally, a negative sign constraint was imposed on the unemployment rate.[23]

Given the number of potential predictors (11) and the settings for the maximum model dimension (maximum four lags of exogenous variables beyond their contemporaneous inclusion), the number of equations in the model space for each country equals 562. For some countries such as Poland and Slovenia that number is smaller because for instance the residential property price time series was too short or not available and therefore excluded.

The structure of the posterior models across the 18 countries is summarized in Figure 1. For about two to three predictor variables per country, the posterior inclusion probability

[22] See EBA (2014b).

[23] Our results are subject to the caveat that the estimates may not be fully immune to some endogeneity bias resulting for instance from simultaneity, i.e. reverse causality from PDs/DDs back to, for example, real activity measures. The risk of simultaneity bias with regard to real activity measures in the model is in our view relatively limited, however, because the PDs/DDs from the Merton-type model are forward-looking, while for measures of contemporaneous realised default rates the simultaneity concern would be more justified.

exceeds the respective prior inclusion probabilities, indicating thereby the significance of the predictor in a Bayesian sense. Variables that appear more prominently as relevant predictors of DDs are long-and short-term interest rates and some measure of real activity, in particular GDP growth or investment. Export growth plays a dominant role for DDs in Germany and the Netherlands, which can be expected due to the significant export orientation of the corporate sector in these countries. Interest rates appear to play a role in many countries, in particular also in peripheral countries such as Italy, Portugal and Ireland which are known to be characterized by 'variable-rate' loan systems, i.e. their sensitivity to interest rate changes can be expected to be higher than for other countries. Unemployment has been found to co-move significantly with corporate DDs in a few countries, e.g., Spain.

We now 'handpick' some selected equations from the model spaces for all countries which in terms of implied scenario-conditional forecasts of DDs fall into the right and left part of the distribution of the posterior models' scenario-conditional forecast. These two alternative choices of handpicked equations will be referred to as an 'optimistic' and 'pessimistic' equation. In addition to the 'optimistic' equation, a second variant of an optimistic model, referred to as optimistic*, will be presented per country. The optimistic* equation is selected from the subset of equations in the model space that imply falling DDs (i.e., rising PDs) under the adverse scenario. The additional optimistic* equation is meant to reflect the choice of an institution that would not employ a model that implies falling PDs under an adverse scenario.

The estimates for the handpicked equations along with the posterior models are presented in Table 2. The estimates and performance measures presented in the table suggest that all models, both handpicked and posterior, perform well in terms of predictive measures such as the R-square and residual statistics such as the DW. The signs on the macro and financial predictor variables are in the very majority of handpicked models conform to economic theory. The posterior models' coefficient signs are in line with theory as the sign constraints were imposed as outlined in the previous section.

We shall note that indeed all equations in the model space meet the basic requirements for predictive performance and residual behavior. The distribution of R-squares and DW statistics based on the individual equations in the model space for each country range very closely around the posterior models' statistics. This is due to the way we design the model space, which as outlined in the previous section, envisages the optimization of lag structures of distributed lags for every single equation in the model space.

The implied model projections at the country level for the three handpicked equations as well the posterior model are visualized in Figure 2. The grey area in the charts depicts the 5th and 95th percentile of the adverse scenario-conditional distribution from the posterior models.[24] The handpicked equations were chosen so that their projections fall approximately into the center of the posterior models' mean and the respective upper and lower bounds from the posterior model (5th and 95th percentile).

The DD projections conditional on the adverse scenario from the three handpicked and the one posterior model per country are now applied to the bank-specific starting points for the 108 banks in the sample. Figure 3 shows the difference of CET1 ratios from a handpicked equation system relative to the posterior model-implied CET1 ratio. The difference is the average difference based on the 2014, 2015, and 2016 projected capital position of the banks. Panel A and B in Figure 3 refer to the impact estimates when including and excluding the stress on foreign exposures, respectively. In Panel B, for example, the Austrian banks' German exposure would not be stressed, while only the Austrian exposure is stressed with the Austrian model. Because the banks all tend to have the most significant exposure in their home countries, the differences between Panel A and B are not very pronounced, implying that the main stress for the banks arises from their domestic loan exposures. Note that the impact estimates in Panel B, the ones excluding foreign stress, still mean that the banks' foreign exposures generate loan losses, as the PDs and LGDs are not zero; they are just not stressed, i.e., held constant.

Figure 4 (Panel A and B) displays the corresponding Kernel density distributions based on the underlying sample of 108 banks for the difference in projected capital ratios (again on average over the three years).

With a view to the handpicked 'optimistic' equations, the optimistic* should be the focus for the majority of countries. For only a few countries the optimistic equation (without *) and the implied capital ratio differential should be looked at, namely for the countries whose adverse scenario does not imply a further deterioration in macro conditions but rather a continuation of weak macro conditions. Countries that fall into that category include Greece, Ireland and Slovenia. For these countries, the domestic DD projections from the posterior model are rather flat, which is reflective of the fact that the underlying macro factors are not further deteriorating in the adverse scenario. Institutions in these countries may argue that some indicators improve under the adverse scenario and should therefore imply that DDs rise (PDs fall) even under stress. This claim would be acceptable, and it is via the choice of the optimistic model (without *) that this aspect is reflected.

The estimates presented in Figures 3 and 4 (focus on Panel A in the following) suggest that the aggregate average difference between the optimistic and optimistic* models relative

[24]Note that the adverse scenario-conditional forward distribution is reflective of three sources of uncertainty: model uncertainty, coefficient uncertainty and residual uncertainty. A nonparametric bootstrap has been employed to draw from the posterior models' residuals. A parametric bootstrap has been employed to draw from the posterior coefficient space.

to the posterior model equal +2.8 and +1.7 percentage points (pp) for the CET1 ratio, respectively. For the French banking system, for instance, the optimistic* model choice would imply for its average capital ratios (average along the scenario horizon) to stand +2.3pp above the posterior model result. On the downside, on average across countries, the handpicked pessimistic model specifications result in a -3.2pp average differential for the capital ratios relative to the posterior model projections.

As an example for the over-optimistic models, the more pronounced CET1 ratio differentials can be observed for the Netherlands, where the optimistic* equation implies a +5.2pp CET1 ratio gap to the posterior model. On the opposite side, for the German banking system, the optimistic* equation would result in a rather limited gap of about +0.8pp. For Spain, Luxembourg, Portugal and Slovenia the estimates are close to that of Germany.

Figure 5 indicates how the different components – loan losses, forgone interest income, and changes in RWA – contribute to the CET1 ratio change over the three-year scenario horizon until 2016.[25] Initially, the contributions are all negative percentage point contributions to the system-wide CET1 ratio, which we sum and normalize so that the relative contributions as depicted in the chart sum to 100%.

It can be seen that loan losses have as expected the highest contribution, ranging between 69% and 87% depending on the model scheme. In addition, as expected, the contribution of loan losses is higher for the pessimistic handpicked equations and the posterior model compared to the optimistic models, as the default flows are stronger due to higher PDs. Second and third in the contribution rank forgone interest and RWA changes, amounting to about 11%-12% and up to 20%, respectively. The fact that the forgone interest income contribution increases slightly for the pessimistic and posterior models reflects that the default flow is stronger (due to higher PDs) under these models and therefore the foregone interest income is higher. The RWA contribution is small, around 1%, for the pessimistic and posterior model which is primarily because we floor the RWAs at 2013 starting values under all model schemes; this constraint becomes binding for these two model schemes. If the RWA floor was to be deactivated, the RWA contribution would become negative.

