BANKA SLOVENIJE

EVROSISTEM

DELOVNI ZVEZKI BANKE SLOVENIJE/
BANKA SLOVENIJE WORKING PAPERS:

EARLY WARNING FAVAR MODEL FOR THE ASSESSMENT OF THE EFFECTS OF MACROPRUDENTIAL POLICY ON RISKS IN THE BANKING SECTOR

Selcuk Ozsahin

1/2021

Title/*Naslov*: Early warning FAVAR model for the assessment of the effects of macroprudential policy on risks in the banking sector

No./*Številka*: 1/2021

Published by/*Izdajatelj*: BANKA SLOVENIJE
Slovenska 35
1505 Ljubljana
tel.: 01/+386 1 47 19 000
http://www.bsi.si

The BANKA SLOVENIJE WORKING PAPERS collection is drawn up and edited by the Banka Slovenije's Analysis and Research Department (Tel: +386 01 47 19 680; Email: arc@bsi.si).
The views and conclusions expressed in the papers in this publication do not necessarily reflect the official position of Banka Slovenije or its bodies.

Zbirko DELOVNI ZVEZKI BANKE SLOVENIJE *pripravlja in ureja Analitsko-raziskovalni center Banke Slovenije (telefon: 01/47 19 680, e-pošta: arc@bsi.si).*
Mnenja in zaključki, objavljeni v prispevkih v tej publikaciji, ne odražajo nujno uradnih stališč Banke Slovenije ali njenih organov.

https://www.bsi.si/publikacije/raziskave-in-analize/delovni-zvezki-banke-slovenije

Katložni zapis o publikaciji (CIP) pripravili v Narodni in univerzitetni knjižnici v Ljubljani
COBISS.SI-ID 86321923
ISBN 978-961-6960-55-7 (PDF)

Early Warning FAVAR Model for the Assessment of the Effects of Macroprudential Policy on Risks in the Banking Sector*

Selcuk Ozsahin†

March 30, 2021

Abstract

This paper presents a model that combines a logistic-based early warning model with the factor-augmented vector autoregression (FAVAR) methodology to simulate and assess the effects of capital-based macroprudential policy on the risks in the banking sector at the sector- and individual-bank level. Using the integrated Early Warning FAVAR (EW-FAVAR) model developed in this paper, I show that a counter-cyclical implementation of the capital requirements prior to the 2008 global financial crisis, by introducing stringent requirements early in the build-up phase and an easing as the crisis unfolded, would significantly reduce the risks in the banking sector in Slovenia in this period. I contrast the effectiveness of the prudential policy using different signalling horizons and show that a *late* intervention by means of a tightening, in the face of material risks, risks pro-cyclical effects.

Keywords: Macroprudential policy, financial crisis, bank distress, early-warning system, capital requirements, regulation, banking system resilience

JEL Classification: E58, G01, G17, G21, G28, C38, C53, C54

*Disclaimer: The views expressed in this paper are solely the responsibility of the author and should not be interpreted as reflecting the views of the Bank of Slovenia.

†Bank of Slovenia. Email: selcuk.ozsahin@bsi.si

Povzetek

V članku je predstavljen model, ki združuje logistični model zgodnjega opozarjanja z metodo vektorske avtoregresije s faktorji (FAVAR) z namenom simulacije in ocene učinkov kapitalskih makrobonitetnih instrumentov na tveganja v bančnem sektorju (tako na ravni sektorja kot na ravni bank). Na podlagi integriranega modela zgodnjega opozarjanja FAVAR (EW-FAVAR) utemeljujem, da bi proticiklično izvajanje kapitalskih zahtev pred svetovno finančno krizo iz leta 2008 oziroma z uvedbo strogih zahtev v predkriznem obdobju in njihovo sproščanje v fazi umirjanja krize, znatno zmanjšalo tveganje v bančnem sektorju v Sloveniji. V analizi primerjam učinkovitost makrobonitetne politike skozi različna signalna obzorja in ugotavljam, da pozno ukrepanje v luči povečanih makrofinančnih ranljivosti povečuje tveganje za neželene prociklične učinke.

