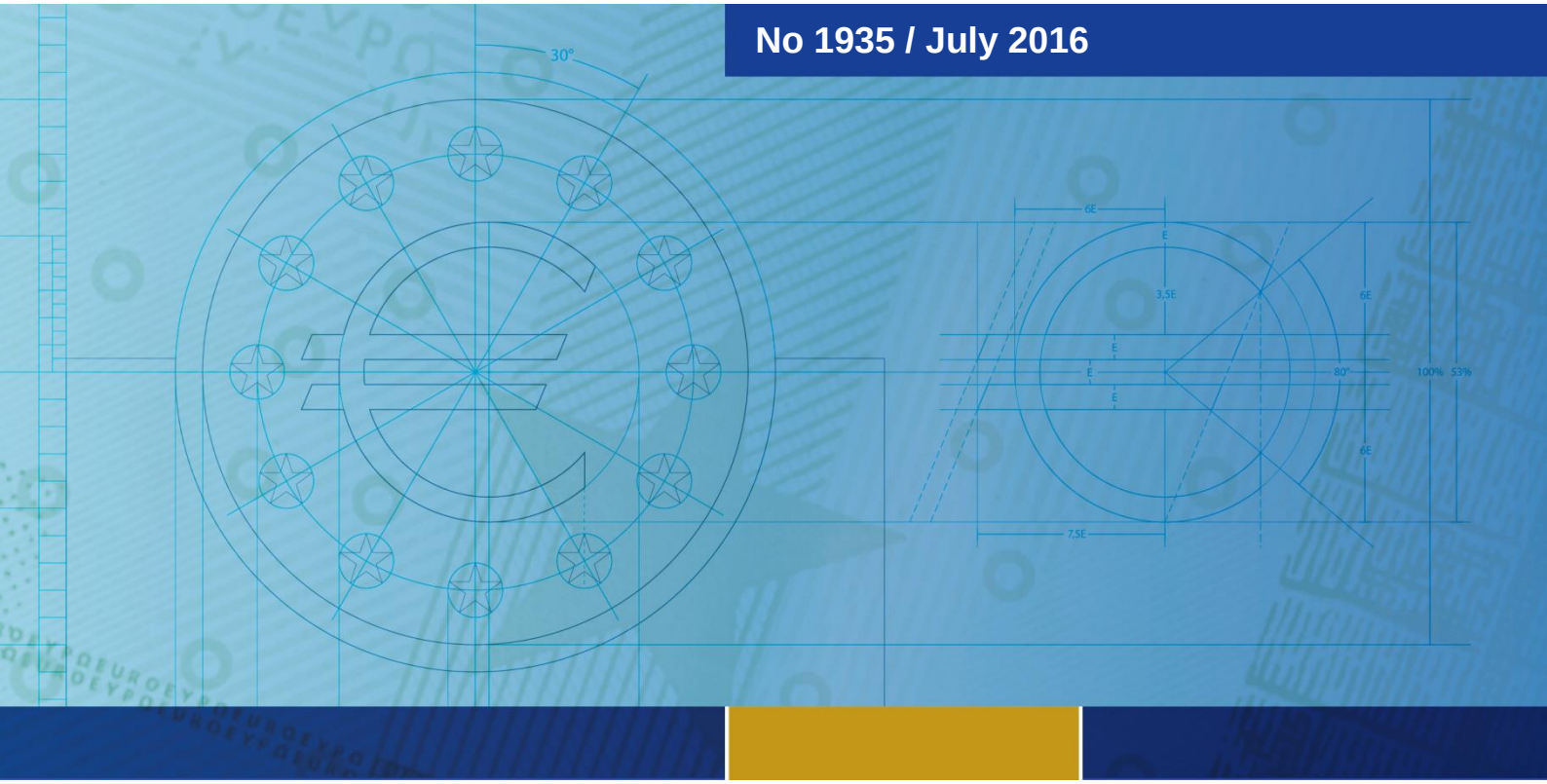
EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

Markus Behn,
Marco Gross and
Tuomas Peltonen

Assessing the costs and benefits of capital-based macroprudential policy



No 1935 / July 2016

Abstract

We develop an integrated Early Warning Global Vector Autoregressive (EW-GVAR) model to quantify the costs and benefits of capital-based macroprudential policy measures. Our findings illustrate that capital-based measures are transmitted both via their impact on the banking system's resilience and via indirect macro-financial feedback effects. The feedback effects relate to dampened credit and asset price growth and, depending on how banks move to higher capital ratios, can account for up to a half of the overall effectiveness of capital-based measures. Moreover, we document significant cross-country spillover effects, especially for measures implemented in larger countries. Overall, our model helps to understand how and through which channels changes in capitalization affect bank lending and the wider economy and can inform policy makers on the optimal calibration and timing of capital-based macroprudential instruments.

Keywords: Macroprudential policy, cost-benefit analysis, early-warning system, GVAR

JEL classification: G01, G21, G28

Non-technical summary

We develop an integrated Early Warning Global Vector Autoregressive (EW-GVAR) model that can be used to assess the macroeconomic impact of capital-based macroprudential policy measures. Specifically, we investigate the effects of policy-induced shocks to banking sector capitalization on the probability of future banking crises while accounting for potential endogenous responses that higher banking sector capitalization may imply for macro-financial variables.

The contribution of our model is threefold: First, it can be used to quantify both costs (in terms of output losses that might result from banks' responses to higher capital requirements) and benefits (expected output gains due to a reduction of systemic risk in the form of lower probabilities of banking crises) of capital-based macroprudential measures, thus estimating their net benefits. Net benefit estimations are crucial for policy makers who need to decide on the calibration and timing of measures. Second, the model is able to assess the relative importance of direct effects of higher bank capitalization and indirect feedback effects related to dampened credit and asset price growth. As such, it helps understanding the precise transmission channels and informs the debate on the objectives of macroprudential policies (i.e., increasing the banking system's resilience vs. smoothening the financial cycle). Third, the multi-country, multi-banking system nature of the model allows to quantify possible spillover effects, e.g due to banks' cross-border lending at the banking-system level, or the trade channel at the macro level. Accounting for cross-country spillover effects is important when it comes to coordination of national measures.

Our findings illustrate that the effects of dampened credit and asset price growth on predicted crisis probabilities can be sizable. Depending on how banks move to higher capital ratio, they can account for up to a half of the overall reduction in crisis probabilities and are thus of equal importance as the direct effects of higher bank capitalization. Moreover, we find some significant cross-country spillover effects, particularly for the larger countries, which illustrates the importance of cross-country coordination of macroprudential policy measures. Further, the simulation results from the model indicate that the net benefits of macroprudential measures depend on *how* banks move to higher capital ratios. Under an asset-side deleveraging scenario net benefits would, at the current stage, be negative in the vast majority of EU countries. In contrast, if banks achieved higher capital ratios mainly via raising fresh capital net benefits would be positive in all countries.

Our model framework can not only be used for gauging the impact of an *activation* of capital-based instruments, as illustrated in the paper, but also help to quantify the net benefit of the *release* of measures. During crisis times, the release of accumulated buffers would contribute to slight upward pressure on future crisis probabilities by fuelling credit growth, yet would come along with the benefit of supporting growth and rendering the recession less deep. Overall, the model framework can therefore help to assess a current *stance* of capital-based measures, in the sense that an outstanding measure would be deemed appropriate if neither a further tightening nor a release would imply positive net benefits.

1 Introduction

In recent years, a macroprudential approach to financial regulation has increasingly gained ground, where the emphasis is on both enhancing the resilience of financial institutions and the need to smoothen fluctuations in financial cycles, with the ultimate objective of addressing and containing systemic risk.[1] In this context, policy makers need to take decisions on the activation and calibration of macroprudential instruments, such as the various capital buffers mentioned in the Basel III framework (see Basel Committee on Banking Supervision 2010). When taking decisions, benefits of macroprudential measures need to be weighed against potential costs: while the macroprudential measures aim to ultimately address systemic risk by reducing the probability of future financial and banking crises which tend to be associated with considerable output losses, they might come at a cost in the short run, e.g. if banks react to higher capital requirements by reducing their credit supply to the real economy. To enable effective decisions, it is of vital importance to enhance our understanding of the transmission mechanism of macroprudential policy measures, including various opposing effects.

In this paper, we combine two well-established econometric modelling methods to assess the macroeconomic impact of capital-based policy measures from a macroprudential perspective: the Global Vector Autoregressive (GVAR) methodology and a logistic model-based early warning (EW) methodology.[2] The former is used to capture the joint dynamics of GDP, inflation, equity prices, house prices, loan volumes, loan interest rates and bank capital ratios, to account for the fact that changes to bank capitalization levels, if followed by price or volume responses on the side of banks, are expected to exert some impact on the economy. The endogenous responses from the GVAR of these macro-financial variables to an assumed capital ratio shock are then fed through the logistic EW model, to assess how predicted crisis probabilities change in response to capital ratio shocks, assuming that the capital ratios are adjusted by the amount required by the prudential supervisors (see Section 3.3 for a discussion).

The contribution of our model is threefold: First, it can be used to quantify both costs (in terms of output losses that might result from banks' responses to higher capital requirements) and benefits (expected output gains due to a reduction of systemic risk in the form of lower

[1] See, for instance, some recent speeches by the ECB's Vice President, highlighting the importance of strengthening macroprudential policy in Europe (e.g., Constâncio 2016). Overview papers and literature reviews summarizing the macroprudential view on regulation are, e.g., Borio and Drehmann (2009), Galati and Moessner (2011), Lim et al. (2011), International Monetary Fund (2011), Shin (2011), and International Monetary Fund (2013). See also Schüler et al. (2015) for a methodology for estimating the financial cycle for European countries).

[2] A useful entry point to the GVAR methodology is a recent survey paper by Chudik and Pesaran (2014). The initial methodological contribution by Pesaran et al. (2004) was followed by a meanwhile significant number of methodological and empirical extensions and applications, see e.g. Pesaran and Smith (2006), Dees et al. (2007), Galesi and Sgherri (2009), Eickmeier and Ng (2010), Chudik and Pesaran (2011), Binder and Gross (2013), Gray et al. (2013), Gross (2013), and Al-Hashimi et al. (2014). We employ a so-called Mixed-Cross-Section (MCS) variant of the GVAR which was developed in Gross and Kok (2013) and further used in Gross et al. (2016b) and Gross et al. (2016a). As an entry point to the literature on EW models see, for instance, Kaminsky et al. (1998), Alessi and Detken (2011), Behn et al. (2013), Lo Duca and Peltonen (2013), and Betz et al. (2014).

probabilities of banking crises) of capital-based measures, thus estimating their net benefits from a macroprudential perspective. Net benefit estimations are crucial for policy makers who need to decide on the calibration and timing of macroprudential policy measures. Second, the model is able to assess the relative importance of direct effects of higher bank capitalization and indirect feedback effects related to dampened credit and asset price growth. As such, it helps understanding the transmission channels and informs the debate on the objectives of macroprudential policies (i.e., increasing the banking system's resilience vs. smoothening the financial cycle). Third, the multi-country, multi-banking system nature of the model allows to quantify possible cross-country spillover effects, e.g due to banks' cross-border lending at the banking-system level, or the trade channel at the macro level. Accounting for cross-country spillover effects is important when it comes to coordination of national measures. To the best of our knowledge, our model is the first to combine these three features and arrive at an overall assessment of capital-based policy measures from a macroprudential perspective.

The simulation results from the model suggest that the net benefits (and in particular short-term macro costs) of capital-based measures depend on *how* banks move to higher capital ratios. Under the assumption that banks react to higher capital requirements by asset-side deleveraging, the net benefits of activating capital-based measures are, at the end of the sample period (2014Q4), estimated to be negative for the majority of European countries. This reflects the fact that the financial cycle was still in a depressed phase in many countries, so that the potential benefits of activating capital-based macroprudential tools would be rather limited. On the other hand, asset-side deleveraging corresponds to a reduction in banks' loan supply, for which the model in this case suggests a negative GDP response, therefore implying a non-zero gross cost. In contrast, under the assumption that the banking system reacts to higher capital requirements by raising and investing equity capital, the GDP responds positively, so that there is no cost from that perspective. Higher capitalization levels further contribute to increased resilience and a fall in banking crisis probabilities, and consequently the net benefits would be positive in all European countries. A counteracting force arises from somewhat stronger credit and asset price growth, implying a move toward overheating and thus upward pressure on crisis probabilities. This effect, however, is by far outweighed by stronger capitalization and the initially positive short-term GDP response.

Our findings illustrate that the indirect effects of higher bank capitalization through dampened credit and asset price growth on predicted crisis probabilities can be sizable. Under the asset-side deleveraging scenario, they can account up to a half of the overall reduction in crisis probabilities and are thus of equal importance as the direct effects of higher bank capitalization. This supports the view that the feedback effects on credit and financial cycles are an important transmission channel of capital-based measures. Moreover, we find some significant cross-country spillover effects, particularly for the larger countries, where the aggregate foreign effects tend to go in the same direction as the domestic effects at the current stage of the financial cycle. That is, policy measures in countries for which domestic net benefits are currently negative tend to generate negative net benefits also in the other European countries.

Our paper relates to the literature on the empirical relationship between capital, lending and

real activity, which emerged following the recession in the U.S. in the 1990s (see, e.g., Bernanke and Lown 1991, Hancock and Wilcox 1993, Berger and Udell 1994, and Furfine 2000). The studies that evolved since then, including those that were motivated by the recent global financial crisis, can be grouped according to how changes in capital are measured. Using observed capital ratios is one option (see e.g. Bernanke and Lown 1991, Noss and Toffano 2014) while exploiting variation in bank-level capital requirements, i.e. supervisory data which is in general unobservable for the public, is a second (see e.g Ediz et al. 1998, Mishkin 2000, Francis and Osborne 2009, Aiyar et al. 2014b, Bridges et al. 2014, Jiménez et al. 2014, Meeks 2015, and Behn et al. 2016). Our paper circumvents an identification based on capital and instead translates the impulses first to credit supply shocks (of two polar kinds) which can then be identified based on sign restrictions. That is, we assume that capital ratios are adjusted by the amount required by the prudential supervisor and distinguish between 'asset-side deleveraging' and 'raising fresh equity' scenarios. By considering these two polar cases, we are agnostic about the effects of higher capital requirements on banks' funding costs and the pass-through to lending rates.

Studies that find sizable costs in terms of reduced loan supply as a result of higher capital requirements all tend to start from the perception (and embedded model assumption in many cases) that equity is expensive, following the rationale of the pecking order theory of finance (Myers and Majluf 1984).[3] Papers that support the view that higher capital requirements would imply sizable costs through higher lending rates, and thereby compressed loan growth include Gambacorta and Mistrulli (2004), Van Den Heuvel (2008), Francis and Osborne (2009), Martin-Oliver et al. (2012), and Mesonnier and Stevanovic (2013). Carlson et al. (2013) find that the relationship between capital ratios and loan growth is stronger for banks where loans are contracting than where loans are expanding; they also show that the elasticity of bank lending with respect to capital ratios is higher when capital ratios are relatively low, suggesting that the effect of capital ratios on bank lending is nonlinear.

Research that concludes that the costs of higher capital requirements shall be small include e.g. Elliott (2009), Berrospide and Edge (2010), Admati et al. (2011), and Kupiec et al. (2014). These papers argue that the overall funding costs will not materially increase in response to higher capital requirements due to the reduced probability of default for banks individually and also the banking system as a whole. The corresponding downward pressure on the cost of equity and debt would weigh strongly enough to prevent an increase in lending rates, and hence imply no significant downward pressure for loan volume growth. Cohen (2013) provides a useful descriptive analysis to show how banks moved to higher capital ratios during and after the global financial crisis. Decomposing changes in the observed risk-weighted capital ratio for banks in advanced economies he finds that roughly three quarters of the effects were due to capital increases from end-2009 to

[3] A common view is that holding capital imposes a costs on banks so that capital ratios are largely determined by capital requirements (Mishkin 2000). Others have argued that the Modigliani & Miller irrelevance theorem can be extended to banks (Miller 1995) which would diminish the importance of capital requirements. Empirically, there is some evidence that banks operate with target capital ratios that could, to a certain extent, be independent from regulatory requirements (Flannery and Rangan 2008, Adrian and Shin 2010, Gropp and Heider 2010). However, there is a large stream of empirical papers as cited already suggesting that banks adjust capital ratios in response to changes in prudential capital requirements (such as Francis and Osborne 2009, or Bridges et al. 2014).

end-2012; retained earnings were used to build up capital over that time.

Finnally, the Bank for International Settlements (2010) quantifies the costs and benefits of macroprudential policy measures by making use of a compilation of numerous models (in particular DSGE-type models).[4] The paper starts by estimating how higher capital requirements would affect the cost of equity. Then, to estimate the costs of higher requirements, the study assumes that the cost of debt does not decrease, and moreover that the higher cost of capital feeds fully through to loan interest rates. These are strong assumptions, made for the sake of conservatism that are likely to result in an overly conservative cost estimate. Despite these conservative assumptions, the BIS' assessment concludes that the net benefit is likely positive for a wide range of higher capital requirements. The benefit due to lower banking sector crisis probabilities and an associated lower long-run cost in terms of lost output appear to outweigh the possible loss due to temporarily more restricted loan supply.