4.2 Supervisory applications

The supervisory review process, as outlined in (BCBS (2006)), envisages that supervisors review and evaluate bank internal capital adequacy assessments and strategies as well as their ability to monitor and ensure their compliance with regulatory capital ratios. Supervi-

[25] It should be noted that the relative contributions should be interpreted really as 'relative' contributions, meaning that loan losses, for instance, can be higher (lower) in absolute terms while being lower (higher) in relative terms.

sors should expect banks to operate above the minimum regulatory capital ratios and should have the ability to require banks to hold capital in excess of the minimum.

Consequently, in view of the regulation, the supervisor may consider operationalizing the idea of model averaging by developing a model space based on a predefined set of potential predictor variables (inspired by a set of predictor variables that the supervised institution uses or suggested additional covariates) to then position a model from a bank in that model space. The bank model-implied scenario conditional forecast, for instance, for PDs for a certain portfolio of the bank, can be ranked in the model space according to, for example, the average PD along the scenario horizon to then consider a rule that would imply the rejection of the bank model in case its projection is less severe than the median from the model space (the posterior model projection, say). The rationale of the rejection would be that a significant number of alternative models in the model space, which are equally well performing with regard to economic and econometric criteria, imply a more adverse parameter response than the bank's model.

Following that rationale would, however, imply that the choice (the acceptance or rejection of a bank model) depending on a posterior model projection would depend on the underlying scenario. This is not necessarily bad. Based on one scenario, the supervisor may reject a satellite model from a bank, whereas based on another scenario of a different type (risk factor constellation), the supervisor would accept it.

Alternatively, the supervisor can recommend that the banks themselves employ the Bayesian model averaging approach and therefore a posterior model to produce scenario-conditional forecasts of its risk parameters. An institution may wish to simulate the bounds around the scenario conditional forecasts and employ them for estimating the scenario-conditional loan loss provisioning needs, to thereby account even more explicitly for model uncertainty.

We shall note that alternative model schemes, based, for instance, on transition matrices, which banks might employ, can be combined with the model averaging approach. A compressed measure of the evolution of the transition matrix as a whole or compartments of the matrix (or in the limit case, a time series of every single cell of a transition matrix) can be well modeled as a function of the macro and financial variables by means of the Bayesian model averaging technique.

Moreover, model averaging in itself does not need to be based on the particular sort of underlying model structure (ADL model structure) as presented in this paper. It can also be based on a set of concrete structural or semi-structural or other reduced-form model structures, linear or nonlinear. Hence, any model that a bank presents can as such be embedded in the model space.

5 Conclusions

The purpose of the paper is to promote the use of Bayesian model averaging techniques for supervisors and institutions that are being supervised in a stress test context for the development of satellite equations that link risk measures at bank-level with macroeconomic and financial indicators. The aim of the model averaging methodology is to help develop robust specifications that institutions can employ for stress testing, in particular in the context of the Basel framework (Pillar II). The methodology shall help develop a level playing field across banks for a risk assessment across institutions to be adequate and comparable.

With the models and the illustrative stress test simulation results for a sample of 108 SSM banks we were aiming to make a simple point: that the deviation with regard to the projected capital position of a bank can be very significant when either employing some overoptimistic handpicked satellite equations or, as we argue, a more robust satellite model based on the BMA approach. Handpicked equations may pass a set of basic criteria for economic and econometric soundness, while implying however unduly benign risk parameter responses to an assumed adverse macroeconomic scenario. They therefore pose a risk for the institution to be significantly under-provisioned.

Supervisors may consider operationalizing the idea of model averaging by developing a model space based on a predefined set of potential predictor variables to then position a model from a bank in that model space. The bank model-implied scenario conditional forecast can be ranked in the model space to then consider a rule that would imply the rejection of the bank model in case its projection is less severe than the median (or another quantile, depending on the supervisor's risk aversion). The rationale of the rejection would be that a significant number of alternative models in the model space, which are equally well performing with regard to economic and econometric criteria, imply a more adverse parameter response than the bank's model.

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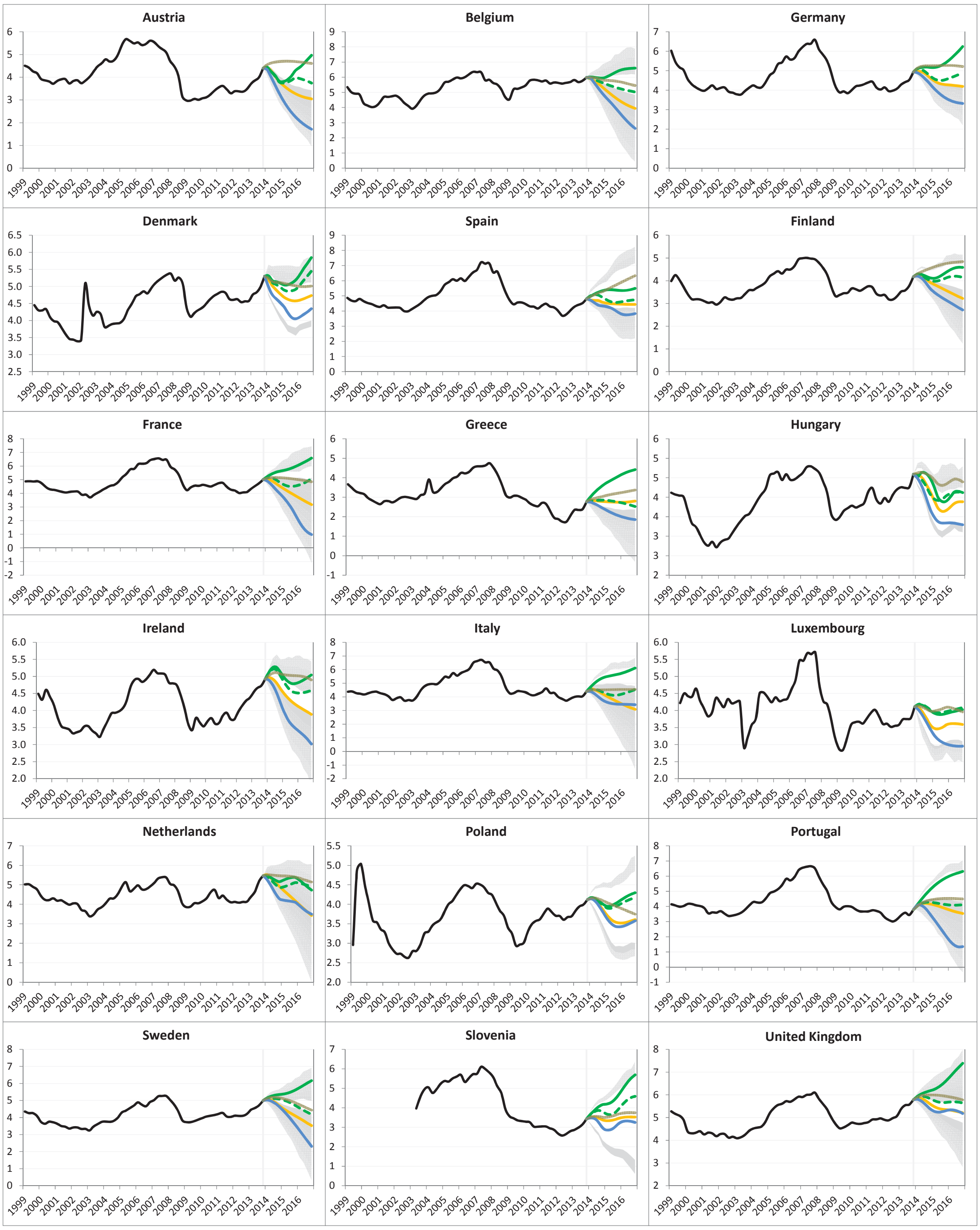
Figure 1: Posterior DD model structures