1 Introduction

The period since the global financial crisis demonstrated the necessity of counter-cyclical policies and led to the emergence of macroprudential policy as a new policy area. The macroprudential policy tool kit has expanded since then. There have also been extensive efforts to develop analytical tools and match the variety of new policy instruments. Nonetheless, research on quantifying the impact of macroprudential policy on systemic risk is nascent and operational tools remain lacking or scarce[1].

In this paper, I develop an integrated model that combines two methodologies, a logistics-based early warning (EW) model and a structural factor-augmented vector autoregression (FAVAR), to measure the effect of capital-based prudential policy on the vulnerability of the banks. The EW side of the integrated model enables us to monitor banking sector risks, while the FAVAR serves as a tool for simulating the dynamic effects of capital requirements on bank and macro-level variables, which are identified as the risk indicators on the EW side. The FAVAR projections are then fed into the EW model to predict the effects of the policy on the evolution of the risk in the banking sector.

As such, the EW-FAVAR model can guide policy in activating and calibrating the capital-based macroprudential instruments. Using the EW-FAVAR model and data from Slovenian banks, I show that a countercyclical implementation of capital requirements prior to the global financial crisis, a tightening in terms of banks' capital ratios introduced at the inception of the growing imbalances in Slovenia before the global financial crisis, in 2005 Q3, followed by a release as the crisis unfolded, would significantly reduce the risks in the banking sector[2]. However, the timing and the signalling horizon affects the outcomes. A *late* intervention in the face of material risks, when tightening is introduced in 2007 Q4[3], would have had pro-cyclical effects and would have been less effective overall.

On the EW side, the EW-FAVAR builds on an early warning framework as developed in Lang et al. (2018). The EW side of the integrated model enables predicting distress at the bank level, using macro and sector level indicators alongside the bank-level variables considering the impact of the environment that the banks operate. EW model output is presented in terms of distress probabilities both over the time dimension and with the distribution of risks across the individual banks. Following Lang et al. (2018), distress probabilities are given with a decomposition of contributing factors. I use four categories of factors: bank-level, sector-level, macro-financial and the direct effect of the bank capital.

[1] As a recent vice president of the European Central Bank stated 'we need to quantify the impact of macroprudential tools on the macro-finance interaction and on the systemic risk indicator. This is still a major open field for research' (Vítor Constâncio, 5th Macroprudential Conference at Deutsche Bundesbank, August 2019).

[2] 2005 Q3 is determined by the EW model as the date the predicted overall distress probability across the banks surpassed a signalling threshold using 9-to-16 quarters ahead distress prediction horizon. According to the counterfactual exercise, the overall Tier 1 capital ratio increases by 2pp until 2006 Q3 over one year; this level is preserved until 2007 Q3. Release is simulated by cancelling positive tightening capital regulation shocks in the data in this period.

[3] This time using a distress prediction horizon of 1-to-8 quarters.

Budnik et al. (2019) show that structural factor-augmented vector autoregression methodology suits the purpose of macroprudential policy analysis, as it allows for considering cyclical and structural (cross-sectional) aspects -the two dimensions of macroprudential policy- within one empirical-macro framework[4]. EW-FAVAR differs from the policy assessment approach in Budnik et al. (2019) as I link the benefits from regulation to the concept of risk and distress probability, instead of gains in credit provision. The EW-FAVAR approach serves particularly to countercyclical policy analysis.

A similar integrated approach is taken in Behn et al. (2016), which combines a logistic based early warning model with global vector autoregression (GVAR). Behn et al. (2016) develop an EW-GVAR methodology to conduct cost and benefit analyses of capital-based policies in a multi-country setup. Their model uses country-level banking sector variables: average capital ratio, loan interest rates and loan growth, together with a set of macro variables. The EW-GVAR approach in Behn et al. (2016) has an advantage in taking into account cross-country spillovers in the European context.