The remainder of the paper is structured as follows: Section 2 summarizes the data on banking sector crises used in the empirical analysis. In Section 3 we explain our methodology and data, i.e. the logistic early warning model, the GVAR model and how the two are integrated. Empirical results are presented in Section 4. Section 5 concludes.

2 Systemic banking crises and vulnerable states

We obtain data on systemic crises from the database developed by Duprey et al. (2015) who use a Markov Switching (MS) method to distinguish low from high financial stress periods and define systemic banking crises as those episodes of financial stress that are associated with a significant negative impact on the real economy (see Table 1). The crisis dates correlate strongly with those in other databases such as the one developed by Laeven and Valencia (2012) and are listed in Table 1.

Given that it may be difficult to accurately predict potential triggers for crisis episodes, early warning models often focus on predicting vulnerable states rather than crises episodes themselves (see e.g. Behn et al. 2013 and the references cited there). In that spirit, we set the dependent variable for the early warning model equal to one between (and including) twelve to seven quarters prior to a systemic crisis as identified by Duprey et al. (2015) and zero otherwise. The definition of the vulnerable state strikes a balance between being early enough without loosing accuracy (i.e., 12 quarters before the past crises) and late (i.e., 7 quarters before the past crises) to allow policy makers to take macroprudential policy actions that require in some cases an extended implementation phase (e.g. 4 quarters in the case of countercyclical capital buffer in the CRD IV/CRR). In order to avoid so-called crisis/post-crisis bias in the estimations, we omit all country

[4] Arregui et al. (2013) build on Bank for International Settlements (2010) and provide another conceptual framework for quantifying costs and benefits.

quarters which witnessed a systemic banking crisis.[5]

To assess the benefit of a reduction in crisis probabilities we need an estimate for the cost of a systemic crisis. We follow the methodology developed by Laeven and Valencia (2012) and define the cost of a crisis as the cumulated loss in real GDP relative to a pre-crisis trend, expressed as a percentage of pre-crisis real GDP.[6] The average cumulative output losses associated with systemic crises in our sample countries are quite substantial (see Table 1). For the main part of the paper, we use the sample median (27 percent of GDP) as an estimate for the cost of a systemic crisis. In alternative specifications, we use different percentiles of the distribution, country-specific cost estimates, or estimates associated with different horizons for cumulating output losses, in order to assess the robustness of our results (see Section 4.5).

3 Methodology and data

3.1 A logistic early warning system

We assess the predictive ability of credit, macro-financial and banking sector variables in a multivariate framework, estimating logistic regressions of the following form:

$$P(y_{it} = 1) = \frac{e^{\alpha_i + X'_{it}\beta}}{1 + e^{\alpha_i + X'_{it}\beta}} \tag{1}$$

where $P(y_{it} = 1)$ denotes the probability of country i being in a vulnerable state in quarter t. The vector X_{it} includes Year-on-Year (YoY) growth rates of credit to the private non-financial sector (either total credit or credit provided by the banking sector), GDP, a consumer price index, a residential property price index, a stock price index, and banking sector capitalization in levels (defined as capital and reserves over total assets) which we obtain from the ECB's internal databases.[7] Country dummy variables are denoted by α_i and account for unobserved heterogeneity across countries which may for example result from differences in regulatory and supervisory

[5] Bussière and Fratzscher (2006) suggest using a multinomial logit model with a distinction between pre-crisis, crisis/post-crisis and tranquil periods to avoid crisis/post-crisis bias. As we show in Section 4.5 doing so does not significantly alter the results, which is why we keep the more simple logit model in the main parts of the paper.

[6] Differences between actual and trend real GDP are cumulated over a three-year horizon, where trend real GDP is calculated by applying an HP filter ($\lambda = 6.25$) over the 20 years preceding the start of the respective banking crisis. Of course, the choice of the horizon for cumulating output losses (and possibly also the choice of a non-zero discount factor to down-weigh the more distant future) has a significant impact on the crisis cost estimate (see Bank for International Settlements 2010 for a detailed discussion). The three-year horizon was chosen to reflect the fact that banking crises tend to have rather long-lasting, almost permanent effects (i.e., post-crisis GDP paths tend to not converge back to pre-crisis trends). In Section 4.5 we assess how our results change when applying different horizons for cumulating the output loss.

[7] We use YoY growth rates for the macro-financial indicators as our finding is that these have a stronger predictive ability than e.g. quarter-on-quarter growth rates (see also Behn et al. 2013).

frameworks. Alternatively, we estimate eq. (1) without country dummies.[8] Since many of the countries in our sample were affected by the global financial crisis, robust standard errors are clustered at the quarterly level in order to account for potential correlation in the error terms.

To extract early warning signals from the logistic model we make use of the signalling approach that was developed by Kaminsky et al. (1998) and extended by Alessi and Detken (2011), Lo Duca and Peltonen (2013) and Sarlin (2013). The idea is to define a probability threshold above which a model issues a warning signal, where the optimal threshold depends on policy makers' relative aversion against Type I errors (not issuing a signal when a crisis is imminent) and Type II errors (issuing a signal when no crisis is imminent). Specifically, the logistic model issues a warning signal whenever the predicted probability of being in a vulnerable state exceeds a threshold τ, defined as a percentile of the country-specific distribution of predicted probabilities. In this way, predicted probabilities $P(\widehat{y_{it}=1})$ are transformed into binary predictions $\hat{Q}_{it}$ that equal one if the threshold τ is exceeded for the respective observation and zero otherwise. The predictive ability of the model can then be evaluated by comparing the signals issued by the model to the actual outcome C_{it} (equal to one if the country experiences a crisis seven to twelve quarters ahead of the respective period and zero otherwise.). Each observation is allocated to one of the quadrants in the contingency matrix depicted in Figure 1: A period with a signal by a specific indicator can either be followed by a systemic crisis seven to twelve quarters ahead (TP) or not (FP). Similarly, a period without a signal can be followed by a crisis seven to twelve quarters ahead (FN) or not (TN). The number of observations classified into each category depends on the threshold τ.

The optimal threshold τ^* depends on policy makers' relative aversion with respect to Type I errors (missing a crisis, $T_1(\tau) = FN/(TP+FN) \in [0,1]$) and Type II errors (issuing a false alarm, $T_2(\tau) = FP/(FP+TN) \in [0,1]$). We account for this by defining a loss function that depends on the two types of errors as well as the policy maker's relative aversion against either type, indicated by the preference parameter $\mu \in [0,1]$. For the results that we present we assume that $\mu = 0.85$, which means that policy makers are more averse against missing a crisis than against issuing a false alarm. Taking into account the relative frequencies of crises $P_1 = P(C_{it} = 1)$ and tranquil periods $P_2 = P(C_{it} = 0)$ (see Behn et al. 2013 and Sarlin 2013), we define the following loss function:

$$L(\tau) = \mu P_1 T_1(\tau) + (1-\mu) P_2 T_2(\tau) \tag{2}$$

The optimal threshold τ^* can be derived as the one that minimizes the loss function:

$$\tau^* = \arg\min_{\tau} L(\tau) \tag{3}$$

[8] While the omission of country dummies allows including countries that did not have a crisis episode throughout our sample period it complicates controlling for heterogeneity across countries (see some related discussion in Demirgüç-Kunt and Detragiache 1998, Davis and Karim 2008, or Behn et al. 2013). We do not include time dummies since they would significantly reduce the sample size (as only quarters where at least one country is in a vulnerable state could be used for identification) and are of little use for out-of-sample forecasting (as they are unknown *ex ante*).

To assess the predictive ability of the model we use several evaluation criteria, such as the area under the receiver operating characteristic curve (AUROC), the absolute and the relative usefulness, the adjusted noise-to-signal ratio, and the percentage of stress periods correctly predicted by the model.[9] An important criterion for the analysis in Section 4.3 is the *Probability difference*, the difference between the probability of being in a vulnerable state conditional on a signal being issued and the absolute probability of being in a vulnerable state.

3.2 A mixed-cross-section global vector autoregressive model

The Mixed-Cross-Section GVAR model (MCS-GVAR, see Gross and Kok 2013 and Gross et al. 2016b) is used to assess how the right hand-side variables of the logistic EW model respond to changes in banking sector capitalization. The MCS-GVAR comprises two cross-sections: a cross-section of $i = 1, ..., N = 14$ EU countries and a cross-section of banking systems $j = 1, ..., M = 14$. Such an MCS structure is superior to a 'standard' GVAR with variable-specific weights because the weights that link the various cross-sections are indeed very much different from each other.[10] The endogenous variables belonging to the two cross-sections are collected in the vectors $\boldsymbol{x}_{it}$ and $\boldsymbol{y}_{jt}$, respectively. For a given cross-section item, the two vectors are of size $k_i^x \times 1$ and $k_j^y \times 1$.

The model has the following form:

$$\begin{aligned}
\boldsymbol{x}_{it} &= \boldsymbol{a}_i + \sum_{p_1=1}^{P_1} \boldsymbol{\Phi}_{i,p_1} \boldsymbol{x}_{i,t-p_1} + \sum_{p_2=0}^{P_2} \boldsymbol{\Lambda}_{i,0,p_2} \boldsymbol{x}_{i,t-p_2}^{*,C-C} + \sum_{p_3=0}^{P_3} \boldsymbol{\Lambda}_{i,1,p_3} \boldsymbol{y}_{i,t-p_3}^{*,C-B} + \boldsymbol{\epsilon}_{it} \\
\boldsymbol{y}_{jt} &= \boldsymbol{b}_j + \sum_{q_1=1}^{Q_1} \boldsymbol{\Pi}_{j,q_1} \boldsymbol{y}_{j,t-q_1} + \sum_{q_2=0}^{Q_2} \boldsymbol{\Xi}_{j,0,q_2} \boldsymbol{x}_{j,t-q_2}^{*,B-C} + \sum_{q_3=0}^{Q_3} \boldsymbol{\Xi}_{j,1,q_3} \boldsymbol{y}_{j,t-q_3}^{*,B-B} + \boldsymbol{\omega}_{jt}
\end{aligned} \tag{4}$$

The intercept terms $\boldsymbol{a}_i$ and $\boldsymbol{b}_j$ are of size $k_i^x \times 1$ and $k_j^y \times 1$, respectively. The two equation blocks contain a set of autoregressive terms — $(\boldsymbol{\Phi}_{i,1}, ..., \boldsymbol{\Phi}_{i,P_1})$ and $(\boldsymbol{\Pi}_{j,1}, ..., \boldsymbol{\Pi}_{j,Q_1})$ — which are of size $k_i^x \times k_i^x$ and $k_j^y \times k_j^y$, respectively. The within- and across-cross-section dependence is introduced via the star variable vectors. The corresponding coefficient matrices in the first equation block for the $\boldsymbol{x}_{it}$ — $(\boldsymbol{\Lambda}_{i,0,0}, ..., \boldsymbol{\Lambda}_{i,0,P_2})$ and $(\boldsymbol{\Lambda}_{i,1,0}, ..., \boldsymbol{\Lambda}_{i,1,P_3})$ — are of size $k_i^x \times k_i^{*x}$ and $k_i^x \times k_i^{*y}$. The corresponding coefficient matrices in the second equation block for the $\boldsymbol{y}_{jt}$ — $(\boldsymbol{\Xi}_{j,0,0}, ..., \boldsymbol{\Xi}_{j,0,Q_2})$ and $(\boldsymbol{\Xi}_{j,1,0}, ..., \boldsymbol{\Xi}_{j,1,Q_3})$ — are of size $k_j^y \times k_j^{*x}$ and $k_j^y \times k_j^{*y}$. The cross-section-specific shock vectors

[9] See Alessi and Detken (2011) or Behn et al. (2013) for details.

[10] To grasp the intuition, consider the following example: For a bank it does not matter how much the country in which it is located trades with other countries. Instead, what matters is its own exposure to those countries. Hence, it makes more sense to use cross-border exposure volumes to link the banking system cross-section, instead of the trade volumes commonly employed in 'standard' GVAR applications. Using trade weights to link all cross-sections would imply a material distortion (i.e., a significant bias) and thus inferior predictive performance for all model variables (see Gross et al. 2016b for details).

— $\boldsymbol{\epsilon}_{it}$ and $\boldsymbol{\omega}_{jt}$ — are of size $k_i^x \times 1$ and $k_j^y \times 1$ and have covariance matrices $\boldsymbol{\Sigma}_{ii}^x$ and $\boldsymbol{\Sigma}_{jj}^y$, along with zero means. A global matrix $\boldsymbol{\Sigma}$ shall cover the covariance structure of the combined set of residuals from the two equation blocks.

There are seven variables involved in the model; four in the country cross-section and three in the bank cross-section. The country cross-section vector includes nominal GDP, a GDP deflator, residential property prices and stock prices. All four variables are modelled in quarter-on-quarter (QoQ) differences of natural log levels. The three variables for the banking systems include nominal credit, nominal loan interest rates, and a capital ratio.[11] Nominal credit volumes are sourced from the ECB's Balance Sheet Statistics (BSI) which capture domestic lending as well as direct cross-border lending to households and non-financial corporations in Europe. The capital ratio is defined as equity capital over total assets. Nominal credit is modelled in QoQ differences of natural log levels. Loan interest rates and the capital ratio are modelled in QoQ differences.[12]

The variable vectors that are assigned an asterisk in eq. (4) need to be generated by means of a set of weights that link the items within and across the cross-sections. All weights are time-varying at a quarterly frequency over the 1995Q1-2014Q4 period. We calibrate the weight matrices as follows.

Countries — Countries ($\boldsymbol{W}^{C-C}$): A measure of *bilateral trade* (sum of nominal imports and exports between any two countries) is used to calibrate the cross-country weights. The weight of a country to itself is zero at any point in time. The trade data is sourced from the IMF trade statistics. It has an annual frequency which is interpolated to quarterly frequency by means of a quadratic match sum conversion method.

Banking systems — Countries ($\boldsymbol{W}^{B-C}$): The weights are calibrated based on BSI domestic and cross-border credit exposures.

Countries — Banking systems ($\boldsymbol{W}^{C-B}$): These can be seen as the mirror of the weights for linking countries to banking systems ($\boldsymbol{W}^{B-C}$), i.e. $\boldsymbol{W}^{C-B}$ will be the transpose of the bank-country matrix for every quarter over the sample period.

Banking systems — Banking systems ($\boldsymbol{W}^{B-B}$): We employ domestic and cross-border

[11] We excluded loan interest rates from the logistic model as they reduced the predictive performance with respect to vulnerable states, potentially due to overfitting problems (see also Behn et al. 2013).

[12] We use QoQ differences in the GVAR as YoY differences would come along with additional (artificial) persistence which would require longer lag structures that we cannot quite afford given the relatively short sample period. Moreover, using YoY differences would not improve the GVAR's abilities to capture the economic relationship between the variables. The 'asymmetric' transformation structure, with YoY variables in the logistic EW model and QoQ in the GVAR was therefore a deliberate choice. At the point where the two models are technically connected, proper account is of course taken of the different transformations when the model is used for scenario simulation purposes. Moreover, we did not consider a GVAR in levels because this structure would have ruled out long-run non-zero effects of capital or the implied credit supply shocks on GDP flows, as level impulse response deviations would converge back to zero after a while by construction of the model; the model based on differences on the other hand does not preclude that long run effects are non-zero.

credit exposures to financial corporations as a basis for calibrating these weights.[13]

Two of the four weight matrices are square in size that have zero entries on their diagonals at every point in time, namely the $\boldsymbol{W}^{C-C}$ and $\boldsymbol{W}^{B-B}$ matrix. The other matrices which cross-link the cross-sections are not square unless the number of items in two cross-sections would be equal. Moreover, their diagonals do not need to equal zero. The model set-up is therefore flexible in the sense that countries can be included in the model for which there are no corresponding banking systems. Vice versa, banking systems could be included in the model for which the corresponding country would not be included.

The model is estimated based on data covering the 1995Q1-2014Q4 period (80 observations). It has $4 \times 28 + 3 \times 28 = 196$ equations which are all individually estimated by means of an Iteratively Reweighted Least Squares (IRLS) method (using a Cauchy weighting function). The method is more robust to outliers than Ordinary Least Squares (OLS) and helps stabilize the dynamics of the global model. Since the system presented in the set of eqs. (4) contains time-contemporaneous relationships, it needs to be solved, meaning that the equations for all countries and banking systems need to be stacked and reformatted in a way to contain only lagged relationships. The global solution of the model is derived in Appendix A. The standard built-in assumption in the GVAR is that the contemporaneous foreign variable vectors are weakly exogenous. Several tests and robustness checks indicate that this is a valid assumption in our setup (see Section 4.5).

3.3 Shock identification and impulse responses

We assess how the macro-financial variables contained in our model react to changes in bank capital ratios, while applying different assumptions on how banks move to higher capital ratios. In doing so, we assume that changes in bank capital ratios reflect changes in regulatory requirements and interpret the responses of other macro-financial variables as the likely impact of capital-based policy measures.[14] More specifically, we circumvent an identification based on capital and instead translate the impulses first to credit supply shocks (of two polar kinds) which can then be identified based on sign restrictions (see, e.g., Faust 1998, Canova and Nicolo 2002, and Uhlig 2005). As the credit supply shocks represent polar cases, the results in the paper can be interpreted to provide upper and lower bounds for the likely impact of policy measures.