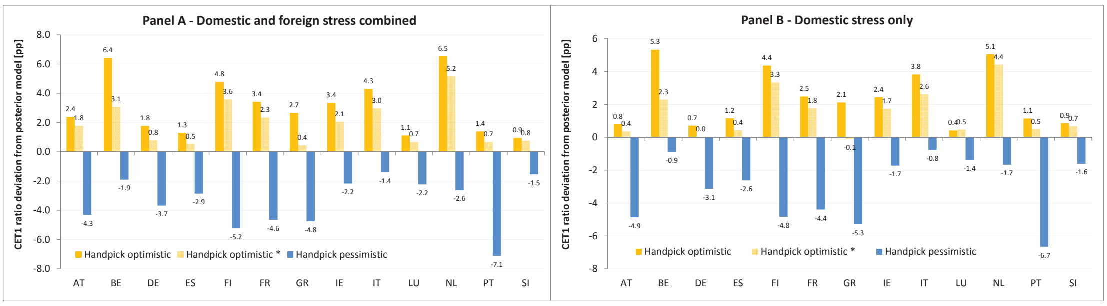
Note: The figure displays the posterior model structures for the 18 countries. The predictor variables are sorted by descending posterior inclusion probability. The long-run multipliers combine the contemporaneous and lagged coefficient estimates for a given predictor in one multiplier. Moreover, the multipliers are normalized so that they can be compared across predictor variables both within models and across countries.

Figure 2: Posterior and handpicked model equation-implied scenario-conditional forecasts



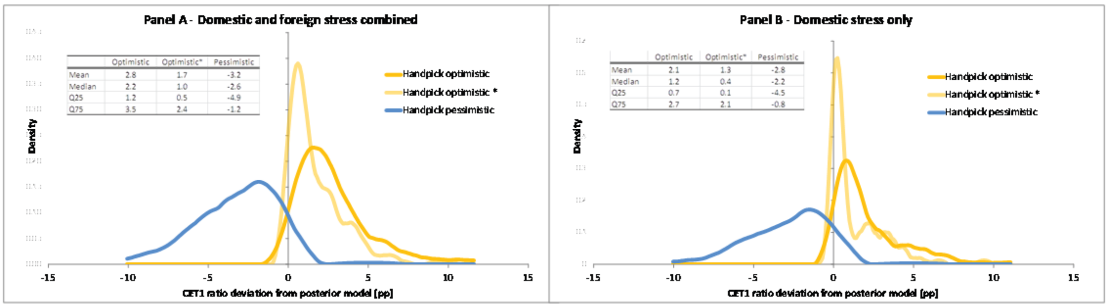
Note: The DD measure is to be understood as multiples of standard deviations (vertical axes). The underlying data, models and projections are at quarterly frequency. The forward horizon covers the 12 quarters from 2014Q1 to 2016Q4. The brown line indicates the posterior model implied baseline path; the orange line indicates the posterior model's adverse path; the blue line indicates the pessimistic handpicked model implied adverse path. The solid and dashed green lines indicate the optimistic and optimistic* models' adverse projection. The grey area indicates the 5^{th}-95^{th} percentile bounds corresponding to the adverse scenario-conditional DD forecast from the posterior models.

Figure 3: Difference in CET1 capital ratios from handpicked versus posterior models – Banking system aggregate results



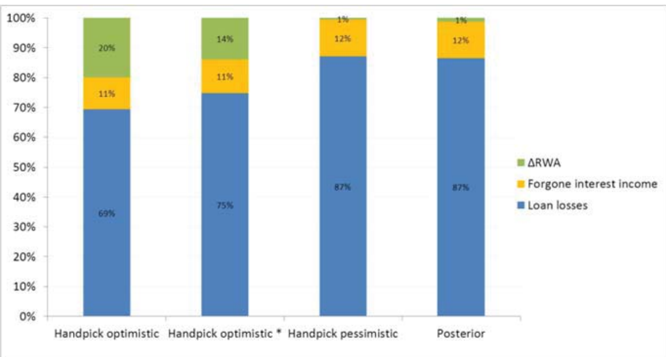
Note: Panel A shows the difference in CET1 ratios (at the end of the scenario horizon in 2016) implied by the hand-picked equations relative to the posterior model's implied CET1 ratio. Panel B shows the difference while not stressing the banks' foreign exposures (i.e. keeping PDs and LGDs for foreign exposures constant at 2013 starting points).

Figure 4: Difference in CET1 capital ratios from handpicked versus posterior models – Kernel density distributions based on underlying bank sample



Note: Panel A shows the distribution of differences in CET1 ratios (end-2016) implied by the hand-picked equations relative to the posterior model's implied CET1 ratio. Panel B shows the distribution of differences while not stressing the banks' foreign exposures (i.e. keeping PDs and LGDs for foreign exposures constant at 2013 starting points).

Figure 5: Relative contribution of loan losses, forgone interest income and changes in RWA to the total CET1 ratio change from 2013 to 2016 (adverse scenario, total banking system)



Note: The chart indicates the relative contributions from loan losses, forgone interest income and changes in RWA over the 3-year horizon (2014-16) under the adverse scenario. The contributions for each model sum to 100%. The underlying absolute contributions to the CET1 ratios are initially all negative percentage point contributions.