When implemented at the individual country level, however, the EW-FAVAR approach developed in this paper has a number of advantages. First of all, the bank-level approach allows for an assessment of the cross-sectional distribution of risks across the banking sector. Second, using granular bank-level data can improve identification of the shocks and transmission mechanisms on the FAVAR side, while it also increases the number of distress observations on the EW side of the model. Lastly, EW-FAVAR can be the preferred approach where national banks have actually adapted an EW approach at the bank level -as bank level data, covering all banks in the system, is available to them.

The remainder of the paper is organized as follows: Section 2 explains the methodology; Section 3 presents the results and Section 4 concludes.

2 Methodology

In this section, I first describe the EW side of the integrated EW-FAVAR model, which is used to monitor and measure the risks in terms of future distress probabilities. Next, I introduce the FAVAR methodology that enables simulating the evolution of the variables defined as the vulnerability indicators in response to capital regulation and under predetermined scenarios.

[4] Early implementations of the factor model approach to VARs and the FAVARs were aimed at exploiting information from richer datasets to overcome model misspecification (omitted variable) and measurement error issues (e.g., in Bernanke et al. 2005). Dave et al. (2013) employs FAVAR methodology to use macro data with micro banking data for a research on the bank lending channel and Buch et al. (2014) uses FAVAR for the analysis of interactions between developments at the macro level and bank-level factors. Budnik et al. (2019) extends this approach to build a cost-benefit analysis framework for the assessment of the optimal level of capital buffers through the cycle.

2.1 The early warning model

Early warning models seek to capture the dynamics that lead to a crisis or distress in the banking sector and identify vulnerable states. The aim is often to predict potential future distress events. An early warning model can also be used to explain past distress events and understand the contributing factors and dynamics that lead to the build-up of imbalances.

My analysis uses the EW methodology and the model that is currently in use at Bank of Slovenia (Volk, 2017)[5]. The Bank of Slovenia model corresponds to the EW modelling framework that is introduced in Lang et al. (2018): It combines logistic regression for predicting distress at the bank level[6], using bank-level, sector-level and macro data, with a loss function to set signalling thresholds. The model output is represented, following Lang et al. (2018), with a visualisation of overall risk and the contributing factors, as bank-level, banking sector, macro-financial risks and the direct effect of the bank capital[7], over the time dimension and at both the bank level and aggregated level by applying appropriate weights to individual banks.

The probability of being in a vulnerable state is estimated via the following logit model:

$$P(I_{i,t}^{h} = 1 \mid X_{i,t} = x_{i,t}) = p_{i,t} = \frac{e^{\beta' x_{i,t}}}{1 + e^{\beta' x_{i,t}}} \tag{1}$$

Being in distress state for bank i at period t is a binary state variable $I_{i,t} \in \{0, 1\}$ and $I_{i,t}^{h} \in \{0, 1\}$ indicates being in a vulnerable state where the h is the prediction horizon. X is a vector of risk drivers plus an intercept and β is a coefficient vector. The model is estimated using maximum likelihood[8]. $p_{i,t}$ is the estimated probability of being in vulnerable state. $p_{i,t}$ is translated into a binary signal $P_{i,t} \in \{0, 1\}$ by specifying a threshold τ^{*}.

The threshold, which also guides the activation of prudential policy by classifying observations into vulnerable and not vulnerable states, is determined by optimizing a loss function, as in Sarlin (2013), taking into account the policy maker's preferences between type I errors (missing distress events) and type II errors (issuing false alarms).

[5] The documentation of the overall Bank of Slovenia EW system is not yet publicly available.

[6] Distress events are defined at the bank-level for two reasons: First, it provides a larger number of distress events and allows for better identification. Otherwise, Slovenia has experienced only one systemic banking crisis. The concept of distress, which we define referring to cases of significant deterioration in certain ratios or to events of government intervention, is broader than actual bank defaults too, where the latter is also rare. Second, it enables predicting distress for each individual bank. Hence, it is possible to present the cross-section distribution of risks and predict vulnerabilities for certain bank groups, such as those identified as 'systemically important institutions'.