Specifically, we introduce three different shock types, with the first two involving the use of

[13] Despite the fact that our measure of loan volume at the core of the model captures only credit to the nonfinancial private sector we use a banking system exposure measure to generate the weights that link the banking systems. The rationale is that a shock propagation channel for loan volumes and prices toward the private sector can nonetheless be a function of the size of interbank exposure. Various robustness checks with different weighting schemes in particular in this respect confirm that our simulation results are robust.

[14] A more precise identification of the impact of changes in regulatory capital requirements would require micro-level bank data that is currently not at our disposal. Recent evidence, however, has shown that changes in capital requirements induce sizable adjustments in bank capital ratios and lending (see, for instance, Brun et al. 2013, Carlson et al. 2013, Aiyar et al. 2014a, Bridges et al. 2014, Behn et al. 2016).

sign constraints. All three shock types – to which we refer as Type 1, Type 2, and Type 3 – start from the same positive capital ratio shock Δ and are defined as follows:

1. **Contractionary deleveraging** (Type 1): Banks are assumed to move to the higher capital ratio by shrinking their balance sheet, with equity capital by assumption being constant and debt shrinking along with assets.

2. **Expansionary deleveraging** (Type 2): Banks are assumed to raise equity capital or retain earnings, giving them thereby more capacity to lend, while holding debt constant by assumption.

3. **Unconstrained deleveraging** (Type 3): Banks are not constrained as to how they move to a higher capital ratio. They may partly shrink their balance sheet size or raise equity, to also replace debt if they wish.[15]

The magnitude of credit supply shocks under the Type 1 and 2 scenarios is calibrated based on the formulas in eqs. (5) and (6), with E_0, A_0, and Δ denoting capital, total assets, and the capital ratio shock respectively:

$$S_1 = \ln\left(\frac{E_0}{\frac{E_0}{A_0}+\Delta}\right) - \ln\left(A_0\right) \tag{5}$$

$$S_2 = \ln\left(A_0 - E_0\left(\frac{\left(\Delta+\frac{E_0}{A_0}\right)\left(A_0-E_0\right)}{E_0\left(\Delta+\frac{E_0}{A_0}-1\right)}+1\right)\right) - \ln\left(A_0\right) \tag{6}$$

The respective first terms in the two equations reflect the total asset values after the capital ratio shock Δ is applied. The shocks are the log difference between total assets *post* and *pre*-shock. We assume that this log percent shock computed based on equity and total assets applies to the loan stock of the banking system; that is, the stock of loans decreases by S_1 percent under Type 1 and increases by S_2 percent under Type 2 shocks. The size of $T = 1$ shocks is scaled such that S_1 and S_2 met over a cumulative 3-year horizon. For Type 3, the scaling is done with regard to the underlying capital ratio shocks directly. For all three shock types, we employ a grid of shock sizes for the capital ratios Δ, ranging from 25 to 250 basis points.

The capital ratio shock under the Type 1 simulation is combined with the sign restriction imposed on banking system loan volumes and loan interest rates which are assumed to be negative

[15] An additional, fourth simulation type could in principle be one under which a bank or banking system is assumed to raise equity capital to replace debt while holding total assets constant by assumption. This scenario is one that can be referred to as *static deleveraging*, which is not overly relevant, as too hypothetical, for what concerns the empirical assessment that we wish to conduct. Macroprudential policy is precisely meant to induce changes to the structure of bank balance sheets, via volume and price changes.

and positive, respectively, for only the first period in which the shock arrives.[16] This combination of sign constraints makes the shock an identified negative loan supply shock. Under the Type 2 simulation the same capital ratio shock is combined with the opposite of the Type 1 restrictions, i.e. a positive and negative constraint on the $T = 1$ responses for loan volumes and loan rates, respectively. It is therefore an identified positive credit supply shock. The Type 3 simulation is meant to reveal how banking systems went about the deleveraging process on average historically. Under none of the three simulation types are there any constraints imposed on nominal GDP, the GDP deflator, and long-term interest rates.

Figure 2 shows the capital ratio shock-implied Type 1 and Type 2 credit supply shocks. The credit supply shocks are implied by *risk-weighted* shocks of 100 bps which are scaled in a first step to non-risk weighted shocks based on the aggregate RWA/TA ratios as observed in the banking systems in the year 2014 on average.[17] In Figure 2 one can see an asymmetry in the absolute size of shocks under Type 1 versus 2, with the former being larger (more negative) than the latter (only slightly positive). This effect is mechanic and reflects that it requires more of an asset-side reduction than an increase in equity to achieve the same higher capital ratio.

Figures 3 to 5 show the long-run impacts of real GDP, house prices and equity prices corresponding to the 100 bps scenarios across banking systems, now distinguishing between the Type 1, 2, and 3 reaction of banks. The results suggest that the stronger negative credit contraction under Type 1 implies the most adverse macro feedback effect in terms of contraction of GDP and house price growth. The Type 2 responses are slightly positive, on the other hand, while the Type 3 scenario responses fall in between the other two polar cases.[18]

3.4 Estimating benefits, costs, and net benefit of capital-based measures

To arrive at estimates for their *net benefit* we need to quantify both *benefits* and *costs* of capital-based measures. For the former, we proceed in two steps: First, we feed the simulated responses

[16] The number of periods over which sign restrictions are being imposed is a crucial choice. To our knowledge there are no agreed best practices or principles in that respect in the literature, however, and our preference is to impose rather minimal assumptions, to constrain only *shocks* in the first period, not *responses* beyond $T = 1$. In particular for Type 2 shocks some counteracting behaviour of banks may drive price responses in the opposite direction, which we allow right from a second period onward. With sign restrictions imposed for more than 1 quarter the scenario responses (e.g., the respective "corridors" for GDP responses to Type 1 and 2 shocks) become wider than they currently are from period 2 onward, which therefore also holds for the cumulative responses.

[17] The advantage of translating risk-weighted shocks into non-risk weighted shocks is that longer time series are available for the latter, coupled with the argument that non-risk weighted measures are more immune to distortions possibly resulting from banks' attempts to manipulate risk weights (see Mariathasan and Merrouche 2014 and Behn et al. 2015), which would hamper a cross-bank/banking system comparison and the estimation of models. Shocks are, however, scaled to risk-weighted impulses, since policy instruments are cast in terms of risk-weighted measures.

[18] We leave it at presenting cumulative impulse responses (IRs). Many of the underlying dynamic IR paths were displaying a 'basic' shape, i.e. an initial shock or shock response is followed by a decay back toward zero after about two years. Adding such detailed dynamic paths would not add much value over the size and sign of the cumulative responses for that reason. A comprehensive catalogue containing all dynamic IR for all model variables as well as all related dynamic net benefit estimates is available from the authors upon request.

from the GVAR through the EW model and calculate the reduction in the probability of being in a vulnerable state, Δp, as the difference between the predicted probability from the EW model at the end of our sample period, p_{2014Q4}, and the average predicted probability over the 3-year simulation horizon, $\overline{p_{sim}}$.

$$\Delta p = \overline{p_{sim}} - p_{2014Q4} \tag{7}$$

This calculation implies that we assume a constant probability of being in a vulnerable state in the 'baseline' scenario and assess by how much it can be reduced in the scenario with increased capital ratios and corresponding responses of other macro-financial variables. The second step entails the multiplication of Δp with the median output loss associated with banking crises in our sample, as calculated in Section 2. That is,

$$\text{benefit} = -\Delta p \times \text{crisis cost} \tag{8}$$

To quantify the potential *cost* of implementing capital-based measures, we refer directly to the cumulative real GDP responses from the GVAR component of the model. This cost measure is constructed in the same way as the 'crisis cost' measure for the benefit calculation in eq. (8) (see Section 2 for details). That is, we compute the implied level deviations from a baseline trend over a 1-year horizon and express them as a percentage of end-sample GDP. This way, the two measures—benefit and cost—are fully conform and can be subtracted eventually to obtain an estimate for the *net benefit*, expressed in percent of end-sample GDP. That is,

$$\text{net benefit} = \text{benefit} - \text{cost} \tag{9}$$

The choice of a longer horizon for the 'crisis cost' estimate (3 years) compared with the cost of measures (1 year) reflects our interpretation that the benefit of macroprudential policy is longer lasting (as banking crises tend to result in permanent output losses that successful policy would render less likely to happen), while costs should arise rather in the short term. Robustness checks concerning different horizon settings are reported in Section 4.5.

3.5 Cross-border effects

Since the GVAR generates not only the responses of domestic variables but also the responses of the variables in countries abroad, the cost, benefit, and net benefit calculations can be conducted not only for the country in which the capital-based measures are applied, but also for all other countries in the sample. That is, cross-border credit supply and trade spillover effects are well-captured by the model and will be explored in Section 4.4, where we analyze the weighted foreign or area wide net benefits of measures in individual countries.

Further, the model has an element of reciprocity built in since it includes a measure of domestic and foreign lending. That is, the credit aggregate in the GVAR contains domestic and foreign loan business of domestic parent banks along with that of *foreign branches and subsidiaries* in the domestic host country. The same applies for the capital (capital ratio, respectively) which pools the capital and reserves from domestic banks and foreign subsidiaries and branches in a country. The concept of *reciprocity* is built into the model because the capital shocks that we simulate are applied at country level, affecting thereby banks that are providing loans to that country. The reason for this is that broad capital-based macroprudential policy measures do likely exert their impact on banks' business irrespective of their geographical location, i.e., they have cross-border effects for those banks that are active abroad. In the logistic model part of our framework, we include the same extended measure of credit as the likelihood of bank or banking system distress would to some extent depend on macro and credit conditions in the country to which a cross-border active banking system is exposed.

4 Empirical results

4.1 Predicting the probability of being in a vulnerable state

Results for the logistic model in eq. (1) are presented in Table 2. Credit growth has a positive and significant impact on the probability of being in a vulnerable state. This illustrates that accelerated credit growth may be a sign of overheating and can be associated with systemic events in the banking sector (see also, e.g., Schularick and Taylor 2012 or López-Salido et al. 2015) which provides a rationale for the introduction of countercyclical macroprudential instruments. GDP growth is negatively associated with predicted probabilities, indicating that countries that grow relatively faster are less likely to experience banking sector crises. Inflation does not have a significant impact, whereas house price and equity price growth both have a positive sign. This confirms the common view that asset price booms can be associated with the build-up of risks and imbalances in the financial sector. Finally, as expected, banking sector capitalization exerts a significantly negative influence on the probability of being in a vulnerable state, reflecting that better capitalized banks are more resilient against shocks.

When adding country fixed effects results remain stable (columns 2, 4, 6, and 8) which indicates that the effects are not driven by heterogeneity across countries. Not surprisingly, the model's fit and predictive ability—measured by Pseudo R^2 and AUROC—improve vis-à-vis the models without fixed effects. Also when we use weighted averages instead of country-specific values for the explanatory variables—where the country-specific weights in each quarter correspond to the relative exposures of the country's banks vis-à-vis each country (including domestic)—coefficients remain relatively stable, while the model's fit and predictive ability improve slightly with respect to the unweighted models (columns 3-4 and 7-8). This illustrates that developments abroad can be relevant for the stability of the domestic financial system. Finally, the model's fit and its predictive

ability also increase when using bank credit growth instead of total credit growth as a explanatory variable in the model (columns 5-8).

Using a preference parameter of $\mu = 0.85$, all models exhibit reasonable values for the various evaluation criteria listed at the bottom of Table 1 and explained in Section 3.1, which makes us confident about their predictive ability with respect to systemic crisis episodes. The evaluation criteria generally look more favourable for models that include country fixed effects, for models using weighted regressors instead of country regressors, and for models using bank credit growth instead of total credit growth. We therefore use the specification in column 8 as our benchmark model in the subsequent analysis. This model issues a warning signal whenever the predicted probability is above the 71^{st} percentile of the country-specific distribution.[19]

4.2 Assessing the cost, benefit and net benefit of capital measures

(i) Type 1 simulation results (negative credit supply shock)

Benefit estimates in our model depend on the evolution of predicted probabilities of being in a vulnerable state over the simulation horizon. That is, they depend on the simulated responses of macro-financial variables obtained from the GVAR and the coefficient estimates from the EW model. Higher banking sector capitalization and lower credit growth associated with Type 1 simulations reduce the likelihood of being in a vulnerable state (see Table 2). Further, Figures 4 and 5 show that house prices and equity prices tend to react negatively under Type 1 simulations, illustrating that macroprudential policy may help containing unsustainable asset price booms under the assumption that banks primarily engage in asset-side deleveraging, thus reducing predicted probabilities. Finally, GDP growth is negatively affected by the reduction in credit supply in all countries, which increases the likelihood of a banking sector crisis according to Table 2. Hence, there are two opposing effects under Type 1 simulations: On the one hand, the increase in banking sector capitalization and the dampening effects on credit and asset price growth have a positive impact on financial stability; on the other hand, the corresponding reduction in GDP growth may exert negative feedback effects from the real economy to the financial sector.

Panel A of Table 3 indicates that macroprudential policy has the potential to contain the build-up of imbalances in the banking sector: In the average country, the probability of being in a vulnerable state is reduced by 0.6 to 2.8 percentage points, which corresponds to a reduction of 3.1 to 13.9 percent of the average probability of being in a vulnerable state, or by 17.6 to 80.2 percent of the probability in 2014Q4. In other words, the positive effects of higher banking sector capitalization and dampened credit and asset price growth dominate the negative feedback effects arising from a reduction in GDP growth.

In contrast to linear models, assessing the relative contribution of individual macro-financial

[19] As expected, using alternative values for the preference parameter μ changes the optimal threshold (with lower thresholds for higher values of μ), but not the relative ranking of models according to the evaluation criteria.

indicators on the reduction in predicted probabilities is not straightforward in the nonlinear model we employ. To evaluate the contribution of each variable, we make use of the following procedure:

- First, we assess how the development of individual variables under the scenario with increased capital ratios (as obtained from the GVAR) affects predicted probabilities relative to the baseline scenario, assuming that all other variables remain at their values in 2014Q4, i.e. at their values in the baseline scenario;
- Second, for each indicator, we calculate the difference between predicted probabilities in the baseline scenario and predicted probabilities obtained from Step 1 and average the difference over the forecast horizon from 2015Q1 to 2017Q4;
- Third, we sum the average probability differences obtained from Step 2 over all variables and calculate the relative contribution of each variable as the probability difference generated by this variable divided by the sum of all probability differences;
- Fourth, we multiply the relative contribution of each variable obtained from Step 3 with the aggregate reduction in crisis probabilities associated with the respective scenario.

Assuming a capital ratio shock of 250 basis points, Panel A of Figure 6 illustrates that in most countries the reduction in crisis probabilities under a Type 1 shock is mainly driven by the increase in bank capitalization, the reduction in credit growth, and to a somewhat lesser extent by the reduction in house price growth. In many countries the contribution of the reduction in credit growth is of equal importance as the contribution of the increase in bank capitalization, indicating that the effectiveness of macroprudential policy depends to a large degree on its ability to smoothen the credit cycle. The most important counterbalancing factor is the reduction in GDP growth associated with asset-side deleveraging which tends to increase crisis probabilities, while the influence of developments in inflation and equity price growth appear to be negligible in many countries. Of course, the reduction in predicted probabilities depends on the level of predicted probabilities towards the end of the sample period: Countries with predicted probabilities close to zero in 2014Q4 (including most notably Ireland, Italy, Greece, Portugal, and Spain) cannot experience a much greater reduction in predicted probabilities since these are constrained by the zero lower bound.[20] Consequently, changes in predicted probabilities are negligible in these countries.

Figure 7 shows the benefits, the costs and the net benefits—calculated as explained in Section 3.4—of imposing the respective increase in capital ratios. All variables are expressed as

[20]Strikingly, these are precisely the countries which were most affected by the European sovereign debt crisis. Of course, the fact that the model assigns low probabilities of being in a vulnerable state to these countries does not mean that there are no problems in their banking sectors. Rather, the results indicate that the developments of credit and asset prices are currently not excessive in these countries and that broadly-based countercyclical policies are not warranted for them at the current stage of the cycle. Other, more structural issues may still require the attention of policy makers.

expected output gains or losses in percent of GDP or percentage points for the net benefit measure. As expected, the benefits are close to zero for the countries with predicted probabilities close to zero in 2014Q4. These countries do not have much do gain from imposing additional buffers and hence broadly based countercyclical tools are currently not warranted for them. For other countries, most notably Sweden, the benefits can be quite substantial as higher capital buffers would succeed in reducing elevated levels of crisis probabilities.

Since we assume in this scenario that the increase in capital requirements is fully translated into asset-side deleveraging, i.e. a reduction in loans, also the costs of macroprudential measures can be very substantial in many countries. Interestingly, significant decreases in GDP in Sweden are outweighed by even larger benefits resulting from the reduction in crisis probabilities, so that net benefits are positive and reach their maximum value at a buffer rate of 150 bps. Net benefits do not increase monotonously since the additional benefits of a further increase in the capital ratio decrease faster than the corresponding additional costs. Net benefits are negative (or zero for some small buffer rates) in all other countries, reflecting the currently subdued phase of the financial cycle in Europe.