Table 1: List of banks included in the illustrative stress test simulation

Country	#	SSM ID	Bank name	CET1 2013 [EUR mn]	RWA 2013 [EUR mn]	CET1R 2013 [%]
Austria	1	ATBAWA	BAWAG P.S.K. Bank für Arbeit und Wirtschaft und Österreichische Postsparkasse AG	2,445	16,853	14.5
	2	ATERST	Erste Group Bank AG	11,275	100,953	11.2
	3	ATRANI	Raiffeisenlandesbank Niederösterreich-Wien AG	2,279	13,010	17.5
	4	ATRAOB	Raiffeisenlandesbank Oberösterreich AG	3,015	26,407	11.4
	5	ATRAZE	Raiffeisen Zentralbank Österreich AG	9,487	91,504	10.4
	6	ATVBH	Österreichische Volksbanken-AG with credit institutions affiliated according to Article 10 of the CRR	3,151	27,451	11.5
Belgium	7	BEABIG	Argenta Bank- en Verzekeringsgroep	1,388	5,716	24.3
	8	BEAXA	AXA Bank Europe SA	794	5,225	15.2
	9	BEBELF	Belfius Banque SA	7,248	52,338	13.8
	10	BEBNY	The Bank of New York Mellon SA	1,612	10,853	14.9
	11	BEDXIA	Dexia NV	8,808	53,839	16.4
	12	BEKBC	KBC Group NV	12,277	92,543	13.3
Germany	13	DEAAB	Aareal Bank AG	2,187	13,344	16.4
	14	DEAPAE	Deutsche Apotheker- und Ärztebank eG	1,752	10,593	16.5
	15	DEBLB	Bayerische Landesbank	13,128	93,669	14.0
	16	DEBSW	Wüstenrot Bausparkasse AG	778	7,346	10.6
	17	DECOMM	Commerzbank AG	24,587	215,925	11.4
	18	DEDEBK	Deutsche Bank AG	48,976	353,103	13.9
	19	DEDEKA	DekaBank Deutsche Girozentrale	3,644	25,708	14.2
	20	DEDZB	DZ Bank AG Deutsche Zentral-Genossenschaftsbank	9,721	99,453	9.8
	21	DEHASP	HASPA Finanzholding	3,935	31,546	12.5
	22	DEHSH	HSH Nordbank AG	3,790	37,878	10.0
	23	DEHYMU	Münchener Hypothekenbank eG	532	7,730	6.9
	24	DEHYRE	Hypo Real Estate Holding AG	4,086	24,484	16.7
	25	DEIKB	IKB Deutsche Industriebank AG	1,340	14,069	9.5
	26	DEKFW	KfW IPEX-Bank GmbH	2,458	18,698	13.1
	27	DELBB	Landesbank Berlin Holding AG	3,112	31,192	10.0
	28	DELBW	Landesbank Baden-Württemberg	12,359	88,416	14.0
	29	DELHTG	Landesbank Hessen-Thüringen Girozentrale	7,065	56,531	12.5
	30	DELKBW	Landeskreditbank Baden-Württemberg-Förderbank	2,933	21,740	13.5
	31	DELWREB	Landwirtschaftliche Rentenbank	2,906	17,179	16.9
	32	DENLG	Norddeutsche Landesbank-Girozentrale	7,761	73,090	10.6
	33	DENRW	NRW.Bank	17,973	48,098	37.4
	34	DESEB	SEB AG	2,009	11,726	17.1
	35	DEVWFS	Volkswagen Financial Services AG	7,926	82,488	9.6
	36	DEWBP	Wüstenrot Bank AG Pfandbriefbank	393	4,576	8.6
	37	DEWGZ	WGZ Bank AG Westdeutsche Genossenschafts-Zentralbank	2,354	22,137	10.6
Spain	38	ESBANK	Banco Financiero y de Ahorros, S.A.	11,278	105,345	10.7
	39	ESBBVA	Banco Bilbao Vizcaya Argentaria, S.A.	37,058	344,741	10.7
	40	ESBKT	Bankinter, S.A.	2,864	23,799	12.0
	41	ESBMN	Banco Mare Nostrum, S.A.	2,018	21,382	9.4
	42	ESBSAB	Banco de Sabadell, S.A.	8,227	80,189	10.3
	43	ESCAJAM	Cajas Rurales Unidas, Sociedad Cooperativa de Crédito	2,422	22,023	11.0
	44	ESCX	Catalunya Banc, S.A.	2,619	21,266	12.3
	45	ESIBER	Caja de Ahorros y M.P. de Zaragoza, Aragón y Rioja	2,655	26,475	10.0
	46	ESKTXB	Kutxabank, S.A.	4,375	36,027	12.1
	47	ESKXA	Caja de Ahorros y Pensiones de Barcelona	17,544	170,679	10.3
	48	ESLIBER	Liberbank, S.A.	1,565	18,080	8.7
	49	ESPOPU	Banco Popular Español, S.A.	8,942	84,109	10.6
	50	ESSAN	Banco Santander, S.A.	56,086	540,248	10.4
	51	ESUNIC	Unicaja Banco, S.A.	3,693	33,321	11.1
Finland	52	FIDBK	Danske Bank Oyj	2,323	15,210	15.3
	53	FINBF	Nordea Bank Finland Abp	8,286	58,617	14.1
	54	FIPOPO	OP-Pohjola Group	6,897	40,157	17.2
France	55	FRBNPP	BNP Paribas	66,347	621,307	10.7
	56	FRBPCE	Groupe BPCE	42,261	409,383	10.3
	57	FRBPI	BPI France (Banque Publique d'Investissement)	13,193	43,226	30.5
	58	FRCAGR	Groupe Crédit Agricole	59,692	544,049	11.0
	59	FRCMUT	Groupe Crédit Mutuel	32,859	236,969	13.9
	60	FRHSBC	HSBC France	4,116	32,013	12.9
	61	FRLBP	La Banque Postale	5,748	57,239	10.0
	62	FRPSA	Banque PSA Finance	2,679	19,054	14.1
	63	FRRCIB	RCI Banque	2,562	21,890	11.7
	64	FRSFL	Société de Financement Local	1,494	6,153	24.3
	65	FRSOCG	Société Générale	37,362	343,115	10.9
Greece	66	GRALPH	Alpha Bank, S.A.	8,211	51,754	15.9
	67	GREURO	Eurobank Ergasias, S.A.	4,049	38,114	10.6
	68	GRNBG	National Bank of Greece, S.A.	6,058	56,686	10.7
	69	GRPIRE	Piraeus Bank, S.A.	8,171	59,715	13.7
Ireland	70	IEAIB	Allied Irish Banks plc	9,123	60,883	15.0
	71	IEBAML	Merrill Lynch International Bank Limited	5,989	39,488	15.2
	72	IEBIRE	The Governor and Company of the Bank of Ireland	6,851	55,264	12.4
	73	IEPTSB	Permanent tsb plc.	2,203	16,775	13.1
	74	IEUBIL	Ulster Bank Ireland Limited	4,490	38,879	11.5
Italy	75	ITBAPO	Banco Popolare - Società Cooperativa	5,314	52,806	10.1
	76	ITBPER	Banca Popolare Dell'Emilia Romagna - Società Cooperativa	3,968	43,351	9.2
	77	ITBPM	Banca Popolare Di Milano - Società Cooperativa A Responsabilità Limitata	3,166	43,447	7.3
	78	ITBPS	Banca Popolare di Sondrio, Società Cooperativa per Azioni	1,923	23,603	8.1
	79	ITBPV	Banca Popolare di Vicenza - Società Cooperativa per Azioni	2,669	28,476	9.4
	80	ITCARI	Banca Carige S.P.A. - Cassa di Risparmio di Genova e Imperia	1,187	22,989	5.2
	81	ITCRED	Credito Emiliano S.p.A.	1,769	16,152	11.0
	82	ITCRVA	Banca Piccolo Credito Valtellinese, Società Cooperativa	1,590	18,096	8.8
	83	ITICCH	Iccrea Holding S.p.A	1,494	13,480	11.1
	84	ITISP	Intesa Sanpaolo S.p.A.	33,995	284,456	12.0
	85	ITMDB	Mediobanca - Banca di Credito Finanziario S.p.A.	4,682	50,640	9.2
	86	ITMPS	Banca Monte dei Paschi di Siena S.p.A.	8,504	83,490	10.2
	87	ITUBI	Unione Di Banche Italiane Società Cooperativa Per Azioni	7,787	63,540	12.3
	88	ITUCG	UniCredit S.p.A.	39,900	408,587	9.8
	89	ITVENE	Veneto Banca S.C.P.A.	1,844	25,167	7.3
Luxembourg	90	LUBCEE	Banque et Caisse d'Epargne de l'Etat, Luxembourg	2,374	13,886	17.1
	91	LUCLST	Clearstream Banking S.A.	652	3,363	19.4
	92	LUPCAP	Precision Capital S.A. (Holding of Banque Internationale à Luxembourg and KBL European Private Bankers S.A.)	1,273	8,622	14.8
	93	LURBC	RBC Investor Services Bank S.A.	742	2,860	25.9
	94	LUSTST	State Street Bank Luxembourg S.A.	1,474	6,162	23.9
	95	LUUBS	UBS (Luxembourg) S.A.	459	3,288	14.0
Netherlands	96	NLABN	ABN Amro Bank N.V.	14,120	115,442	12.2
	97	NLGEM	Bank Nederlandse Gemeenten N.V.	2,767	11,665	23.7
	98	NLING	ING Bank N.V.	30,918	297,958	10.4
	99	NLNWNV	Nederlandse Waterschapsbank N.V.	1,261	1,669	75.5
	100	NLRABO	Coöperatieve Centrale Raiffeisen-Boerenleenbank B.A.	26,832	209,537	12.8
	101	NLRBS	The Royal Bank of Scotland N.V.	3,227	22,203	14.5
	102	NLSNS	SNS Bank N.V.	2,300	14,842	15.5
Portugal	103	PTBCP	Banco Comercial Português, SA	5,563	45,502	12.2
	104	PTBPI	Banco BPI, SA	3,317	21,710	15.3
	105	PTCGD	Caixa Geral de Depósitos, SA	6,933	63,869	10.9
Slovenia	106	SINKBM	Nova Kreditna Banka Maribor d.d.	543	2,777	19.5
	107	SINLB	Nova Ljubljanska banka d. d., Ljubljana	1,171	7,283	16.1
	108	SISID	SID - Slovenska izvozna in razvojna banka, d.d., Ljubljana	354	1,463	24.2
Total				**979,862**	**8,333,417**	**11.8**