[7] Besides the categories suggested in Lang et al. (2018), I include the effect of bank capital at the individual bank level as a fourth category. Having bank capital as a stand-alone category helps to distinguish the direct impact of bank capital from the other dynamics the changes in capital requirements can create.

[8] The regression model does not include random- or fixed-effects.

The loss function is the following:

$$L(\mu, \tau) = \mu T_1(\tau) P + (1 - \mu) T_2(\tau) N \quad (2)$$

$T1$ and $T2$ are the ratios of the number of false negative (FN) and false positive (FP) realisations divided by the total number of positives and negatives, respectively. Weighting by unconditional probabilities of distress and non-distress, denoted by P and N, is introduced to take into account the relative size of the two classes of events. μ is the preference parameter and stands for the preference of the policy maker between missing crises and issuing false alarms, and I set this parameter to 0.9 (assuming a risk averse prudential authority and referring to its frequent use in literature) and use 0.5 as the benchmark. The optimal threshold τ^* is derived as the one that minimizes the loss function L.

The EW model specification needs to correspond to the structural nature of the FAVAR side of the model and to correctly present the causal effects and the transmission of capital regulation (shocks) to measured risk in banking sector. Therefore, I adopt an expert model approach in choosing the variable set and pay attention to have intuitive signs on coefficients at logistic regressions (rather than prioritising to maximise the forecast performance) that present a meaningful mechanism of how risks build up and materialise[9]. I also aimed to include a large set of variables, while having comparable models that are consistent across the prediction horizons.

Table 2.1 presents the variables of the model. The variable set contains bank-level variables together with banking sector and macro-financial variables, as the environment the banks operate is critical to their vulnerability. Bank-level variables aim to cover categories of CAMELS[10], and banking sector and macro-financial variables contain a number of indicators that are considered to be relevant from the macroprudential policy perspective. The variables that are statistically significant are used when the alternatives are present. For instance, I use leverage ratio instead of the risk-weighted capital ratio because leverage ratio was a better predictor with statistically significant coefficients. For two of the bank-specific variables, credit default swap (CDS) proxy and return on equity, I use first differences, again because this specification provided statistically significant and intuitive estimates. Banking sector and macro variables introduce the economy wide dynamics.

[9] In developing an early warning approach for predicting financial imbalances in France, Coudert and Idier (2018) similarly retain models which have all or all except one coefficients statistically significant with expected signs (using two alternative approaches, as stringent and relaxed) from a larger possible set of logit models and variables. They employ model-averaging across the models and aim maximizing the in and out of sample prediction performance. I apply the significance and sign criteria for the validation of the single expert model.

[10] CAMELS is an acronym for categories that capture the important dimensions and state of banks' balance sheets: Capital adequacy, asset quality, management quality, earnings, liquidity and sensitivity to market risk. Most of the categories are covered in the model, except management quality. Cost to income ratio, which could stand for management quality, did not turn out to be a good predictor of distress for Slovenia and it is not among the model variables in Table 2.1.

Table 2.1: Variables of the early warning model

Variable name	Definition	Transformation
Bank level		
leverage ratio	Bank equity to total assets ratio	%
roe	Return on equity	%, 1-year difference
nonIr	Non-interest income ratio over gross income	%
ltd	Loan-to-deposits ratio (liquidity proxy)	%
cds_proxy	Deposit rate and 3m Euribor spread	%, 1-year difference
RWA_TA	Risk-weighted assets to total assets ratio	%
Banking sector		
bs_npl	Non-performing loan ratio (D, E rating loans in total assets)	%, 2-year difference
bs_credit_gap	Credit (to non-banking sector) to GDP gap	%, 3-year difference
bs_loans_hh	Credit to households real growth	%, 2-year growth
Macro-financial		
mf_DSR	Debt service-to-income ratio	%, 2-year difference
mf_pti_rre_gap	House price price-to-income gap	%, 3-year difference
mf_gdp	Real GDP growth	%, 2-year growth

Notes: mf_ and bs_ indicate the variables that are in macro-financial and banking sector categories and the other variables are observed at the individual bank level. All variables are seasonally adjusted, in case seasonality is present. The variable loan growth to households (bs_loans_hh) is deflated by the GDP deflator. Credit-to-GDP gap is calculated by HP filtering ($\lambda = 4000$). House price-to-income gap is the % deviation from sample average. Where D_t is outstanding debt, i_t is interest rate on debt, s_t is average maturity of debt and Y_t is annual income, Debt service-to-income ratio is calculated according to the formula: $DSR_t = \frac{i_t \times D_t}{(1-(1+i_t)^{-s_t}) \times Y_t}$.