(ii) Type 2 simulation results (positive credit supply shock)

For the second type of shock, we assume that banks raise new equity to achieve higher capital ratios instead of contracting their balance sheet as under the Type 1 scenario. While higher banking sector capitalization decreases crisis probabilities also under this scenario, credit growth and also asset price growth tend to be slightly stronger relative to the baseline, thus exerting extra upward pressure on the predicted crisis probabilities (Figures 2 to 5).

Panel B of Table 3 illustrates that the reduction in crisis probabilities is much less pronounced under this type of shock, where the effects have about half the size of the effects under the first type of shock in the average country. Still, all countries exhibit decreases in crisis probabilities, illustrating that the influence of higher capitalization dominates the influence of moderate increases in credit and asset price growth on crisis probabilities. This is illustrated in Panel B of Figure 6 which shows the contribution of individual variables to the reduction in crisis probabilities, assuming a capital ratio shock of 250 basis points. While the increase in bank capitalization significantly reduces crisis probabilities, credit and house prices tend to increase slightly under Type 2 shocks, so that their contributions to the reduction in crisis probabilities are negative, i.e. their development increases crisis probabilities. The remaining variables do not react strongly, so that their influence on crisis probabilities is negligible under this type of shock.

The benefits, costs and net benefits of increases in capital ratios under the second type of shock are illustrated in Figure 8. Since GDP reacts positively to the positive credit supply shock and since crisis probabilities are reduced (albeit only slightly) in all countries, the effects of macroprudential measures are unambiguously positive under this type of shock.

(iii) Type 3 simulation results (unconstrained capital ratio shock)

Under the Type 3 simulation, credit and with it also GDP respond negatively in all countries and also asset prices are negatively affected in most countries (Figures 2 to 5). This illustrates that historically periods where banks moved to higher capital ratios involved some asset-side deleveraging, since the illustrated patterns are closer to Type 1 than to Type 2. Predicted probabilities of being in a vulnerable state are reduced in all countries and, as expected, average reductions lie somewhere between the first two types of shocks (Table 3, Panel C). Also the net benefits of increases in capital ratios under Type 3 shocks lie somewhere between those of the first two types (see Figure 9), with positive net benefits only for Sweden (for moderate shock sizes).

4.3 An alternative way to derive the optimal buffer size

In the previous subsection, the benefit was calculated based on the reduction in crisis probabilities in the EW model. An alternative way to estimate the benefit is to make stronger use of the binary signals issued by the model, i.e. the optimal warning threshold. In this section, we assume that implementing macroprudential measures can have benefits only when the model actually issues a warning, i.e. when the predicted probability of being in a vulnerable state is higher than the optimal warning threshold. Moreover, the benefits accrue only if the implemented buffer is successful in pushing the predicted probability below the optimal threshold.

Specifically the procedure involves four steps: First, we check whether the model currently issues a warning signal. Second, if it does issue a signal, we assess whether the macroprudential policy measure would succeed in pushing the predicted probability below the warning threshold. Third, if this is the case we calculate the reduction in the probability of being in a vulnerable state as the difference between the probability of being in a vulnerable state conditional on a signal being issued and the unconditional probability of being in a vulnerable state (i.e., the probability difference in the last row of Table 2). Fourth, we multiply the reduction in the probability of being in a vulnerable state with the median output loss associated with banking crises in our sample, as before, where the product corresponds to the benefit of the measure. In cases where the models currently does not issue a warning signal or where the model does give a signal but the measure does not succeed in pushing the predicted probability below the threshold the benefit is assumed to be zero. Costs of the measure are obtained from the GVAR in the same way as before.

Results for this alternative approach are presented in Figure 10. Since the model issues a warning signal only for Sweden, it is the only country that could benefit from countercyclical macroprudential policies. A buffer rate of 25 bps would be insufficient to push the probability of being in a vulnerable state below the warning threshold, so that the benefit would still be equal to zero for such a measure. In contrast, predicted probabilities are pushed below the threshold for buffer rates of 50 bps or more and since the resulting benefits are higher than the costs we obtain positive net benefits for such rates. Benefits are the same for buffer rates from 50 to 250 bps (since all rates succeed in pushing probabilities below the threshold), but costs are higher for the higher

rates, so that this procedure would recommend an optimal buffer rate of 50 bps for Sweden. For all other countries, the model does not issue a warning and hence the recommendation would be to have a zero buffer rate.

4.4 Spillover effects of macroprudential measures

The model setup can be further employed to consider spillover effects when assessing the net benefit of capital-based macroprudential policy measures in a specific country, as we can derive how predicted crisis probabilities evolve in response to the implementation of higher capital ratios for banks abroad. For each country, we calculate the benefit of capital-based macroprudential measures (domestic or abroad) as the product of the corresponding reduction in crisis probabilities and the average output loss associated with banking crises in the respective country (see Section 3.4). Similarly, one can also estimate the cost of measures, domestic or abroad, by looking at GDP responses from the GVAR. To estimate foreign spillover effects we calculate the weighted average of the net benefits in non-domestic countries, where the weights are set based on the countries' nominal GDP as of 2014. Euro area total weighted averages are calculated in the same way, but also include domestic economies to which the capital ratio shocks were applied.

Results accounting for spillover effects are presented in Figures 11. For Type 1 shocks there are significant spillover effects for measures implemented in the larger countries, in particular Germany (see Panel A). For Germany, the weighted foreign effects are even larger than domestic effects. In the vast majority of cases, weighted foreign effects move in the same direction as domestic effects. For Type 2 shocks, spillover effects are negligible in all countries, reflecting the fact that net benefits are mainly driven by higher domestic banking sector capitalization and the associated lower crisis probabilities in this case (see Panel B).

4.5 Robustness tests

We conduct several tests in order to assess the robustness of the results. The results presented thus far involved the historical cost estimate of a crisis that was defined as a three-year cumulated loss in real GDP relative to a pre-crisis trend. In Figure 12, we cumulate losses over two years (Panel A) and four years (Panel B), respectively, to illustrate the sensitivity of the results with respect to this parameter.[21] The patterns remain the same as in the main part, with a slightly smaller optimal rate for Sweden under the two-year horizon, and positive net benefits also in Finland and Germany (for small buffer rates) along with a larger optimal rate for Sweden under the four-year horizon.

Another way to vary the the size of the benefit estimate is to take different percentiles of the crisis cost distribution. In Figure 13, we employ the 25^{th} (Panel A) and the 75^{th} percentile

[21] Naturally, benefit estimates (the product between the reduction in predicted probabilities and the estimate for the crisis costs) become smaller if losses are cumulated over two years and larger if they are cumulated over four years.

(Panel B), respectively. Benefits are somewhat smaller in the former and somewhat larger in the latter case, but the overall patterns remain the same. In Figure 14, Panel A, we use country-specific estimates for the crisis costs, by taking the country-specific median. The crisis costs in Finland were higher then the sample median, resulting in positive estimates of the net benefits for smaller shocks to capital ratios.

We also analyse how the performance of the models and the estimation of benefits changes if the definition of the dependent variable in the logit model is altered. First, following Bussière and Fratzscher (2006), we use use a multinomial logit model to further address potential crisis/post-crisis bias. Coefficients for the distinction between pre-crisis and tranquil periods are very similar to those in the main specifications (Table 4, column 1; compare with Table 2, column 8), and predicted probabilities from the two models are closely correlated (the correlation is 0.979). Column 2 shows that there are also some significant differences between tranquil and crisis/post-crisis periods, which are, however, omitted in the main specifications. Further, Table 4 shows the results for four alternative definitions of vulnerable states: 5-12, 1-12, and 1-8 quarters preceding the crisis in order to properly take into account potential late signals of the model; and 9-16 quarters, so as to analyse potential early crisis signals. The overall fit (as given by the Pseudo R-squared and the AUROC metrics) of the models with the alternative definitions of a vulnerable state is lower or in the same ballpark as for the main specification in column 8 of Table 2. Coefficients are also similar to the main specification, where the model with a 1-8 quarter prediction horizon stands out to some extent, since GDP growth tends to be more positive in the quarters directly preceding a crisis, while house price growth tends to be less pronounced. Figure 14, Panel B, illustrates that benefit estimates remain relatively stable with a different prediction horizon (5-12 quarters).

For additional robustness tests concerning the GVAR part of our model we refer the reader to Gross et al. (2016b), where the results from numerous robustness checks are presented. Additional model diagnostics such as residual cross-correlation statistics show that the GVAR structure manages well to capture local and global effects, as the residuals do not significantly correlate over time or in the cross-section. Durbin Watson (DW) statistics confirm that all equations' residuals are sufficiently free of serial correlation (DWs ranging between 1.7 and 2.3). Average pair-wise cross-section correlation estimates for the residuals confirm that the model manages well to capture the within and across cross-section dependencies which is an indirect test and a confirmation that the weak exogeneity assumption holds. The residual correlation estimates fall into a narrow -3/+3 percent interval. Finally, we conducted a robustness check with regard to the lag structure of the model, adding a second lag beyond the contemporaneous inclusion and first lag of the foreign variable vectors in the model. The eventual cost, benefit, and net benefit estimates change by only a small margin across countries, compared to the responses presented here by a factor ranging between 0.9 and 1.1.

5 Conclusions

Using a sample of 14 European countries, this paper presents an integrated Early Warning Global Vector Autoregressive (EW-GVAR) model that can assist policy makers in their decision to activate and calibrate capital-based macroprudential policy instruments. The model can be used to quantify the cost and benefits of capital-based measures from a macroprudential perspective. Moreover, it is able to assess the relative importance of direct effects of higher bank capitalization and indirect feedback effects related to dampened credit and asset price growth, which is useful for understanding the transmission channels of capital-based policies. Finally, the multi-country, multi-banking system nature of the model allows to quantify possible cross-country spillover effects, e.g due to banks' cross-border lending at the banking-system level, or the trade channel at the macro level.

Our findings illustrate that the effects of dampened credit and asset price growth on predicted crisis probabilities can be sizable. Depending on how banks move to higher capital ratio, they can account for up to a half of the overall reduction in crisis probabilities and are thus of equal importance as the direct effects of higher bank capitalization. Moreover, we find some significant cross-country spillover effects, particularly for the larger countries, which illustrates the importance of cross-country coordination of macroprudential policy measures. Further, the simulation results from the model indicate that the net benefits of macroprudential measures depend on *how* banks move to higher capital ratios. Under an asset-side deleveraging scenario net benefits would, at the current stage, be negative in the vast majority of EU countries. In contrast, if banks achieved higher capital ratios mainly via raising fresh capital net benefits would be positive in all countries.

The results highlight that in order to increase the effectiveness of capital-based measures, policy makers should consider giving concrete guidance as to how banks are to move to higher capital ratios, with this choice depending on the stages of the financial and business cycles. During recession periods, an uncontrolled asset-side deleveraging response to increased capital requirements could induce even more recessionary pressure. During boom times, on the other hand, stronger macroprudential response of higher capital ratios could be achieved by shrinking or growing less intensely the asset side of the banks' balance sheet, as otherwise the risk is that asset price growth might not decelerate to the extent that macroprudential policy makers wish.

References

Admati, A., P. DeMarzo, P., Hellwig, M., and Pfleiderer, P. (2011). Fallacies, irrelevant facts, and myths, in the discussion of capital regulation: Why bank equity is not expensive. *Max Planck Institute Preprint*.

Adrian, T. and Shin, H. S. (2010). Liquidity and leverage. *Journal of Financial Intermediation*, 19(3):418–437.

Aiyar, S., Calomiris, C., and Wiedalek, T. (2014a). Does macro-pru leak? Evidence from a UK policy experiment. *Journal of Money, Credit and Banking*, 46(1):181–214.

Aiyar, S., Calomiris, C., and Wieladek, T. (2014b). Does macropru leak? Evidence from a UK policy experiment. *Forthcoming in the Journal of Money, Credit and Banking*.

Al-Hashimi, A., Dees, S., di Mauro, F., and Jancokova, M. (2014). Linking distress of financial institutions to macrofinancial shocks. *ECB Working Paper No. 1749*.

Alessi, L. and Detken, C. (2011). Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity. *European Journal of Political Economy*, 27(3):520–533.

Arregui, N., Benes, J., Krznar, I., Mitra, S., and Oliveira Santos, A. (2013). Evaluating the net benefits of macroprudential policy: A cookbook. *IMF Working Papers No. 13/167*.

Bank for International Settlements (2010). Final Report — Assessing the macroeconomic impact of the transition to stronger capital and liquidity requirements.

Basel Committee on Banking Supervision (2010). Basel III: A global regulatory framework for more resilient banks and banking systems. *Bank for International Settlements*.

Behn, M., Detken, C., Peltonen, T., and Schudel, W. (2013). Setting countercyclical capital buffers based on early warning models: Would it work? *ECB Working Paper No. 1603*.

Behn, M., Haselmann, R., and Vig, V. (2015). The limits of model-based regulation. *Working Paper*.

Behn, M., Haselmann, R., and Wachtel, P. (2016). Procyclical capital regulation and lending. *Journal of Finance*, 71(2):919–956.

Berger, A. and Udell, G. (1994). Did risk-based capital allocate bank credit and cause a 'credit crunch' in the United States? *Journal of Money, Credit and Banking*, 26(3):585–628.

Bernanke, B. and Lown, C. (1991). The credit crunch. *Brookings Paper on Economic Activity*, pages 205–247.

Berrospide, J. and Edge, R. (2010). The effects of bank capital on lending: What do we know, and what does it mean? *Federal Reserve Board, Finance and Economics Discussion Series*.

Betz, F., Oprica, S., Peltonen, T., and Sarlin, P. (2014). Predicting distress in european banks. *Journal of Banking and Finance*, 45:225–241.

Binder, M. and Gross, M. (2013). Regime-switching global vector autoregressive models. *ECB Working Paper No. 1569*.

Borio, C. and Drehmann, M. (2009). Towards an operational framework for financial stability: Fuzzy measurement and its consequences. *BIS Working Paper No. 284*.

Bridges, J., Gregory, D., Nielsen, M., Pezzini, S., Radia, A., and Spaltro, M. (2014). The impact of capital requirements on bank lending. *Bank of England Working Paper No. 486*.

Brun, M., Fraisse, H., and Thesmar, D. (2013). The real effects of bank capital requirements. *Working Paper, Banque de France*.

Bussière, M. and Fratzscher, M. (2006). Towards a new early warning system of financial crises. *Journal of International Money and Finance*, 25(6):953–973.

Canova, F. and Nicolo, G. D. (2002). Monetary disturbances matter for business cycle fluctuations in the G-7. *Journal of Monetary Economics*, 49(6):1131–1159.

Carlson, M., Shan, H., and Warusawitharana, M. (2013). Capital ratios and bank lending: A matched bank approach. *Journal of Financial Intermediation*, 22:663–687.

Chudik, A. and Pesaran, M. (2011). Infinite dimensional VARs and factor models. *Journal of Econometrics*, 163:4–22.

Chudik, A. and Pesaran, M. (2014). Theory and practice of GVAR modeling. *FED Bank of Dallas Working Paper No. 180*.

Cohen, B. (2013). How have banks adjusted to higher capital requirements? *BIS Quarterly Review*.

Constâncio, V. (2016). Principles of macroprudential policy. Available online: `https://www.ecb.europa.eu/press/key/date/2016/html/sp160426.en.html`. European Central Bank, Speech on 26 April.

Davis, E. P. and Karim, D. (2008). Could early warning systems have helped to predict the sub-prime crisis? *National Institute Economic Review*, 206(1):35–47.

Dees, S., di Mauro, F., Pesaran, M., and Smith, L. (2007). Exploring the international linkages of the euro area: A global VAR analysis. *Journal of Applied Econometrics*, 22(1):1–38.

Demirgüç-Kunt, A. and Detragiache, E. (1998). The determinants of banking crises in developing and developed countries. *IMF Staff Papers*, 45(1):81–109.

Duprey, T., Klaus, B., and Peltonen, T. (2015). Dating systemic financial stress episodes in the eu countries. Mimeo.

Ediz, T., Michael, I., and Perraudin, W. (1998). The impact of capital requirements on UK bank behaviour. *FRBNY Economic Policy Review*.

Eickmeier, S. and Ng, T. (2010). Forecasting national acitivity using lots of international predictors: An application to new zealand. *International Journal of Forecasting*, 27(2):496–511.

Elliott, D. (2009). Quantifying the effects on lending of increased capital requirements. *Briefing Paper No 7, Brookings Institutions*.

Faust, J. (1998). The robustness of identified VAR conclusions about money. *Carnegie-Rochester Conference Series on Public Policy*, 49(1):207–244.

Flannery, M. J. and Rangan, K. P. (2008). What caused the bank capital build-up of the 1990s? *Review of Finance*, 12:391–429.

Francis, W. and Osborne, M. (2009). Bank regulation, capital and credit supply: Measuring the impact of prudential standards. *FSA Occasional Paper No. 36*.

Furfine, C. (2000). Evidence on the response of US banks to changes in capital requirements. *BIS Working Paper No. 88*.

Galati, G. and Moessner, R. (2011). Macroprudential policy — A literature review. *BIS Working Paper No. 337*.

Galesi, A. and Sgherri, S. (2009). Regional financial spillovers across europe: A global VAR analysis. *IMF Working Paper No. 09/23*.