Table 2: Handpicked equations versus posterior models – Estimates and model diagnostics

Country	Model	Intercept	AR1	AR2	GDP			ITR			XTR			Δ4URX			URX		
					(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)
		Intercept	AR1	AR2	GDP	GDP (-1)	GDP (-2)	ITR	ITR (-1)	ITR (-2)	XTR	XTR (-1)	XTR (-2)	Δ4URX	Δ4URX (-1)	Δ4URX (-2)	URX	URX (-1)	URX (-2)
AT	posterior	0.53 **	1.226 ***	-0.331 *	0.001			0.005	0	0	0.001			0					
		(0.25)	(0.201)	(0.185)	(0.004)			(0.011)	(0.011)	(0.005)	(0.002)			(0.005)					
	handpicked optimistic	-0.392	1.157 ***	-0.206				0.185 ***	-0.275 ***	0.122 **				0.088			0.128		
		(0.29)	(0.148)	(0.149)				(0.058)	(0.098)	(0.051)				(0.075)			(0.078)		
	handpicked optimistic*	0.236	1.366 ***	-0.418 ***				0.175 ***	-0.289 **	0.139 **									
		(0.151)	(0.147)	(0.144)				(0.065)	(0.113)	(0.061)									
	handpicked pessimistic	0.588 **	0.999 ***	-0.102				0.016 **											
		(0.234)	(0.169)	(0.158)				(0.008)											
BE	posterior	0.401	1.215 ***	-0.287 *	0			0.001 ***			0			-0.003					
		(0.269)	(0.151)	(0.151)	(0.005)			(0)			(0.001)			(0.022)					
	handpicked optimistic	0.472 *	1.144 ***	-0.216	0.02	-0.085 *		0.021 *											
		(0.278)	(0.156)	(0.151)	(0.035)	(0.043)		(0.011)											
	handpicked optimistic*	0.408	1.164 ***	-0.219	-0.02			0.018 *											
		(0.272)	(0.152)	(0.151)	(0.025)			(0.01)											
	handpicked pessimistic	0.466 *	1.118 ***	-0.204	-0.04			0.016 *											
		(0.26)	(0.151)	(0.144)	(0.026)			(0.009)											
DE	posterior	0.337	1.368 ***	-0.439 **	0.025	-0.018		0.001	-0.001		0.005 ***	-0.003							
		(0.261)	(0.181)	(0.181)	(0.034)	(0.026)		(0.007)	(0.004)		(0.001)	(0.006)							
	handpicked optimistic	0.183	1.272 ***	-0.308							0.018 *	-0.005		0.111			-0.008		
		(0.279)	(0.188)	(0.216)							(0.01)	(0.008)		(0.11)			(0.043)		
	handpicked optimistic*	0.418	1.353 ***	-0.431 **	0.06 **	-0.037													
		(0.459)	(0.186)	(0.206)	(0.03)	(0.027)													
	handpicked pessimistic	-0.153	1.215 ***	-0.2							0.019 *	-0.003		0.105					
		(0.404)	(0.189)	(0.233)							(0.01)	(0.008)		(0.068)					
DK	posterior	0.916 **	0.806 ***		0.062	-0.048		-0.011	0.014		0.003	-0.001		-0.003			0		
		(0.385)	(0.083)		(0.066)	(0.061)		(0.015)	(0.017)		(0.008)	(0.006)		(0.017)			(0.006)		
	handpicked optimistic	0.837 **	0.793 ***		0.14 ***	-0.112 ***		-0.027 **	0.034 ***								0.015		
		(0.385)	(0.091)		(0.035)	(0.039)		(0.011)	(0.011)								(0.031)		
	handpicked optimistic*	0.883 **	0.805 ***		0.141 ***	-0.115 ***		-0.027 **	0.034 ***										
		(0.375)	(0.088)		(0.036)	(0.038)		(0.011)	(0.011)										
	handpicked pessimistic	0.767 **	0.83 ***		0.136 ***	-0.117 ***		-0.027 **	0.033 ***										
		(0.343)	(0.077)		(0.037)	(0.04)		(0.012)	(0.011)										
ES	posterior	0.213	0.889 ***	0.084	0.001	0	0.001	0			0.001			-0.197 ***	0.141 **				
		(0.177)	(0.196)	(0.2)	(0.008)	(0.006)	(0.022)	(0.005)			(0.002)			(0.073)	(0.059)				
	handpicked optimistic	0.469 **	1.279 ***	-0.353 **	0.061 *														
		(0.184)	(0.154)	(0.147)	(0.036)														
	handpicked optimistic*	0.244	1.258 ***	-0.299 *							0.013 *								
		(0.165)	(0.158)	(0.157)							(0.007)								
	handpicked pessimistic	0.403 *	1.174 ***	-0.27 *	0.14 **	-0.107 *													
		(0.207)	(0.166)	(0.159)	(0.065)	(0.057)													
FI	posterior	0.396	1.057 ***	-0.117	0	0											-0.005		
		(0.384)	(0.171)	(0.195)	(0.001)	(0.001)											(0.023)		
	handpicked optimistic	0.522	1.247 ***	-0.316 **	0.029 **	-0.025 **											-0.021		
		(0.896)	(0.162)	(0.159)	(0.013)	(0.012)											(0.071)		
	handpicked optimistic*	0.252 *	1.259 ***	-0.316 **	0.027 **	-0.027 **													
		(0.133)	(0.157)	(0.155)	(0.013)	(0.012)													
	handpicked pessimistic	1.471 **	1.012 ***	-0.174	0.024 *	-0.023 **		-0.006									-0.086		
		(0.75)	(0.16)	(0.148)	(0.013)	(0.01)		(0.005)									(0.058)		