Higher share of non-performing loans on bank's balance sheets are manifestations of risk at both bank and system level[11]. Credit-to-GDP gap is an integral component of the current macroprudential policy framework (BCBS, 2010) and often regarded as the single most important indicator. It measures the deviation of credit-to-GDP ratio from its trend to inform whether credit growth is in-line with the growth of economy, while allowing adjustments in the ratio's long-run trend. A focus on growth of loans to households is warranted by the findings in literature that suggest boom-bust cycles, generated by a rise in debt, is uniquely linked to household debt, rather than increases in firm or government debt (Mian and Sufi, 2018). Debt-service to income ratio is a useful risk indicator as it allows to consider the debt together with payment capacity and with the developments in incomes and the interest rates. House price to income ratio gap, calculated as the percentage deviation from the long-run mean of the ratio, is introduced as the measure of the the over- and undervaluation in the housing market[12]. Output growth (GDP) is included on a stand-alone basis. Banking sector and macro-financial variables are 2- or 3-year differences as longer lags are found to perform better (e.g., in Lang and Welz 2018 and Lang et al. 2019) and capture the durations the imbalances require to build up.

[11] At system level high share of NPLs has negative consequences for efficiency. NPLs are hard to value, costly to manage and costly in terms of capital resources. Moreover, an increase of NPLs may constrain credit flow and be procyclical in a downturn. Capital based regulation is one reason for the procyclicality as the non-performing loans are assigned higher risk weights implying higher regulatory capital and require provision (Suarez and Serrano, 2018).

[12] Since the global financial crisis in 2008, it is a consensus view that developments in the housing markets have major implications for the financial stability. I use a measure of the valuation gap, instead of house price growth, as low or high growth in housing price itself does not necessarily imply a misalignment with the fundamentals.

I use the distress events as identified for Slovenian banks in Volk (2017), which is based on an analysis, in communication with the supervision unit in Bank of Slovenia, of deterioration in certain bank ratios (capital adequacy, share of non-performing loans, profitability and etc.) and covers government interventions. Distress events appear in 2009-2011, with the first signs of the financial crisis in Slovenia[13]. In this period, eight out of eighteen banks in the sample experienced distress. In constructing the sample for the logit regressions, the distress period and observations that followed up until the date the Slovenian banking system returned to normal conditions, which is set to 2016 Q4 (when loan growth turned positive and banks registered profits), are excluded[14]. The sample covers the period between 2000 Q1 and 2019 Q4.

One can draw a distinction between near- and medium-term risks when developing the EW system[15]. Lang et al. (2018) state longer signalling horizons are appropriate for macroprudential policy, where policy aims to limit the imbalances from building up through endogenous feedbacks and the financial accelerator mechanism (while shorter prediction horizons are relevant from the micro-prudential perspective in assessing the resilience of banks to exogenous shocks). There can also be trade-offs between the medium-to-long run goals of macroprudential policy and the short-run effects; a policy design that ignores potential pro-cyclical effects may increase financial vulnerability[16]. Therefore, I use different time horizons that are chosen from the literature and consider both short- (1-to-8 quarters ahead) and medium-run (9-to-16 quarters ahead) effects in my analysis.

The last steps in the implementation of the EW model involve decomposing the distress probabilities into contributing factors and aggregating distress probabilities from bank-level to system-level, where the bank size is taken as the proxy of systemic importance for the banks, and probabilities at the bank level are weighted by the ratio of respective banks' total assets in overall banking sector assets. Appendix section A.1 presents the details of the procedure for decomposing the risk to driving factors and aggregating from bank to system level.