Gambacorta, L. and Mistrulli, P. (2004). Does bank capital affect lending behaviour. *Journal of Financial Intermediation*, 13(4):436–457.

Gray, D., Gross, M., Paredes, J., and Sydow, M. (2013). Modeling banking, sovereign, and macro risk in a CCA global VAR. *IMF Working Paper No. 13/218*.

Gropp, R. and Heider, F. (2010). The determinants of bank capital structure. *Review of Finance*, 14:587–622.

Gross, M. (2013). Estimating GVAR weight matrices. *ECB Working Paper No. 1523*.

Gross, M., Henry, J., and Semmler, W. (2016a). Destabilizing effects of bank overleveraging on real activity – an analysis based on a Threshold MCS-GVAR. *Macroeconomic Dynamics*, forthcoming.

Gross, M. and Kok, C. (2013). Measuring contagion potential among sovereigns and banks using a Mixed-Cross-Section GVAR. *ECB Working Paper No. 1570*.

Gross, M., Kok, C., and Zochowski, D. (2016b). The impact of bank capital on economic activity — Evidence from a Mixed-Cross-Section GVAR model. *ECB Working Paper No. 1888*.

Hancock, D. and Wilcox, J. (1993). Has there been a "capital crunch" in banking? The effects on bank lending of real estate market conditions and bank capital shortfalls. *Journal of Housing Economics*, 3(1):31–50.

International Monetary Fund (2011). Towards operationalizing macroprudential policies: When to act? *Chapter 3, GFSR*.

International Monetary Fund (2013). Key aspects of macroprudential policy. *IMF background paper*.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2014). Macroprudential policy, counter-cyclical bank capital buffers and credit supply: Evidence from the Spanish dynamic provisioning experiments. *Working Paper, Banco De España*.

Kaminsky, G., Lizondo, S., and Reinhart, C. (1998). Leading indicators of currency crises. *IMF Staff Papers*, 45(1).

Kupiec, P., Lee, Y., and Rosenfeld, C. (2014). Macroprudential policies and the growth of bank credit. *American Enterprise Institute Working Paper 2013-08*.

Laeven, L. and Valencia, F. (2012). Systemic banking crises database: An update. *IMF Working Papers No. 12/163*.

Lim, C., Columba, F., Costa, A., Kongsamut, P., Otani, A., Saiyid, M., Wezel, T., and Wu, X. (2011). Macroprudential policy: What instruments and how to use them? Lessons from country experiences. *IMF Working Paper No. 11/238*.

Lo Duca, M. and Peltonen, T. (2013). Assessing systemic risks and predicting systemic events. *Journal of Banking and Finance*, 37(7):2183–2159.

López-Salido, D., Stein, J., and Zakrajšek, E. (2015). Credit-market sentiment and the business cycle. *Board of Governors of the Federal Reserve System*.

Mariathasan, M. and Merrouche, O. (2014). The manipulation of basel risk-weights. *Journal of Financial Intermediation*, 23(3):300–321.

Martin-Oliver, A., Ruano, S., and Salas-Fumas, V. (2012). Effects of equity capital on the interest rate and the demand for credit: Empirical evidence from spanish banks. *Banco de Espana Working Paper No 1218*.

Meeks, R. (2015). Capital regulation and macroeconomic activity: Empirical evidence and macroprudential policy. *Forthcoming*.

Mesonnier, J.-S. and Stevanovic, D. (2013). Bank leverage shocks and the macroeconomy: A new look in a data-rich environment. *CIRPEE Working Paper No. 13-30*.

Miller, M. (1995). Do the M & M propositions apply to banks? *Journal of Banking and Finance*, 19:483–489.

Mishkin, F. (2000). *The economics of money, banking, and financial markets*. Addison Wesley, New York.

Myers, S. and Majluf, N. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13:187–221.

Noss, J. and Toffano, P. (2014). Estimating the impact of changes in aggregate bank capital requirements during an upswing. *Bank of England Working Paper No. 494*.

Pesaran, M., Schuermann, T., and Weiner, S. (2004). Modelling regional interdependencies using a global error-correcting macroeconometric model. *Journal of Business and Economic Statistics*, 22(2):129–162.

Pesaran, M. and Smith, R. (2006). Macroeconometric modelling with a global perspective. *The Manchaster School, University of Manchaster*, 74(1):24–49.

Sarlin, P. (2013). On policymakers' loss functions and the evaluation of early warning systems. *Economics Letters*, 119(1):1–7.

Schularick, M. and Taylor, A. M. (2012). Credit booms gone bust. *American Economic Review*, 102(2):1029–1069.

Schüler, Y., Hiebert, P., and Peltonen, T. (2015). Characterising the financial cycle: a multivariate and time-varying approach. *ECB Working Paper No. 1846*.

Shin, H. S. (2011). Macroprudential policies beyond Basel III. In for International Settlements, B., editor, *Macroprudential regulation and policy*, volume 60 of *BIS Papers chapters*, pages 5–15. Bank for International Settlements.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52(2):381–419.

Van Den Heuvel, S. (2008). The welfare cost of bank capital requirements. *Journal of Monetary Economics*, 55(2):298–320.

Charts and tables

		Actual class C_{it}	
		1	0
Predicted class Q_{it}	1	True positive (TP)	False positive (FP)
	0	False negative (FN)	True negative (TN)

Figure 1: **Contingency matrix.** The figure shows the relationship between model predictions and actual outcomes. Observations are classified into those where the model issues a warning that is indeed followed by a banking crises seven to twelve quarters ahead (TP), those where the model issues a warning that is not followed by a crisis (FP), those where the model issues no warning and there is no crises seven to twelve quarters ahead (TN), and those where the model issues no warning although there is a crisis coming (FN).

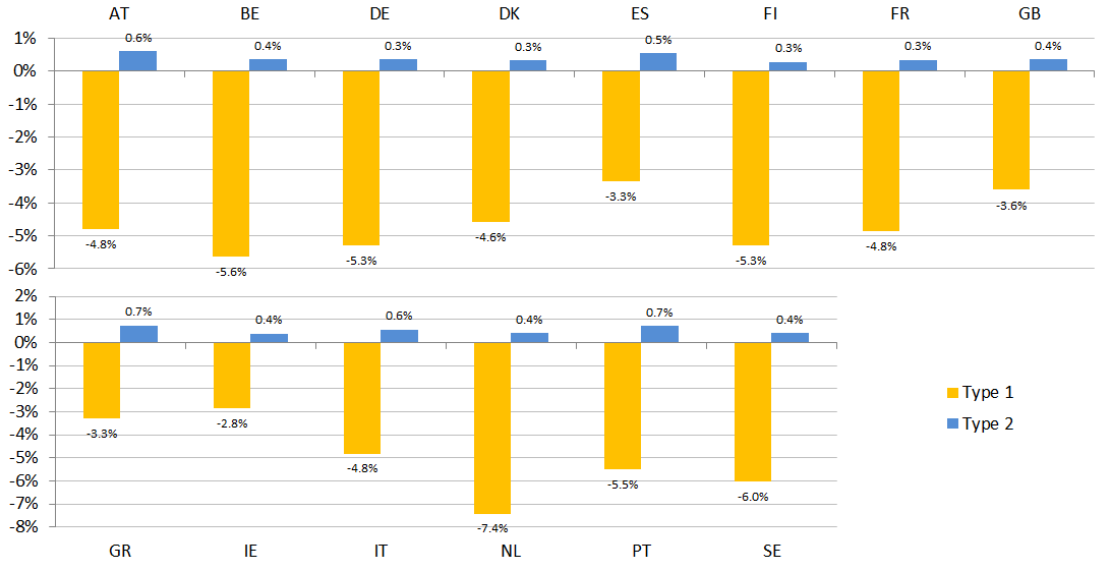


Figure 2: **Credit supply shocks for Type 1 and 2 simulation.** The shock sizes reflect the response of the banking systems to a +100bps shock to their aggregate E/RWA ratios. The Type 1 scenario assumes that the shock is translated fully into asset-side deleveraging. The Type 2 simulation assumes that the same shock translates into an amount of equity that the banking systems raise and invest in assets.

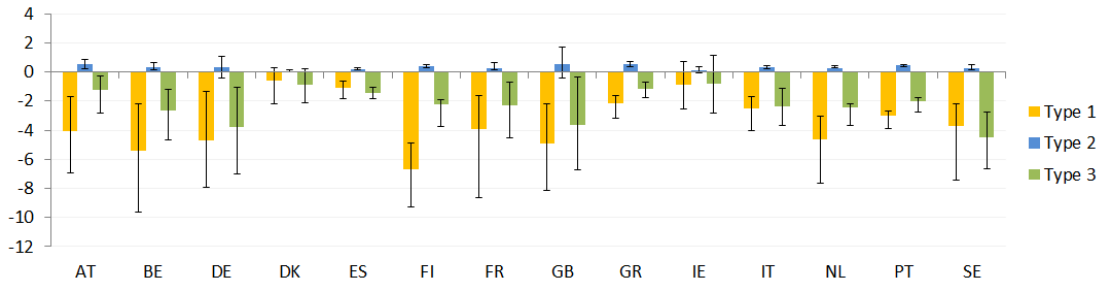


Figure 3: **Domestic real GDP responses under Type 1/2/3 capital ratio shock scenarios.** The long-run real GDP responses reflect the domestic response of the countries to the capital ratio shocks to their banking systems. They are obtained by subtracting the long-run GDP deflator responses from long-run nominal GDP responses. The error bounds mark the 25th and 75th percentile of the cumulative response distributions, reflecting coefficient uncertainty and the outcome from the drawing procedure related to the sign restrictions involved in the Type 1 and 2 simulations.

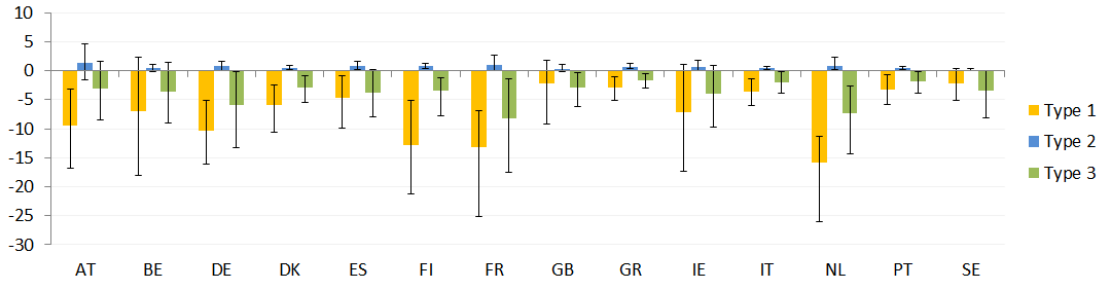


Figure 4: **Domestic house price responses under Type 1/2/3 capital ratio shock scenarios.** The long-run nominal house price responses reflect the domestic response of the housing markets to capital ratio shocks. The error bounds mark the 25th and 75th percentile of the cumulative response distributions, reflecting coefficient uncertainty and the outcome from the drawing procedure related to the sign restrictions involved in the Type 1 and 2 simulations.

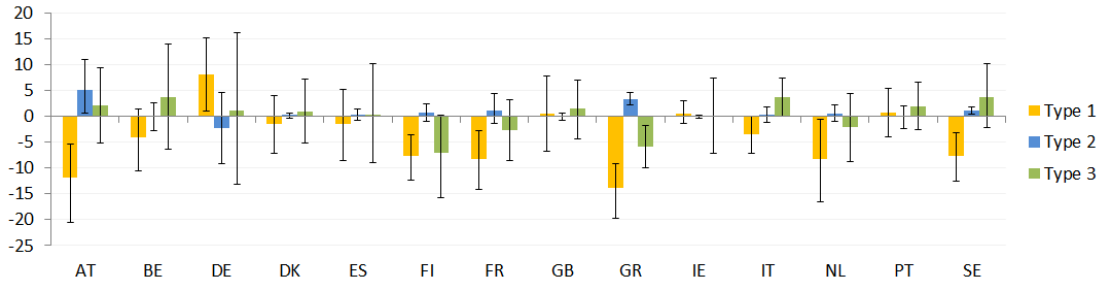


Figure 5: **Domestic stock price responses under Type 1/2/3 capital ratio shock scenarios.** The long-run nominal stock price responses reflect the domestic response of the equity markets to capital ratio shocks. The error bounds mark the 25th and 75th percentile of the cumulative response distributions, reflecting coefficient uncertainty and the outcome from the drawing procedure related to the sign restrictions involved in the Type 1 and 2 simulations.

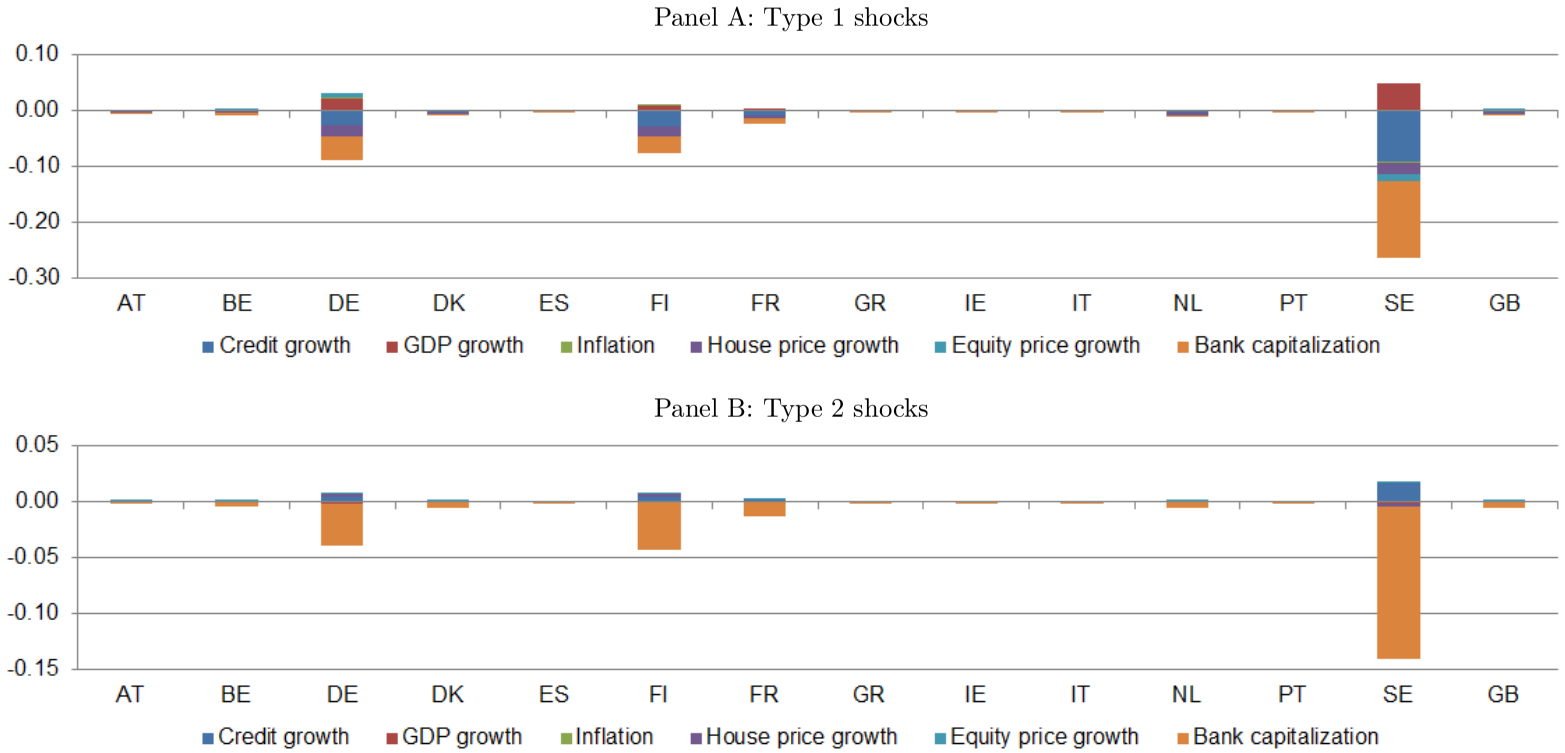


Figure 6: **Contribution charts** The figure illustrates the relative contribution of individual macro-financial indicators to the reduction in crisis probabilities following a Type 1 shock (Panel A) or a Type 2 shock (Panel B) of 250 basis points. To derive the contributions of individual variables we proceed in four steps: First, we assess how the development of individual variables under the scenario with increased capital ratios affects predicted probabilities relative to the baseline scenario, assuming that all other variables remain at their values in 2014Q4. Second, for each indicator, we calculate the difference between predicted probabilities in the baseline scenario and predicted probabilities obtained from step 1, and average the difference over the forecast horizon from 2015Q1 to 2017Q4. Third, we sum the average probability differences obtained from step 2 over all variables and calculate the relative contribution of each variable as the probability difference generated by this variable divided by the sum of all probability differences. Finally, we multiply the relative contribution of each variable obtained from step 3 with the aggregate reduction in crisis probabilities obtained from the full model.