Country	Model	INF			HP			HP2y			HP3y			LTN			STN			R2	DW
		(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)		
		PCD	PCD (-1)	PCD (-2)	HP	HP (-1)	HP (-2)	HP2y	HP2y (-1)	HP2y (-2)	HP3y	HP3y (-1)	HP3y (-2)	LTN	LTN (-1)	LTN (-2)	STN	STN (-1)	STN (-2)		
AT	posterior	0.009			0.001			0			0			-0.529 ***	0.258	-0.039	-0.013	-0.086		97%	1.84
		(0.026)			(0.003)			(0.002)			(0.001)			(0.18)	(0.247)	(0.109)	(0.093)	(0.15)			
	handpicked optimistic																			97%	2.15
	handpicked optimistic*				0.001			-0.005												97%	1.97
					(0.01)			(0.006)													
	handpicked pessimistic				0.001									-0.414 ***			-0.055	-0.234 *		97%	1.67
					(0.007)									(0.137)			(0.128)	(0.124)			
BE	posterior	0			-0.006	0.008		0			0			-0.009			-0.145	-0.002		91%	2.00
		(0.007)			(0.016)	(0.02)		(0.002)			(0.001)			(0.036)			(0.12)	(0.027)			
	handpicked optimistic													-0.01						91%	1.91
														(0.063)							
	handpicked optimistic*	-0.032															-0.177 *			91%	2.05
		(0.042)															(0.105)				
	handpicked pessimistic										0.004						0.006	-0.312 **		92%	1.95
											(0.004)						(0.16)	(0.156)			
DE	posterior																0.014	-0.033		95%	2.20
																	(0.108)	(0.108)			
	handpicked optimistic													0.018						95%	2.11
														(0.075)							
	handpicked optimistic*	-0.038															-0.008			95%	2.23
		(0.084)															(0.181)				
	handpicked pessimistic													0.03			-0.201			95%	2.14
														(0.064)			(0.181)				
DK	posterior	0.001			0			0			0	0		-0.116			-0.001			77%	2.16
		(0.014)			(0.002)			(0.001)			(0.003)	(0.003)		(0.27)			(0.028)				
	handpicked optimistic																0.154			79%	2.30
																	(0.196)				
	handpicked optimistic*										-0.001						0.119			79%	2.31
											(0.002)						(0.173)				
	handpicked pessimistic	0.012						0												78%	2.32
		(0.06)						(0.004)													
ES	posterior	-0.001	-0.004	0.006	0	0	0.001	0			0			-0.013	0.009		-0.009			97%	1.90
		(0.012)	(0.024)	(0.031)	(0.002)	(0.002)	(0.011)	(0.003)			(0.001)			(0.059)	(0.052)		(0.051)				
	handpicked optimistic	-0.062									-0.001									96%	2.10
		(0.041)									(0.002)										
	handpicked optimistic*	-0.041			0.007 **															96%	2.10
		(0.033)			(0.004)																
	handpicked pessimistic				-0.015						0.006									96%	2.14
					(0.013)						(0.004)										
FI	posterior				0			0	0		0			-0.512 ***			-0.015	-0.008	-0.102	97%	1.69
					(0)			(0.002)	(0.002)		(0.001)			(0.157)			(0.071)	(0.081)	(0.123)		
	handpicked optimistic	-0.042																		96%	1.71
		(0.027)																			
	handpicked optimistic*	-0.032									0.003									96%	1.70
		(0.02)									(0.005)										
	handpicked pessimistic													-0.723 ***						97%	1.72
														(0.188)							

Note: Asterisks attached to the coefficient estimates indicate the level of significance (* for at least a 10% level, ** for 5%, *** for 1%). The grey shade of the cells indicates significance at least at the 10% level for the handpicked equations. For the posterior model, the grey shade indicates significance according to either the standard error based measure or the exceedance of prior inclusion probabilities by posterior inclusion probabilities. See text for details.

Table 2 (continued): Handpicked equations versus posterior models – Estimates and model diagnostics

Country	Model	Intercept	AR1	AR2	GDP			ITR			XTR			Δ4URX		
					(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)
		Intercept	AR1	AR2	GDP	GDP (-1)	GDP (-2)	ITR	ITR (-1)	ITR (-2)	XTR	XTR (-1)	XTR (-2)	Δ4URX	Δ4URX (-1)	Δ4URX (-2)
FR	posterior	0.202	1.4 ***	-0.436 ***	0.006	-0.005		0.003	-0.002		0	0				
		(0.204)	(0.153)	(0.156)	(0.024)	(0.021)		(0.01)	(0.009)		(0.001)	(0.001)				
FR	handpicked optimistic	-0.402	1.286 ***	-0.321 **				0.033 **	-0.015					0.089		
		(0.462)	(0.154)	(0.155)				(0.017)	(0.016)					(0.079)		
FR	handpicked optimistic*	0.333 **	1.195 ***	-0.25	0.15 **	-0.037					-0.019					
		(0.158)	(0.178)	(0.176)	(0.066)	(0.046)					(0.011)					
FR	handpicked pessimistic	0.153	1.283 ***	-0.325 *				0.032 **	-0.031 **							
		(0.214)	(0.164)	(0.171)				(0.016)	(0.016)							
GR	posterior	0.402 *	1.097 ***	-0.209	-0.005	0.009		0	0		0.001	0		-0.005	0.002	
		(0.232)	(0.156)	(0.151)	(0.015)	(0.02)		(0.003)	(0.002)		(0.002)	(0.002)		(0.023)	(0.016)	
GR	handpicked optimistic	0.03	1.122 ***	-0.203	-0.024	0.056 **										
		(0.324)	(0.149)	(0.15)	(0.025)	(0.026)										
GR	handpicked optimistic*	-0.229	1.111 ***	-0.122	-0.023	0.056 **										
		(0.378)	(0.148)	(0.161)	(0.024)	(0.026)										
GR	handpicked pessimistic	0.278	1.13 ***	-0.201	-0.025	0.043 *										
		(0.229)	(0.154)	(0.159)	(0.027)	(0.026)										
HU	posterior	2.901 **	0.656 *	-0.276	0.003	-0.001		0.004	0.005		0.011	-0.001		0.033	-0.041	-0.072
		(1.452)	(0.357)	(0.213)	(0.013)	(0.009)		(0.01)	(0.011)		(0.01)	(0.003)		(0.094)	(0.09)	(0.097)
HU	handpicked optimistic	3.056 ***	0.477 **	-0.114							0.015 ***			0.088	-0.055	-0.169 **
		(0.604)	(0.223)	(0.158)							(0.006)			(0.081)	(0.111)	(0.077)
HU	handpicked optimistic*	0.955 **	0.924 ***	-0.153							0.02 ***	-0.015 **		-0.076 **		
		(0.387)	(0.201)	(0.184)							(0.007)	(0.007)		(0.035)		
HU	handpicked pessimistic	0.964 **	0.889 ***	-0.119							0.019 **	-0.014 *		-0.072 **		
		(0.392)	(0.212)	(0.194)							(0.007)	(0.008)		(0.037)		
IE	posterior	0.345 *	1.255 ***	-0.329 **	0.001			0.002			0			-0.002		
		(0.189)	(0.152)	(0.153)	(0.004)			(0.002)			(0.002)			(0.009)		
IE	handpicked optimistic	0.325 *	1.227 ***	-0.322 **				0.006 **						-0.001		
		(0.178)	(0.145)	(0.138)				(0.003)						(0.019)		
IE	handpicked optimistic*	0.469 **	1.229 ***	-0.328 **				0.006 **						-0.002		
		(0.195)	(0.147)	(0.14)				(0.003)						(0.02)		
IE	handpicked pessimistic	0.241	1.243 ***	-0.297 **	0.018 **											
		(0.168)	(0.142)	(0.145)	(0.009)											
IT	posterior	0.293	1.301 ***	-0.358 **	0.001			0.001			0.001			-0.02		
		(0.281)	(0.15)	(0.154)	(0.008)			(0.004)			(0.003)			(0.04)		
IT	handpicked optimistic	0.3	1.302 ***	-0.354 **				0.018 *								
		(0.585)	(0.147)	(0.149)				(0.01)								
IT	handpicked optimistic*	0.587 ***	1.156 ***	-0.248							0.012 *			-0.03		
		(0.2)	(0.162)	(0.155)							(0.006)			(0.056)		
IT	handpicked pessimistic	0.506 **	1.217 ***	-0.325 **	-0.067						0.024 *					
		(0.219)	(0.163)	(0.154)	(0.049)						(0.014)					
LU	posterior	0.948 ***	0.906 ***	-0.159	0.046	-0.027		0			0.009	-0.002		-0.006	0	
		(0.351)	(0.143)	(0.131)	(0.028)	(0.022)		(0.001)			(0.013)	(0.007)		(0.029)	(0.007)	
LU	handpicked optimistic	0.93 **	0.885 ***	-0.177							0.029 **	-0.008		-0.101		
		(0.364)	(0.142)	(0.128)							(0.012)	(0.013)		(0.072)		
LU	handpicked optimistic*	0.947 **	0.859 ***	-0.16							0.027 **	-0.006		-0.108		
		(0.368)	(0.151)	(0.133)							(0.012)	(0.014)		(0.074)		
LU	handpicked pessimistic	0.629	0.919 ***	-0.122							0.031 **	-0.011				
		(0.401)	(0.145)	(0.144)							(0.012)	(0.013)				