[13] Another approach could be referring to the results of the 'comprehensive assessment of capital shortfalls' of banks that took place in 2013 in Slovenia, which could require less reliance on expert judgment regarding the banks' conditions. While Bank of Slovenia EW system offers this option as an alternative, I opt for the 'early' identification of distress, instead of referring to the peak of the crisis. This approach to defining the distress events can help mitigate the confounding factors for the empirical analysis as the non-distressed banks and their ratios were also affected by the deteriorated environment in the late stages of the crisis.

[14] Excluding the post-crisis observations in constructing the sample follows the practice of Lo Duca et al. (2017), which aims to address the issue of 'post-crisis bias' (Bussiere and Fratzscher, 2006).

[15] For example, such distinction is made in ECB's May 2018 Financial Stability Review (ECB, 2018), where two separate risk indicators were introduced to monitor and anticipate risks at short- and medium-run horizons (ECB's 'financial stability risk index' and 'cyclical systemic risk indicator').

[16] A controversial example is the EBA's capital exercise in 2011. The exercise was introduced with the goal to improve major European banking groups' capital ratios in the face of the approaching crisis, yet it received criticism for its timing and for being pro-cyclical. Mesonnier and Monks (2015) and Gropp et al. (2019) show EBA's intervention indeed led to a significant reduction in credit supply by the capital exercise banks.

2.2 The FAVAR model

FAVARs are vector auto-regressions where the variable set in the vector autoregression (VAR) include, in addition to observed variables, unobserved factors that best summarize large set of information. In my application, the observed variables of the FAVAR are key macro variables, real GDP growth (quarter on quarter), inflation (quarter on quarter growth of GDP deflator) and real house price growth (quarter on quarter growth in the real house price index for all dwellings) and the unobserved factors of the FAVAR are extracted using principal components estimation from the bank-level dataset that consists of the bank level variables given in Table 2.2[17].

Variables in Table 2.2 correspond to the variable set in the EW model in Table 2.1. In some cases, the EW variables are not directly the FAVAR variables, but they are combinations and/or aggregations of the variables in the FAVAR model[18]. The leverage ratio in Table 2.1 is T1 ratio / RWA_TA. Credit gap, debt service ratio and house price-to-income gap are also produced from the GDP, aggregated credit growth, loan interest rates and house price variables.

Table 2.2: Variables of the FAVAR model

Variable name	Definition	Transformation
Bank level		
T1 ratio	T1 capital over risk-weighted assets	%
RWA_TA	Risk-weighted assets to total assets ratio	%
npl	NPL ratio (D, E rating loans in total assets)	%
roe	Return on equity	%
nonIr	Non-interest income ratio over gross income	
ltd	Loan-to-deposits ratio (measures liquidity)	%
nim	Net interest margin	%
ir_assets	Interest rates on loans	%
cds_proxy	Deposit rate and 3m Euribor spread	%
loans_nbs	Real loans to non-banking sector	%, q-o-q growth
loans_hh	Real loans to households	%, q-o-q growth
Macro		
mf_gdp	Real GDP	%, q-o-q growth
mf_deflator	GDP deflator	%, q-o-q growth
mf_rre_price	Real house prices	%, q-o-q growth

Notes: mf_ indicates the variables that are in macro category and the other variables are observed at the individual bank level. All variables are seasonally adjusted, in case seasonality is present. The variables loan growth to non-bank sector (loans_nbs), loan growth to households (loans_hh) and house prices (mf_rre_price) are deflated by the GDP deflator.

[17] The FAVAR sample, like the EW side of the model, covers the period between 2000 Q1 and 2019 Q4.

[18] Since the FAVAR side of the model is used for simulations of EW variables, the corresponding EW variables are simulated by processing the responses in FAVAR variables. They correspond to the arithmetic combinations of macro variables (for the EW variables mf_gdp, mf_pti_rre_gap) and bank level variables (EW variable leverage ratio) of the FAVAR, or they are produced by aggregating the bank-level FAVAR variables by weighting them by the respective bank size in terms of their assets in total banking assets (for the EW variables bs_npl, bs_loans_hh) or both aggregations and linear combinations are involved (for the EW variables bs_credit_gap, mf_DSR).