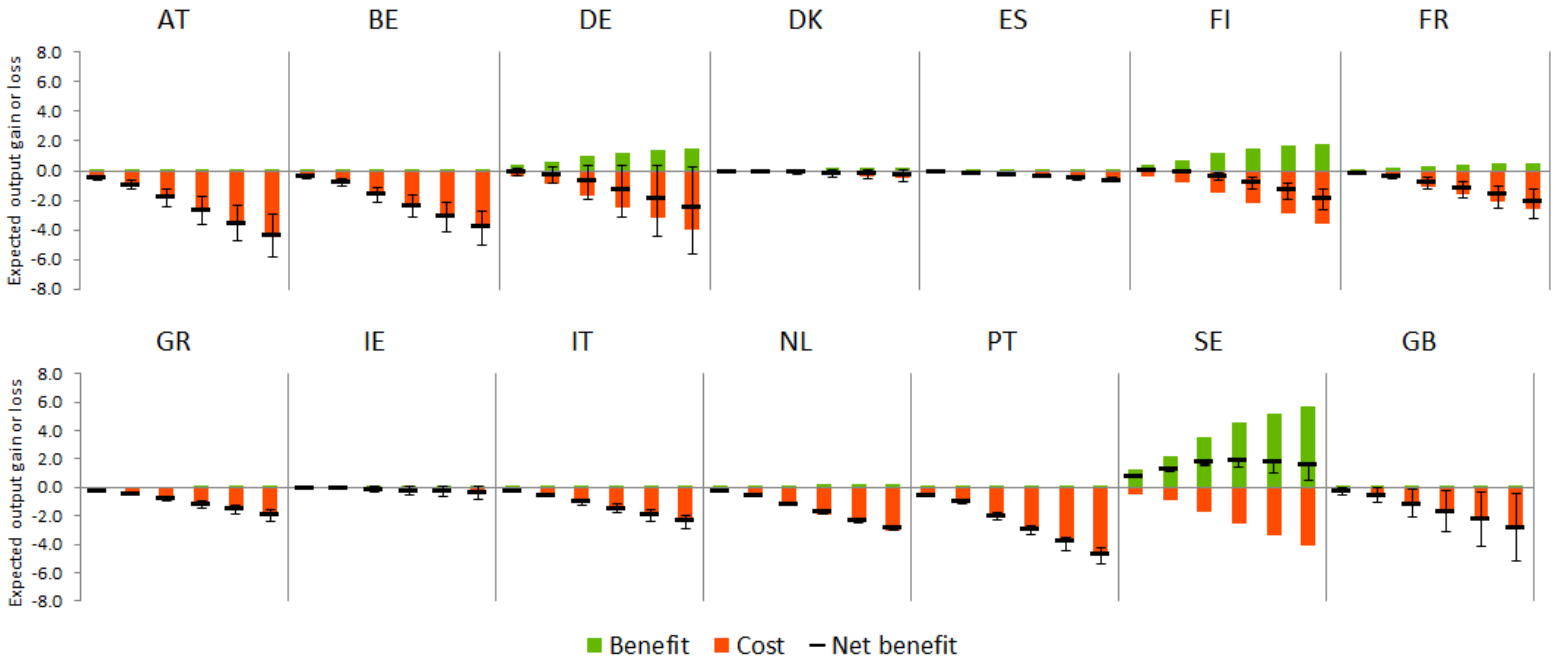


Figure 7: **Costs and benefits – Type 1.** The figure shows the estimates for the benefits, costs, and net benefits of Type 1 shocks to bank capital ratios. For each country, the bars and markers refer to shocks of 25, 50, 100, 150, 200, and 250 basis points, respectively. Benefits (green bars) are calculated as the product of the average reduction in crisis probabilities over the forecast horizon and the average cost (in terms of output loss) of a banking sector crisis in the respective country. The output loss from the GVAR model that is associated with the capital ratio shock provides us with and estimate of the costs of the measure (red bars). Finally, the net benefits (black markers) are calculated as the difference between the benefits and the costs. Error bars for the black markers correspond to the net benefits that arise from feeding error bounds (25^{th} and 75^{th} percentile) of the GVAR responses through the model structure.

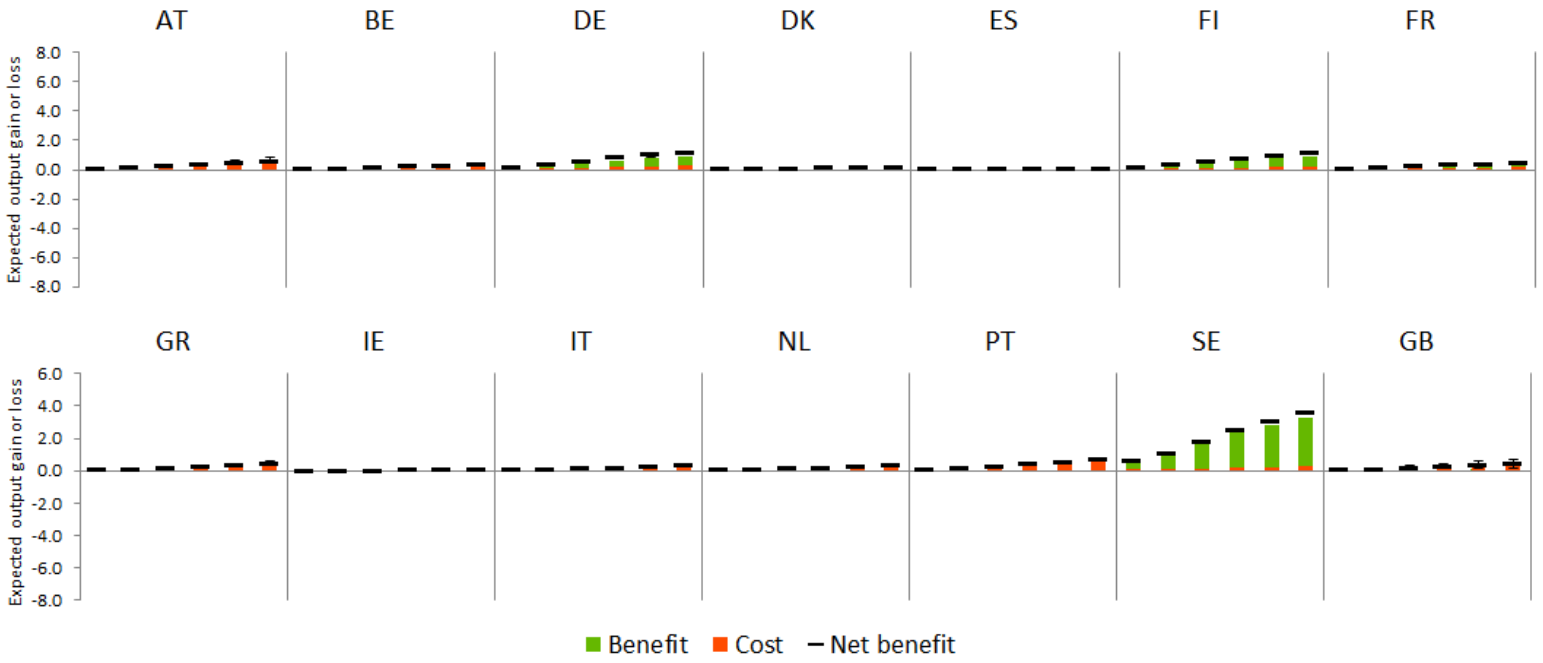


Figure 8: **Costs and benefits – Type 2.** The figure shows the estimates for the benefits, costs, and net benefits of Type 2 shocks to bank capital ratios. For each country, the bars and markers refer to shocks of 25, 50, 100, 150, 200, and 250 basis points, respectively. Benefits (green bars) are calculated as the product of the average reduction in crisis probabilities over the forecast horizon and the average cost (in terms of output loss) of a banking sector crisis in the respective country. The output loss from the GVAR model that is associated with the capital ratio shock provides us with and estimate of the costs of the measure (red bars). Finally, the net benefits (black markers) are calculated as the difference between the benefits and the costs. Error bars for the black markers correspond to the net benefits that arise from feeding error bounds (25^{th} and 75^{th} percentile) of the GVAR responses through the model structure.

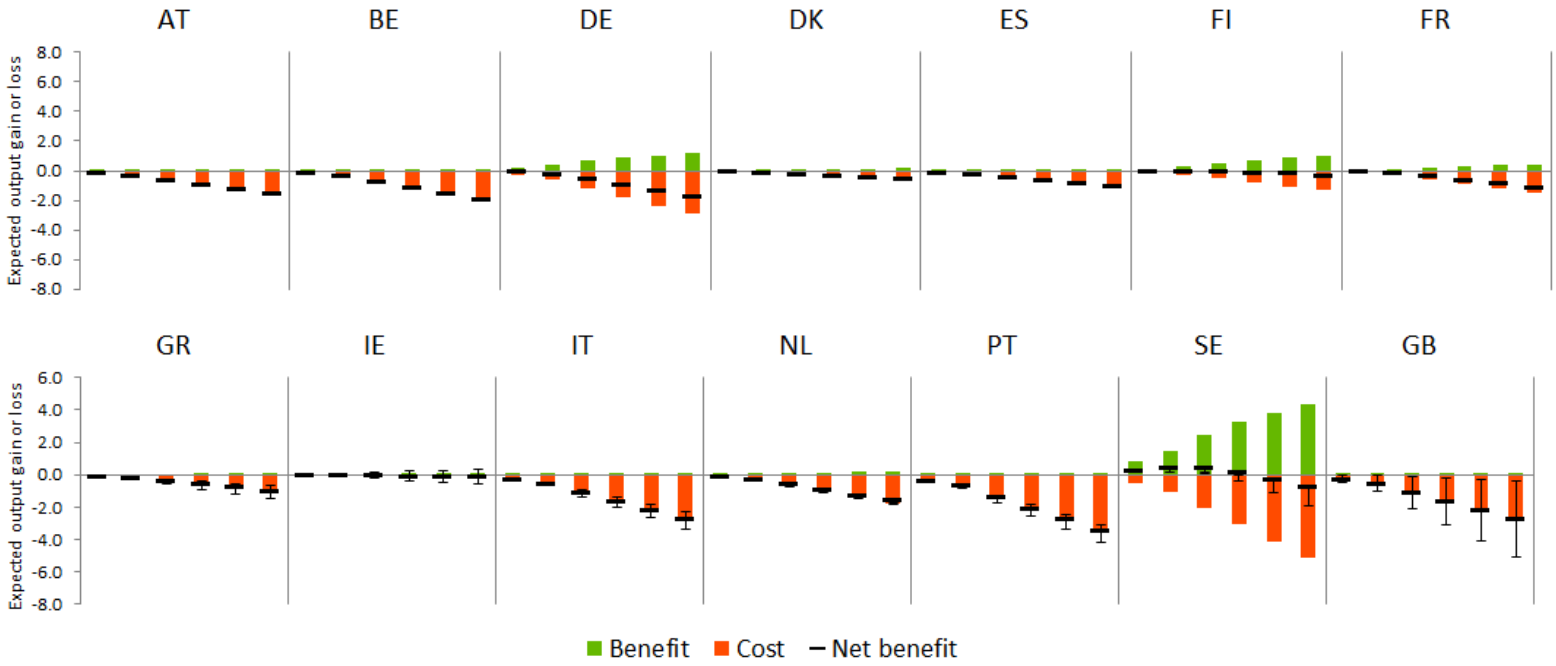


Figure 9: **Costs and benefits – Type 3.** The figure shows the estimates for the benefits, costs, and net benefits of Type 3 shocks to bank capital ratios. For each country, the bars and markers refer to shocks of 25, 50, 100, 150, 200, and 250 basis points, respectively. Benefits (green bars) are calculated as the product of the average reduction in crisis probabilities over the forecast horizon and the average cost (in terms of output loss) of a banking sector crisis in the respective country. The output loss from the GVAR model that is associated with the capital ratio shock provides us with and estimate of the costs of the measure (red bars). Finally, the net benefits (black markers) are calculated as the difference between the benefits and the costs. Error bars for the black markers correspond to the net benefits that arise from feeding error bounds (25^{th} and 75^{th} percentile) of the GVAR responses through the model structure.

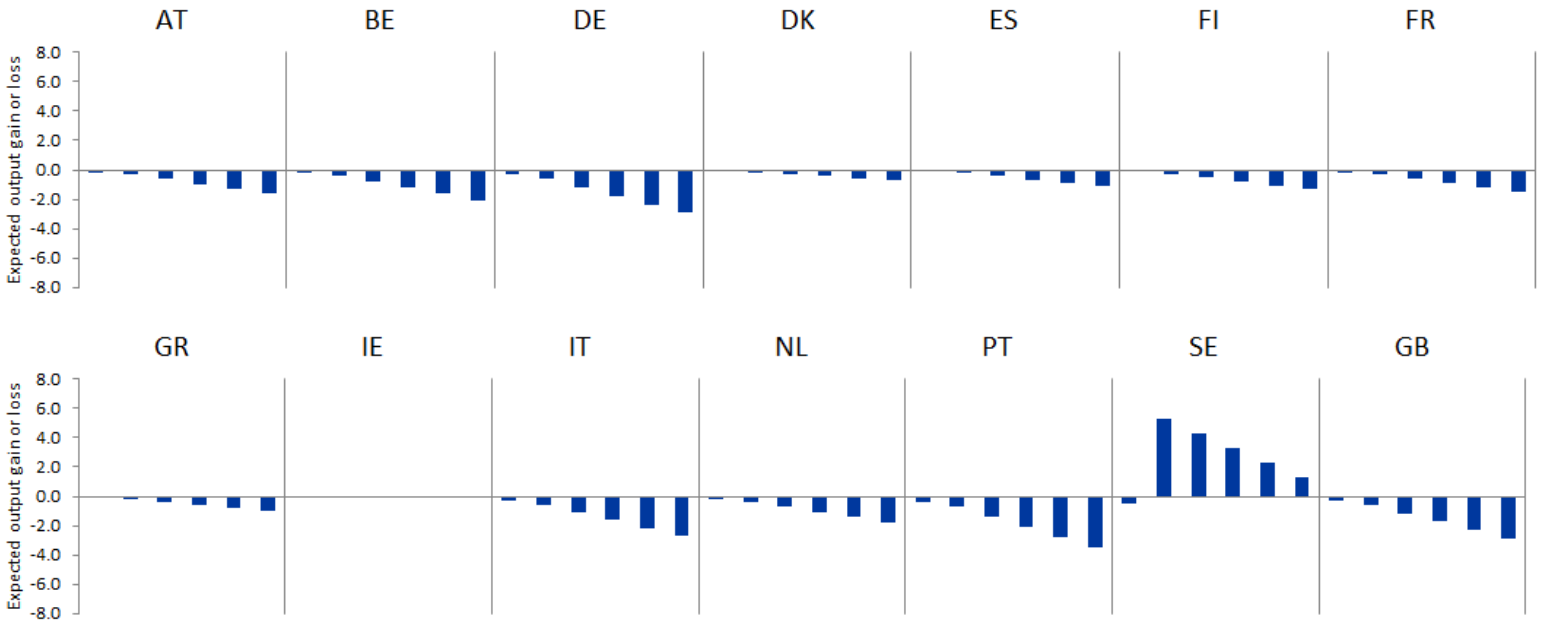


Figure 10: **Net benefit – alternative approach.** The figure shows estimates for the net benefits of Type 3 shocks to bank capital ratios, using an alternative approach to derive estimates for the benefits of the shocks. Specifically, we assume that benefits accrue only in cases where the model is currently issuing a warning signal and where the capital ratio shock succeeds in pushing the predicted probability below the warning threshold. In such a cases, the reduction in crisis probabilities is calculated as the difference between the probability of being in a vulnerable state conditional on a signal being issued and the unconditional probability of being in a vulnerable state. This probability difference is multiplied with the average output loss associated with banking crises in the respective country to arrive at estimate of the benefits of the measure. In cases where the models is currently not issuing a warning signal or where the model is issuing a signal but the measure does not succeed in pushing the predicted probability below the threshold the benefit is assumed to be zero. Costs are calculated as before, and net benefits are the difference between the benefits and the costs. For each country, the bars illustrate the net benefits related to shocks of 25, 50, 100, 150, 200, and 250 basis points, respectively.