Country	Model	URX			INF			HP			HP2y			HP3y			LTN			STN			R2	DW
		(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)		
		URX	URX (-1)	URX (-2)	PCD	PCD (-1)	PCD (-2)	HP	HP (-1)	HP (-2)	HP2y	HP2y (-1)	HP2y (-2)	HP3y	HP3y (-1)	HP3y (-2)	LTN	LTN (-1)	LTN (-2)	STN	STN (-1)	STN (-2)		
FR	posterior							0	0		0	0		0.001	-0.001		-0.239	0.183		0.001	-0.094		97%	2.33
								(0.001)	(0.001)		(0.002)	(0.001)		(0.004)	(0.003)		(0.277)	(0.244)		(0.145)	(0.17)			
FR	handpicked optimistic	0.06																		0.039			96%	2.06
		(0.051)																		(0.142)				
FR	handpicked optimistic*				-0.075			-0.003															96%	2.01
					(0.049)			(0.008)																
FR	handpicked pessimistic							-0.014			0.015 **									-0.113			96%	2.31
								(0.011)			(0.007)									(0.121)				
GR	posterior	0						0	0		0.006 ***	-0.005		0.001	-0.001		-0.01	0.003		-0.041			94%	2.05
		(0)						(0.004)	(0.003)		(0.001)	(0.011)		(0.004)	(0.004)		(0.012)	(0.007)		(0.108)				
GR	handpicked optimistic	0.016			-0.001																		94%	2.06
		(0.011)			(0.026)																			
GR	handpicked optimistic*	0.019 *			0.009															-0.201			94%	2.10
		(0.011)			(0.027)															(0.154)				
GR	handpicked pessimistic				-0.018			0.003												-0.165			94%	2.06
					(0.024)			(0.007)												(0.158)				
HU	posterior	-0.012	0.003		0.001			0						0			-0.053			-0.006			92%	2.07
		(0.042)	(0.027)		(0.007)			(0.002)						(0.001)			(0.04)			(0.052)				
HU	handpicked optimistic				-0.01												-0.081 ***						92%	2.10
					(0.015)												(0.027)							
HU	handpicked optimistic*							0.008															89%	2.05
								(0.007)																
HU	handpicked pessimistic							0.007												-0.106			89%	2.04
								(0.008)												(0.176)				
IE	posterior	0			0			0			0.001	-0.001		0.003	-0.003		0			-0.06	-0.019		95%	1.80
		(0.001)			(0.001)			(0.001)			(0.003)	(0.003)		(0.007)	(0.007)		(0.003)			(0.098)	(0.07)			
IE	handpicked optimistic	0.014															-0.008						95%	1.67
		(0.01)															(0.019)							
IE	handpicked optimistic*													-0.001			-0.004						94%	1.66
														(0.001)			(0.02)							
IE	handpicked pessimistic				-0.011															-0.143 *			94%	1.80
					(0.011)															(0.08)				
IT	posterior	-0.001						0			0.001			0.001			-0.007			0.112	-0.21		95%	2.15
		(0.011)						(0.003)			(0.003)			(0.003)			(0.022)			(0.169)	(0.245)			
IT	handpicked optimistic	0.014			-0.064			0.002															95%	2.10
		(0.04)			(0.043)			(0.011)																
IT	handpicked optimistic*				-0.096 *						0.008												95%	2.06
					(0.049)						(0.007)													
IT	handpicked pessimistic													0.004			-0.072						95%	2.12
														(0.005)			(0.051)							
LU	posterior																0	-0.001		-0.013	-0.003		83%	2.04
																	(0.041)	(0.017)		(0.076)	(0.041)			
LU	handpicked optimistic	0.045																					82%	1.96
		(0.037)																						
LU	handpicked optimistic*	0.054															-0.079						83%	1.97
		(0.041)															(0.147)							
LU	handpicked pessimistic	0.027															0.032			-0.182			82%	2.05
		(0.039)															(0.161)			(0.179)				

Note: Asterisks attached to the coefficient estimates indicate the level of significance (* for at least a 10% level, ** for 5%, *** for 1%). The grey shade of the cells indicates significance at least at a 10% level for the handpicked equations. For the posterior model, the grey shade indicates significance according to either the standard error based measure or the exceedance of prior inclusion probabilities by posterior inclusion probabilities. See text for details.

Table 2 (continued): Handpicked equations versus posterior models – Estimates and model diagnostics