The FAVAR consists of six variables; three observed factors and three unobserved factors. The three unobserved factors are extracted from 180 bank-level variable series[19]. When choosing the number of unobserved factors, I aim that a large share of the co-movement in banking variables is captured by the principal components analysis estimation. Three unobserved factors together with the observed factors explain two thirds of the contemporaneous variation in bank-level variables on average across banks. The estimation procedure ensures the unobserved factors are orthogonal with respect to each other and to the observed variables.

Two dummy variables are included as exogenous variables in the model. One dummy variable aims to control for recapitalisations of major banks in Slovenia, which took place following an asset quality review (AQR) at the end of 2013, and set 1 starting from 2013 Q4 for the next 4 years (set zero in the other periods). The second dummy is set to 1 from 2011 Q1 until 2013 Q2 and stands for the euro area sovereign debt crisis (set zero in other periods)[20].

The number of lags is set to 2[21]. The FAVAR is estimated using Bayesian methods applying Gibbs sampler[22] and the Normal-Wishart prior.

Formally, the structural FAVAR model is given by

$$AF_t = \Gamma(L)F_{t-1} + \xi Z_t + e_t \tag{3}$$

$F_t = \left[F_t^{y'} \ F_t^{x'}\right]'$ is a $(M+K)\times 1$ vector which contains the $Mx1$ vector of observed variables and the $K \times 1$ vector of unobserved common factors in F_t^x. Z_t contains the two exogenous dummy variables. $\Gamma(L)$ is a lag polynomial of order p and $e_t \sim i.i.d.(0,\Omega)$ are the structural shocks with mean zero and diagonal covariance matrix Ω.

The FAVAR model is expressed in its reduced-form representation as

$$F_t = \Phi(L)F_{t-1} + \Theta Z_t + \epsilon_t \tag{4}$$

where $\Phi(L) = A^{-1}\Gamma(L)$ and $\epsilon_t = A^{-1}e_t \sim N(0,\Sigma)$ with $\Sigma = A^{-1}\Omega(A^{-1})'$. The ϵ_t is vector of reduced form innovations.

Equation (5) below relates the $N \times 1$ vector X_t of observable variables, which consist of banking variables observed across different banks, to the observed and unobserved factors.

[19] 18 banks x 11 bank-level variables would make 198 bank-level variables, if all variables were available for all banks in the sample period. One bank in Slovenia, SID-Slovenska Izvozna in Razvojna Banka, is a special type of bank that does not lend households, and loans_hh variable is not present for this bank.

[20] Slovenia was among the countries directly hit by the crisis, where spreads on government bonds in Slovenia returned to pre-crisis levels only in 2014 following the AQR and state recapitalisations of major banks.

[21] Schwarz and Hannan-Quinn information criteria (IC) suggest using one lag (Akaike IC implied a much larger number, eight lags, which I did not consider). I use two lags, despite the two IC suggesting one lag, considering how reasonable the responses at the bank-level variables are, which are estimated in the next step by the factors.

[22] I use 10.000 draws initially. I discard the first 1.000 draws and use every 10th draw by skipping the others.

$$X_t = \Delta^y F_t^y + \Delta^x F_t^x + u_t = \Lambda F_t + u_t \quad (5)$$

X_t includes a set of N observable variables different from those included in F_t^y. The unobserved factors in F_t^x are estimated from the time series contained in X_t. The identification of F_t^x ensures that latent factors are orthogonal to the observed variables F_t^y by applying the principal components estimation to the residuals from regressing X_t on F_t^y (following Budnik et al. 2019 and Budnik and Bochmann 2017)[23]. Δ^y and Δ^x are $N \times M$ and $N \times K$ matrices of factor loadings, where K is assumed to be much smaller than N. u_t is a $N \times 1$ vector of idiosyncratic disturbances assumed to be normally distributed with mean zero and diagonal covariance matrix, where $E[u_(i,t)\, u_(j,s)] = 0$, $\forall i, j = 1, \ldots, N$ and $\forall t, s = 1, \ldots, T$, $t \neq s$.