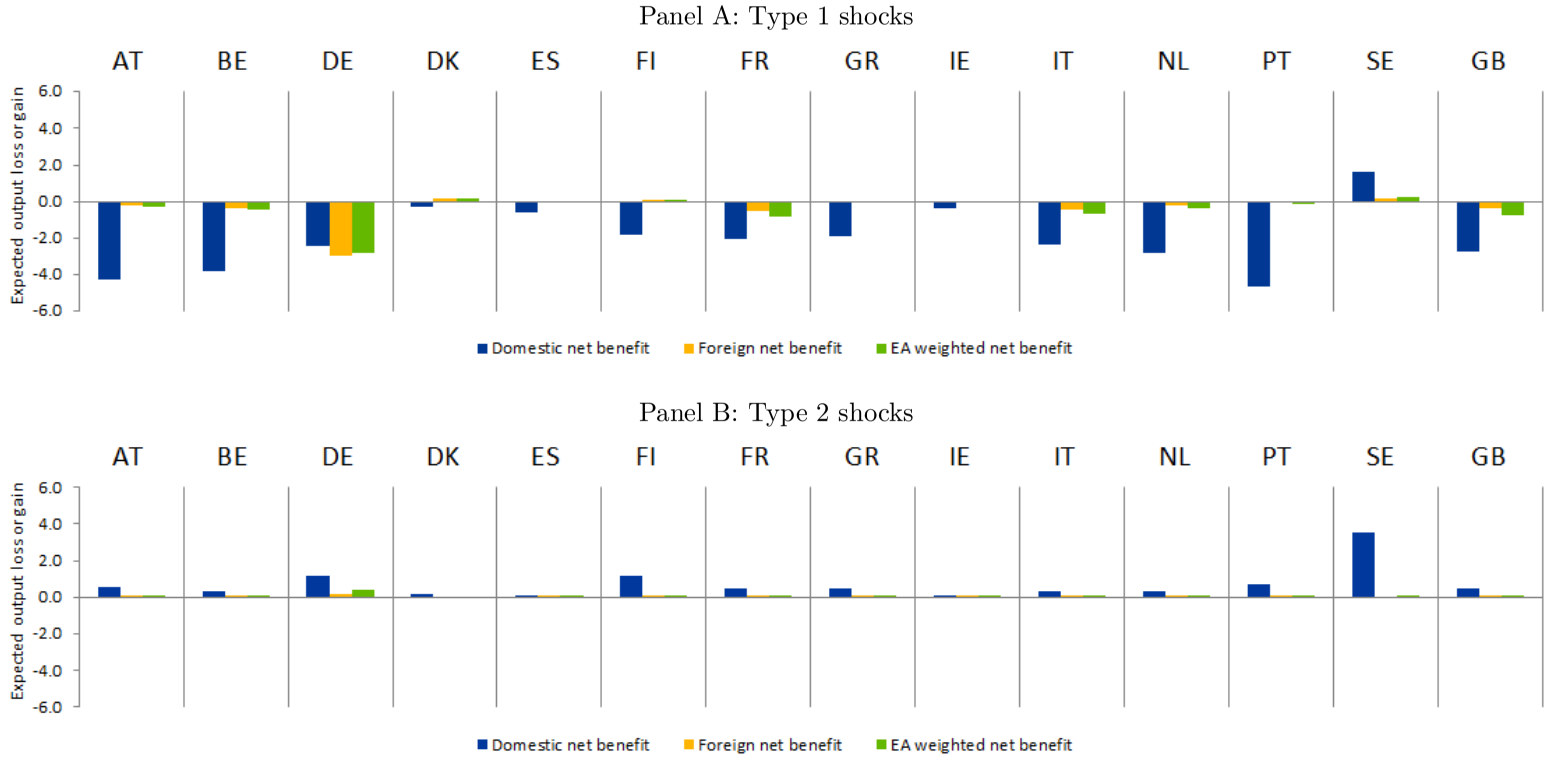


Figure 11: **Spillover effects.** The figure shows estimates for the domestic net benefit (green markers), the foreign net benefit (red markers) and the total net benefit (blue markers) of Type 1 (Panel A) or Type 2 (Panel B) shocks to bank capital ratios (250 basis points). Foreign net benefits are calculated as weighted average of the net benefits in non-domestic countries, where the weights are determined by the countries' nominal GDP in 2014. Euro area weighted averages are calculated in the same way, but also include domestic economies.

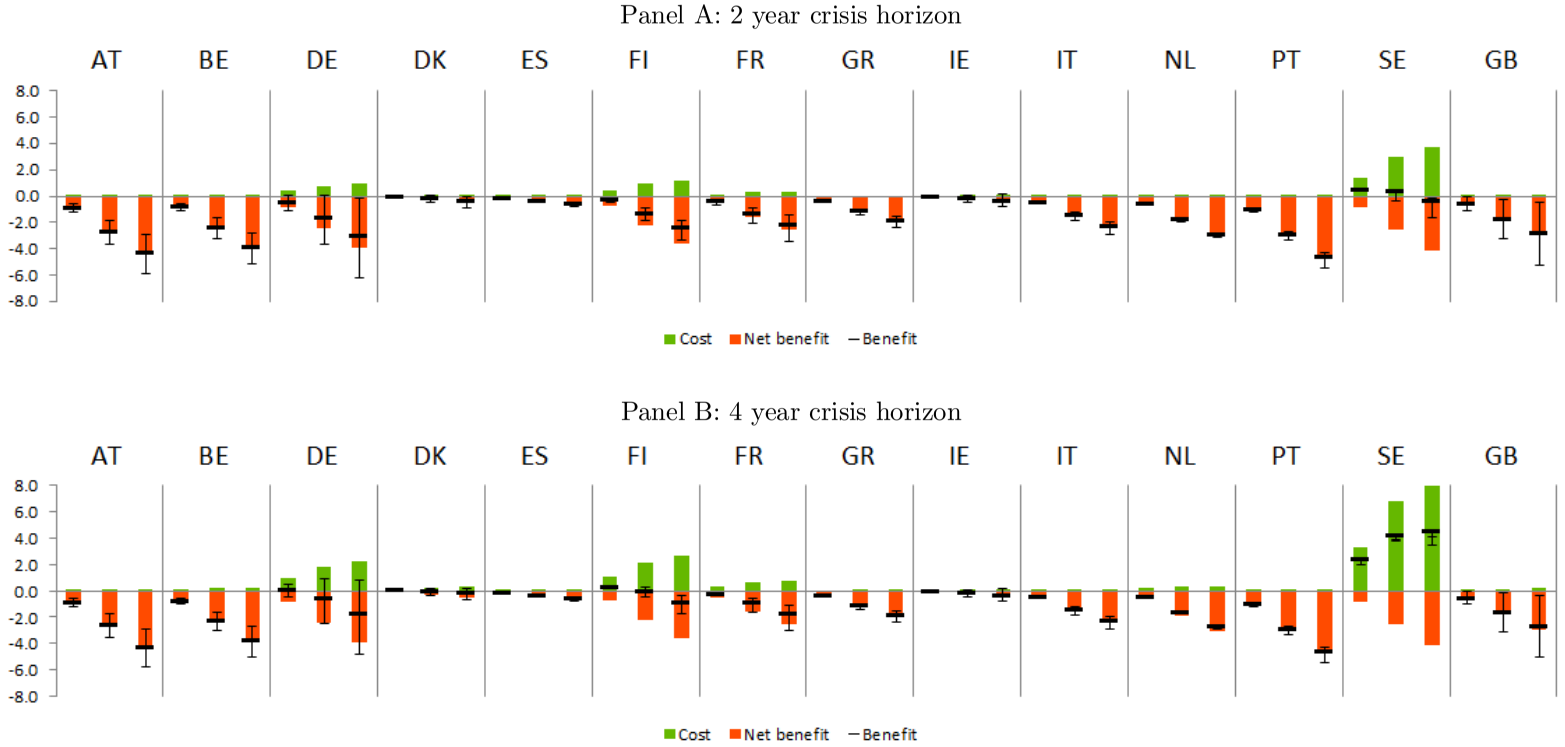


Figure 12: **Costs and benefits – Alternative crisis horizon.** The figure shows estimates for the benefits, costs, and net benefits of Type 1 shocks to bank capital ratios. To arrive at estimates for the median cost of a banking crisis, output losses associated with the crisis are cumulated over a period of 2 years (Panel A) or 4 years (Panel B) instead of the 3 years employed for the estimates in Figure 7. For each country, the bars and markers refer to shocks of 50, 150, and 250 basis points, respectively. Error bars for the black markers correspond to the net benefits that arise from feeding error bounds (25^{th} and 75^{th} percentile) of the GVAR responses through the model structure.

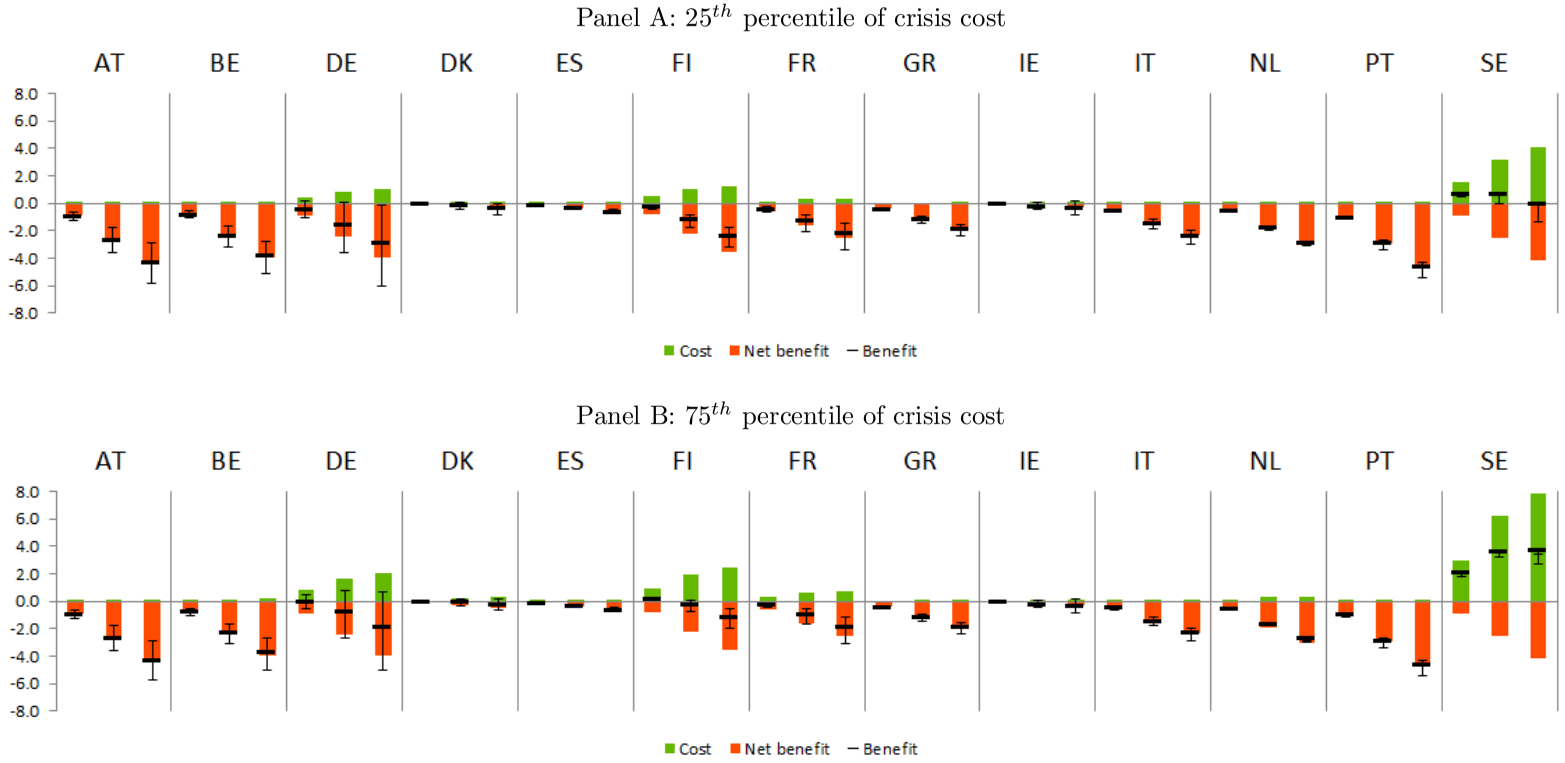


Figure 13: **Costs and benefits – Alternative percentile for crisis cost.** The figure shows estimates for the benefits, costs, and net benefits of Type 1 shocks to bank capital ratios. To estimate the benefits, the figure makes use of the 25^{th} percentile (Panel A) or the 75^{th} percentile (Panel B) of the crisis cost, instead of the median that is used in Figure 7. For each country, the bars and markers refer to shocks of 50, 150, and 250 basis points, respectively. Error bars for the black markers correspond to the net benefits that arise from feeding error bounds (25^{th} and 75^{th} percentile) of the GVAR responses through the model structure.

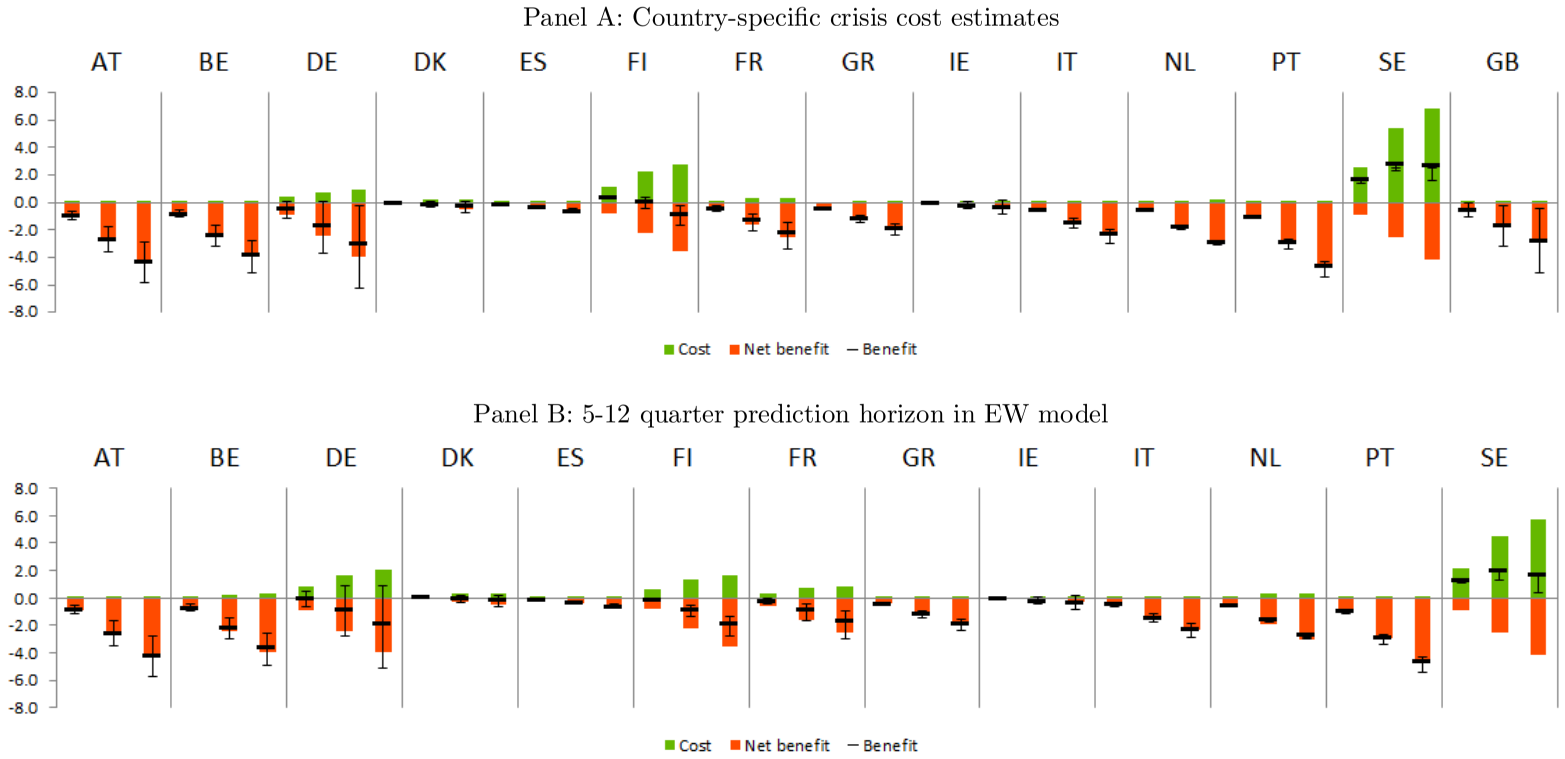


Figure 14: **Costs and benefits – Additional robustness.** The figure shows estimates for the benefits, costs, and net benefits of Type 1 shocks to bank capital ratios. To estimate the benefits, Panel A makes use of the country-specific crisis costs displayed in Table 1, instead of the median that is used in Figure 7. For Panel B, the model underlying the figure seeks to predict the period of 5-12 quarters preceding a crisis, instead of the 7-12 quarter horizon that is used for the model in Figure 7. For each country, the bars and markers refer to shocks of 50, 150, and 250 basis points, respectively. Error bars for the black markers correspond to the net benefits that arise from feeding error bounds (25^{th} and 75^{th} percentile) of the GVAR responses through the model structure.

Table 1:
Dates and costs of banking crises

The table shows crisis dates obtained from Duprey et al. (2015) and average output losses associated with banking crises in our sample countries. Output losses are defined as the cumulative sum of differences between actual and trend real GDP over a period of three years, expressed as percentage of trend real GDP (following Laeven and Valencia 2012).