Country	Model	Intercept	AR1	AR2	GDP			ITR			XTR			Δ4URX			URX			INF			HP			HP2y			HP3y			LTN			STN			R2	DW
					(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)	(0)	(-1)	(-2)		
		Intercept	AR1	AR2	GDP	GDP (-1)	GDP (-2)	ITR	ITR (-1)	ITR (-2)	XTR	XTR (-1)	XTR (-2)	Δ4URX	Δ4URX (-1)	Δ4URX (-2)	URX	URX (-1)	URX (-2)	PCD	PCD (-1)	PCD (-2)	HP	HP (-1)	HP (-2)	HP2y	HP2y (-1)	HP2y (-2)	HP3y	HP3y (-1)	HP3y (-2)	LTN	LTN (-1)	LTN (-2)	STN	STN (-1)	STN (-2)		
NL	posterior	0.237	1.222 ***	-0.268	0.001	-0.001		-0.001	0.002		0.003	-0.002																				-0.045	0.036		0.019	-0.203		87%	2.10
		(0.354)	(0.152)	(0.173)	(0.01)	(0.008)		(0.006)	(0.006)		(0.008)	(0.006)																				(0.171)	(0.149)		(0.162)	(0.197)			
	handpicked optimistic	0.631	1.369 ***	-0.507 ***				-0.013	0.016 *											0.007						-0.005												87%	1.98
		(0.418)	(0.148)	(0.16)				(0.009)	(0.01)											(0.031)						(0.003)													
	handpicked optimistic*	0.327	1.253 ***	-0.335 *				-0.016	0.02 **		0.014 *			0.089						-0.014																		88%	1.81
		(0.472)	(0.157)	(0.181)				(0.01)	(0.01)		(0.007)			(0.069)						(0.03)																			
	handpicked pessimistic	0.488	1.279 ***	-0.394 **				-0.019 **	0.021 **		0.014 *												-0.004												-0.102			87%	1.90
		(0.423)	(0.154)	(0.173)				(0.01)	(0.01)		(0.007)												(0.008)												(0.148)				
PL	posterior	0.297 *	1.466 ***	-0.544 ***				0.01	-0.009		0	0		-0.003	0.002		0															-0.01	0.004					96%	2.48
		(0.161)	(0.115)	(0.1)				(0.009)	(0.008)		(0.001)	(0.001)		(0.015)	(0.011)		(0.001)															(0.021)	(0.014)						
	handpicked optimistic	0.15	1.498 ***	-0.54 ***	0.04 *	-0.039 *					-0.001						0.002			-0.002																		96%	2.44
		(0.17)	(0.137)	(0.13)	(0.023)	(0.023)					(0.003)						(0.004)			(0.011)																			
	handpicked optimistic*	0.19	1.512 ***	-0.56 ***	0.042 **	-0.041 **					-0.001																											96%	2.47
		(0.12)	(0.1)	(0.095)	(0.02)	(0.019)					(0.002)																												
	handpicked pessimistic	0.302	1.469 ***	-0.551 ***				0.015 **	-0.013 **								0																					96%	2.47
		(0.188)	(0.109)	(0.093)				(0.006)	(0.006)								(0.004)																						
PT	posterior	0.271	1.555 ***	-0.608 ***	0.001			0.001			0			-0.001			-0.001			0			0			0			0			-0.007			0.018	-0.07		97%	1.92
		(0.178)	(0.122)	(0.128)	(0.008)			(0.003)			(0.001)			(0.011)			(0.004)			(0.004)			(0.002)			(0.001)			(0.001)			(0.01)			(0.094)	(0.142)			
	handpicked optimistic	0.496 ***	1.444 ***	-0.534 ***	0.011															0.005									-0.01			-0.026 **						97%	1.82
		(0.166)	(0.144)	(0.133)	(0.02)															(0.021)									(0.006)			(0.012)							
	handpicked optimistic*	0.374 ***	1.521 ***	-0.594 ***							0.004									-0.011												-0.019 *						97%	1.88
		(0.142)	(0.141)	(0.135)							(0.006)									(0.022)												(0.011)							
	handpicked pessimistic	0.252	1.483 ***	-0.526 ***				0.004																		0.025			-0.015						0.115	-0.313 *		97%	1.82
		(0.228)	(0.131)	(0.133)				(0.007)																		(0.021)			(0.013)						(0.164)	(0.163)			
SE	posterior	0.237	1.514 ***	-0.563 ***	0.001	-0.001		0	0		0	0		-0.01	0.009								0.004	-0.004											-0.035	-0.028		95%	2.08
		(0.156)	(0.137)	(0.14)	(0.006)	(0.005)		(0.002)	(0.002)		(0.001)	(0.001)		(0.031)	(0.029)								(0.009)	(0.008)											(0.085)	(0.076)			
	handpicked optimistic	-0.021	1.496 ***	-0.547 ***	0.014 *	0.003		0			-0.007						-0.033																					95%	2.12
		(0.244)	(0.156)	(0.155)	(0.019)	(0.017)		(0.006)			(0.01)						(0.023)																						
	handpicked optimistic*	0.174	1.44 ***	-0.449 ***							0.006 *	-0.004																	-0.003			0.013			-0.18 *			95%	2.11
		(0.184)	(0.156)	(0.167)							(0.007)	(0.007)																	(0.002)			(0.09)			(0.107)				
	handpicked pessimistic	0.277	1.46 ***	-0.496 ***	0.011	-0.01								-0.036												0.003									-0.182 *			95%	2.15
		(0.214)	(0.152)	(0.163)	(0.014)	(0.017)								(0.048)												(0.003)									(0.105)				
SI	posterior	0.157	1.385 ***	-0.427 ***	0.002			0.01	-0.009		0.001			-0.003																		-0.001						98%	2.11
		(0.226)	(0.165)	(0.16)	(0.006)			(0.011)	(0.01)		(0.002)			(0.02)																		(0.018)							
	handpicked optimistic	0.311	1.307 ***	-0.337 **				0.01 *			-0.001			-0.002						-0.006	-0.07 **																	98%	2.24
		(0.196)	(0.157)	(0.154)				(0.006)			(0.005)			(0.057)						(0.032)	(0.029)																		
	handpicked optimistic*	0.87 *	1.202 ***	-0.33 **	-0.017			0.02 **												-0.017	-0.061 **											-0.07						98%	2.18
		(0.455)	(0.166)	(0.138)	(0.019)			(0.01)												(0.031)	(0.028)											(0.053)							
	handpicked pessimistic	0.407	1.336 ***	-0.412 ***	-0.018			0.027 **	-0.023 **					-0.079																		-0.026						98%	2.17
		(0.567)	(0.175)	(0.152)	(0.021)			(0.011)	(0.011)					(0.072)																		(0.061)							
UK	posterior	0.145	1.483 ***	-0.51 ***	0.016	-0.013		0.001	-0.001					-0.023	0.018					0.001			0	0		0	0		0	0					-0.013			97%	1.99
		(0.158)	(0.162)	(0.168)	(0.023)	(0.02)		(0.003)	(0.002)					(0.049)	(0.042)					(0.006)			(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)					(0.051)				
	handpicked optimistic	0.101	1.548 ***	-0.578 ***				0.006 *	-0.003								0.015			-0.014																		97%	1.98
		(0.176)	(0.135)	(0.132)				(0.003)	(0.003)								(0.017)			(0.021)																			
	handpicked optimistic*	0.257	1.548 ***	-0.596 ***				0.006 *	-0.003											-0.002						-0.002			0.001									97%	1.94
		(0.19)	(0.137)	(0.135)				(0.003)	(0.004)											(0.022)						(0.003)			(0.002)										
	handpicked pessimistic	0.147	1.362 ***	-0.396 **	0.049 **	-0.037 *														0.006						-0.003			0.002									97%	1.91
		(0.19)	(0.177)	(0.175)	(0.022)	(0.02)														(0.021)						(0.004)			(0.002)										

Note: Asterisks attached to the coefficient estimates indicate the level of significance (* for at least a 10% level, ** for 5%, *** for 1%). The grey shade of the cells indicates significance at least at a 10% level for the handpicked equations. For the posterior model, the grey shade indicates significance according to either the standard error based measure or the exceedance of prior inclusion probabilities by posterior inclusion probabilities. See text for details.

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Marco Gross
European Central Bank, Frankfurt am Main, Germany;
e-mail: marco.gross@ecb.europa.eu

Javier Población
European Central Bank, Frankfurt am Main, Germany;
e-mail: francisco_javier.poblacion_garcia@ecb.europa.eu

Postal address	60640 Frankfurt am Main, Germany
Telephone	+49 69 1344 0
Website	www.ecb.europa.eu

This paper can be downloaded without charge from www.ecb.europa.eu, from the Social Science Research Network electronic library at http://ssrn.com or from RePEc: Research Papers in Economics at https://ideas.repec.org/s/ecb/ecbwps.html.

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