	Crisis dates	Average output loss associated with a banking crisis (in % of GDP)
Austria	2008q1-2010q3	20.9
Belgium	1990q3-1993q3, 2007q4-2013q1	17.9
Germany	1980q2-1982q1, 1992q3-1994q3, 2001q4-2003q3, 2008q3-2010q2	16.7
Denmark	1992q3-1993q3, 2008q1-2010q2	32.6
Spain	1992q3-1992q3, 2008q1-ongoing	37.2
Finland	1990q4-1996q2, 2001q1-2001q3, 2008q4-2010q3	42.2
France	1991q2-1993q1, 2008q1-2012q3	19.1
Greece	2008q1-ongoing	65.6
Ireland	2008q1-ongoing	42.4
Italy	1991q3-1996q3, 2008q1-ongoing	27.0
Netherlands	1980q2-1983q3, 2002q2-2004q2, 2008q1-2010q3	19.7
Portugal	2008q1-ongoing	16.0
Sweden	1982q1-1983q2, 1991q1-1994q3, 2000q4-2001q3, 2008q3-2010q3	32.2
United Kingdom	2007q4-2010q2	24.4
Output loss (25th percentile)		19.1
Output loss (median)		27.0
Output loss (75th percentile)		37.2

Table 2:

Logistic early warning system

The table shows estimation results for multivariate logit models, where the dependent variable is equal to one seven to twelve quarters preceding a banking crisis in a respective country and zero otherwise. Observations for crisis periods are omitted. At the bottom of the table, several evaluation criteria for the models are reported. For these, predicted probabilities are transformed into binary signals via the signaling approach. The preference parameter of $\mu = 0.85$ indicates the policy maker's relative preferences between the detection of crises and the avoidance of false alarms, where a larger μ corresponds to a stronger preference for the former. The optimal threshold is calculated as the one that maximizes the relative usefulness and gives the percentile of the country-specific distribution of predicted probabilities at which the model issues a warning. The table further reports the fraction of type I/II errors made by the models, the relative usefulness and the adjusted noise-to-signal ratio, the percentage of vulnerable periods correctly predicted by the models, the probability of a crisis conditional on a signal being issued, and the difference between the conditional and the unconditional probability of a crisis (see Section 3.1 for details on the evaluation measures). Robust standard errors adjusted for clustering at the quarterly level are reported in parentheses. * indicates statistical significance at the 10 %-level, ** at the 5 %-level, and *** at the 1 %-level.

Dependent variable	*Indicator for vulnerable state*							
	Country regressors		Weighted regressors		Country regressors		Weighted regressors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit growth	0.052**	0.099***	0.076***	0.142***				
	(0.024)	(0.024)	(0.029)	(0.030)				
Bank credit growth					0.133***	0.200***	0.179***	0.256***
					(0.021)	(0.027)	(0.028)	(0.035)
GDP growth	-0.077	-0.092	-0.081	-0.109	-0.162***	-0.138*	-0.190**	-0.190*
	(0.056)	(0.067)	(0.079)	(0.086)	(0.061)	(0.076)	(0.086)	(0.101)
Inflation	0.017	-0.012	0.005	-0.014	0.076	0.039	0.088	0.063
	(0.069)	(0.078)	(0.084)	(0.095)	(0.066)	(0.079)	(0.082)	(0.102)
House price growth	0.105***	0.145***	0.127***	0.184***	0.095***	0.140***	0.113***	0.183***
	(0.013)	(0.018)	(0.017)	(0.023)	(0.013)	(0.017)	(0.017)	(0.024)
Equity price growth	0.016***	0.013**	0.017***	0.014**	0.016***	0.013**	0.017***	0.013**
	(0.005)	(0.006)	(0.006)	(0.007)	(0.005)	(0.005)	(0.006)	(0.006)
Bank capitalization	-0.278***	-0.618***	-0.314***	-0.674***	-0.378***	-0.643***	-0.435***	-0.726***
	(0.055)	(0.137)	(0.058)	(0.142)	(0.061)	(0.133)	(0.065)	(0.144)
Constant	-0.638**		-0.625*		-0.203		-0.124	
	(0.322)		(0.344)		(0.350)		(0.384)	
Country dummies	NO	YES	NO	YES	NO	YES	NO	YES
Observations	920	878	920	878	916	878	916	878
Pseudo R-Squared	0.128	0.185	0.149	0.216	0.177	0.243	0.205	0.279
AUROC	0.758	0.787	0.776	0.806	0.784	0.821	0.805	0.846
Mu	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85
Optimal threshold	61	70	56	64	61	70	58	71
Type 1 errors	0.248	0.338	0.166	0.255	0.214	0.297	0.166	0.276
Type 2 errors	0.327	0.237	0.368	0.293	0.321	0.229	0.347	0.214
Relative usefulness	0.394	0.384	0.446	0.421	0.440	0.438	0.468	0.477
Adj noise-to-signal	0.436	0.359	0.441	0.394	0.408	0.326	0.415	0.296
Perc predicted	0.752	0.662	0.834	0.745	0.786	0.703	0.834	0.724
Cond prob	0.312	0.356	0.309	0.334	0.327	0.378	0.323	0.401
Prob diff	0.147	0.190	0.144	0.169	0.161	0.213	0.158	0.236

Table 3:
Reduction in crisis probabilities

The table shows the reduction in crisis probabilities in average country, either in absolute terms or scaled by the average crisis probability or the crisis probability in 2014Q4 in the respective country. Panel A refers to type 1 shocks to bank capital ratio, Panel B to type 2 shocks and Panel C to type 3 shocks.

Panel A: Type 1 adjustment						
Buffer size (in bps)	25	50	100	150	200	250
Average reduction	0.006	0.011	0.018	0.022	0.025	0.028
Average reduction to average	0.031	0.055	0.090	0.112	0.128	0.139
Average reduction to 2014Q4	0.176	0.316	0.517	0.649	0.739	0.802
Panel B: Type 2 adjustment						
Buffer size (in bps)	25	50	100	150	200	250
Average reduction	0.003	0.005	0.008	0.011	0.014	0.015
Average reduction to average	0.013	0.023	0.042	0.056	0.068	0.078
Average reduction to 2014Q4	0.070	0.133	0.239	0.321	0.385	0.435
Panel C: Type 3 adjustment						
Buffer size (in bps)	25	50	100	150	200	250
Average reduction	0.004	0.006	0.011	0.015	0.018	0.020
Average reduction to average	0.018	0.032	0.056	0.075	0.090	0.101
Average reduction to 2014Q4	0.109	0.205	0.360	0.478	0.569	0.640

Table 4:

Logistic early warning system – horizon robustness

Columns 1 and 2 show results from a multinomial logit model, where the dependent variable is set to 1 for 12 to 7 quarters prior to a systemic crisis, set to 2 for crisis periods and 1 to 4 quarters after a crisis, and set to 0 for tranquil periods. Column 1 shows coefficients for the comparison between pre-crisis and tranquil periods, column 2 shows coefficients for the comparison between crisis/post-crisis and tranquil periods. Columns 3 to 6 show estimation results for multivariate logit models, where the dependent variable is equal to 1 during the quarters preceding a banking crisis specified at the top of the table, while observations for crisis periods are omitted. Robust standard errors adjusted for clustering at the quarterly level are reported in parentheses. * indicates statistical significance at the 10 %-level, ** at the 5 %-level, and *** at the 1 %-level.

Dependent variable	*Indicator for vulnerable state*					
	Multi logit model					
	(1)	(2)	(3)	(4)	(5)	(6)
	Pre-crisis	Crisis/Post-crisis	5−12Q	1−12Q	1−8Q	9−16Q
Bank credit growth	0.248***	-0.029	0.238***	0.191***	0.156***	0.162***
	(0.034)	(0.033)	(0.032)	(0.027)	(0.025)	(0.039)
GDP growth	-0.116	-0.261***	-0.040	0.029	0.097*	-0.087
	(0.077)	(0.059)	(0.098)	(0.057)	(0.051)	(0.077)
Inflation	-0.026	0.207***	-0.049	0.007	-0.005	-0.160*
	(0.083)	(0.066)	(0.091)	(0.070)	(0.075)	(0.087)
House price growth	0.170***	-0.155***	0.139***	0.079***	0.020	0.218***
	(0.022)	(0.029)	(0.027)	(0.021)	(0.019)	(0.035)
Equity price growth	0.012**	-0.022***	0.010*	0.002	-0.003	0.017***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)
Bank capitalization	-0.654***	-0.082	-0.591***	-0.395***	-0.210**	-0.710***
	(0.128)	(0.073)	(0.134)	(0.092)	(0.084)	(0.086)
Observations	1,362		955	1,076	1,076	851
Pseudo R-Squared	0.353		0.271	0.193	0.128	0.270
AUROC	—		0.838	0.785	0.731	0.849
Standard error	—		0.0165	0.0154	0.0191	0.0142

Appendix A: Global solution of the MCS-GVAR model

The system presented in the set of equations (4) contains time-contemporaneous relationships, thus it is not yet ready for being used for forecasting or simulation purposes. The global model has therefore to be solved, meaning that the equations for all countries and banking systems need to be stacked and reformatted in a way to contain only lagged relationships. The global solution of the model can be derived in four steps.

Step 1: Generate A-matrices. We start by stacking the within-cross-section vectors along with the cross-cross-section weighted variable vectors in (here) two vectors $\boldsymbol{m}_{it}^{x}$ and $\boldsymbol{m}_{jt}^{y}$.

$$\begin{aligned} \boldsymbol{m}_{it}^{x} &= \left(\begin{array}{ccc} \boldsymbol{x}_{it\prime} & \boldsymbol{x}_{it}^{*,C-C\prime} & \boldsymbol{y}_{it}^{*,C-B\prime} \end{array} \right)' \\ \boldsymbol{m}_{jt}^{y} &= \left(\begin{array}{ccc} \boldsymbol{y}_{jt\prime} & \boldsymbol{x}_{jt}^{*,B-C\prime} & \boldsymbol{y}_{jt}^{*,B-B\prime} \end{array} \right)' \end{aligned} \tag{10}$$

We can rewrite the equation system with these $\boldsymbol{m}$ vectors as follows.

$$\begin{aligned} \underbrace{\left(\begin{array}{ccc} I_{k_i^x} & -\Lambda_{i,0,0} & -\Lambda_{i,1,0} \end{array} \right)}_{\equiv \boldsymbol{A}_{i0}^{x}} \boldsymbol{m}_{it}^{x} &= \boldsymbol{a}_i + \underbrace{\left(\begin{array}{cc} \Phi_{i1} & \Lambda_{i,1,1} \end{array} \right)}_{\equiv \boldsymbol{A}_{i1}^{x}} \boldsymbol{m}_{i,t-1}^{x} + ... + \boldsymbol{\epsilon}_{it} \\ \underbrace{\left(\begin{array}{ccc} I_{g_j^y} & -\Xi_{j,0,0} & -\Xi_{j,1,0} \end{array} \right)}_{\equiv \boldsymbol{A}_{j0}^{y}} \boldsymbol{m}_{jt}^{y} &= \boldsymbol{b}_j + \underbrace{\left(\begin{array}{cc} \Pi_{j1} & \Xi_{j,1,1} \end{array} \right)}_{\equiv \boldsymbol{A}_{j1}^{y}} \boldsymbol{m}_{j,t-1}^{y} + ... + \boldsymbol{\omega}_{jt} \end{aligned} \tag{11}$$

Step 2: Generate L-matrices ("link" matrices). With a global, stacked variable vector $\boldsymbol{s}_t = (\boldsymbol{x}_{1t}', ..., \boldsymbol{x}_{Nt}', \boldsymbol{y}_{1t}', ..., \boldsymbol{y}_{Mt}')$ at hand, we can link the cross-section-specific variable vectors $\boldsymbol{m}_{it}^{x}$ and $\boldsymbol{m}_{jt}^{y}$ to $\boldsymbol{s}_t$. The link matrices $\boldsymbol{L}_i^{x}$ and $\boldsymbol{L}_j^{y}$ are used to map the local cross-section variables into the global vector, which involve the weights from the weight matrices $\boldsymbol{W}$.

$$\begin{aligned} \boldsymbol{m}_{it}^{x} = \boldsymbol{L}_i^{x} \boldsymbol{s}_t \quad &\rightarrow \quad \boldsymbol{A}_{i0}^{x} \boldsymbol{L}_i^{x} \boldsymbol{s}_t = \boldsymbol{a}_i + \boldsymbol{A}_{i1}^{x} \boldsymbol{L}_i^{x} \boldsymbol{s}_{t-1} + ... + \boldsymbol{\epsilon}_{it} \\ \boldsymbol{m}_{jt}^{y} = \boldsymbol{L}_j^{y} \boldsymbol{s}_t \quad &\rightarrow \quad \boldsymbol{A}_{j0}^{y} \boldsymbol{L}_j^{y} \boldsymbol{s}_t = \boldsymbol{b}_j + \boldsymbol{A}_{j1}^{y} \boldsymbol{L}_j^{y} \boldsymbol{s}_{t-1} + ... + \boldsymbol{\omega}_{jt} \end{aligned} \tag{12}$$

Step 3: Generate G-matrices. The equation-by-equation system can now be stacked into a global system.

$$\boldsymbol{G}_0^x = \begin{pmatrix} \boldsymbol{A}_{10}^x \boldsymbol{L}_1^x \\ ... \\ \boldsymbol{A}_{N0}^x \boldsymbol{L}_N^x \end{pmatrix}, \boldsymbol{G}_1^x = \begin{pmatrix} \boldsymbol{A}_{11}^x \boldsymbol{L}_1^x \\ ... \\ \boldsymbol{A}_{N1}^x \boldsymbol{L}_N^x \end{pmatrix}, ..., \boldsymbol{a} = \begin{pmatrix} \boldsymbol{a}_1 \\ ... \\ \boldsymbol{a}_N \end{pmatrix}$$
$$\boldsymbol{G}_0^y = \begin{pmatrix} \boldsymbol{A}_{10}^y \boldsymbol{L}_1^y \\ ... \\ \boldsymbol{A}_{M0}^y \boldsymbol{L}_M^y \end{pmatrix}, \boldsymbol{G}_1^y = \begin{pmatrix} \boldsymbol{A}_{11}^y \boldsymbol{L}_1^y \\ ... \\ \boldsymbol{A}_{M1}^y \boldsymbol{L}_M^y \end{pmatrix}, ..., \boldsymbol{b} = \begin{pmatrix} \boldsymbol{b}_1 \\ ... \\ \boldsymbol{b}_M \end{pmatrix} \tag{13}$$

These cross-section-specific G matrices can be further combined to a set of global G matrices. The intercept vectors $\boldsymbol{a}$ and $\boldsymbol{b}$ are combined in a vector $\boldsymbol{d}$. That is,

$$\boldsymbol{G}_0 = \begin{pmatrix} \boldsymbol{G}_0^x \\ \boldsymbol{G}_0^y \end{pmatrix}, \boldsymbol{G}_1 = \begin{pmatrix} \boldsymbol{G}_1^x \\ \boldsymbol{G}_1^y \end{pmatrix}, ..., \boldsymbol{d} = \begin{pmatrix} \boldsymbol{a} \\ \boldsymbol{b} \end{pmatrix} \tag{14}$$

Step 4: Generate H-matrices. The global system can now be pre-multiplied by the inverse of $\boldsymbol{G}_0$. The system is now ready to be used for shock simulation and forecast purposes.

$$\boldsymbol{s}_t = \underbrace{G_0^{-1} d}_{\equiv H_0} + \underbrace{G_0^{-1} G_1}_{\equiv H_1} \mathbf{s}_{t-1} + ... + \boldsymbol{G}_0^{-1} \boldsymbol{\varphi}_t \tag{15}$$

Since the weights are time-varying, a choice has to be made as to the reference point in time of which the weights are taken to solve the global model. For the shock simulations that we present we take the end-sample (2014Q4) weight sets as a basis for deriving the global solution.

Based on the estimated and solved model, we conduct a series of impulse response simulations, starting from capital ratio shocks (details concerning the shock size calibration and identification can be found in Section 3.3). The baseline paths for all predictors out of the GVAR along with the simulated deviations from baseline are then fed through the early warning model in order to assess the development of the predicted probability of being in a vulnerable state relative to the baseline scneario. Integrating the two models therefore means that the logistic model equations are appended to the GVAR as a satellite (thus the crisis probability measure as such is not included back in the GVAR, i.e. remains a synthetic summary measure of a crisis propensity as a function of capital and macro variables). If a macroprudential measure works as intended, the predicted probability of being in a vulnerable state should decline in response to their implementation. The question is whether the gain from higher capital ratios would outweigh the possible counteracting pressure on crisis probabilities from lower economic activity. The net benefit aspect will be addressed in Section 4.2.

Acknowledgements
The paper has benefited from useful discussions with seminar participants at the ECB/ESRB, the IMF, the 2015 RiskLab/BoF/ESRB Conference on Systemic Risk Analytics, the 2015 CFE Conference, and the 2016 Research Workshop on Macroprudential Policy at Banco de Portugal. The working paper should not be reported as representing the views of the European Central Bank (ECB) or the European Systemic Risk Board (ESRB), or any of their member institutions. The views are those of the authors.

Markus Behn
European Central Bank, Frankfurt, Germany; email: markus.behn@ecb.europa.eu

Marco Gross
European Central Bank, Frankfurt, Germany; email: marco.gross@ecb.europa.eu

Tuomas Peltonen
European Systemic Risk Board, Frankfurt, Germany; email: tuomas.peltonen@esrb.europa.eu

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

ISSN 1725-2806 (online)
ISBN 978-92-899-2183-1
DOI 10.2866/694075
EU catalogue No QB-AR-16-052-EN-N