The impulse responses functions (IRFs) of the common factors are derived from the moving average representation of the VAR model, i.e., from $F_t = \Psi(L)\epsilon_t = \Psi(L)A^{-1}e_t$ where $\Psi(L)\epsilon_t = I - \Psi(L)$ and the IRFs of the bank-level variables are derived conditionally on the estimates of $\Psi(L)$ and Λ from $X_t = \Lambda\Psi(L)\epsilon_t + u_t = \Lambda\Psi(L)A^{-1}e_t + u_t$.

Identification

The identification approaches and analysis tools of structural vector auto-regressions can be carried over to structural factor models and to FAVAR. The FAVAR model presented above model is identified employing sign restrictions together with zero restrictions[24].

Sign and zero restrictions are presented in Table 2.3. The sign restrictions for the bank-level variables apply to their aggregation, where the impulse response functions at the bank level are aggregated by being weighted by the respective banks' total asset sizes in overall banking sector assets (as of 2008 Q1).

Table 2.3: Identification of structural shocks

Shock	Real GDP	Price level	RRE prices	Tier1 ratio	Credit Growth	Lending margin	Funding cost	Loan interest rate
Aggregate demand	+	+			+			+
Aggregate supply	+	-						
Housing demand	0		+					
Capital regulation	-			+	-	+	-	+
Credit supply	-			+	-	+	+	+

Notes: All restrictions refer to the contemporaneous impact on a variable. Price level in the table is mf_deflator, Credit growth is loans_nbs, Lending margin is nim, Funding cost is cds_proxy and Loan interest rate is ir_assets in Table 2.2.

[23]This procedure and the identification of unobserved factors, the first step of a FAVAR that is estimated in two steps as in Bernanke et al. (2005), is compared in Budnik and Bochmann (2017) in a similar research setting (related to interactions between bank level dynamics and macro variables) with the commonly applied iterative algorithm of Boivin and Giannoni (2007) and the outcome is stated to be negligibly different.

[24]I employ the algorithm proposed in Arias et al. (2016).

Five structural shocks are identified in the model[25]. The structural shocks other than the capital regulation shock are aggregate demand, supply, house demand and credit supply shocks. While I do not investigate the effects of these shocks, they are included in order to improve the identification and isolate the effect if the capital regulation shock[26].

The critical structural shock regarding the research question is the capital regulation shock. While this shock presents a similar pattern to a credit supply shock, which leads to a decrease in credit supply and has a negative impact on real GDP within the same quarter[27] as the banks deleverage in terms the capital ratios, it is distinguished from the credit supply shock as it is associated with a lower market funding cost for the banks[28]. The assumption relies on the insights and evidence from research (e.g., as documented in Gambacorta and Shin 2018) that point out that the banks that increase their capitalisation face lower funding costs compared to other banks[29]. CDS information, which reflects the markets' risk assessment of the banks, is not present for most Slovenian bank. Therefore, this variable is proxied by the spread between the retail deposit rate and the safe short-term rate -the three month Euribor. The impulse response functions estimated by the capital regulation shock are presented in Appendix A.3.

3 Results

3.1 Early warning estimates

Soundness of the coefficients on EW model variables, which stand for the correlations of these variables with the distress probabilities of the banks, is important for the following analysis as they should correctly represent the causal effects and the transmission of capital regulation to risks in the banking sector.

---

[25] The VAR consists of six endogenous variables and equations. Therefore, I include one more shock without an explicit definition and assigned a zero response by GDP to this shock on impact in order to make sure this shock is orthogonal to the capital ratio shock and does not compound its identification.

[26] A positive aggregate demand shock, as standard in the literature, is identified as a shock that leads to an immediate increase in GDP and general price level (GDP deflator) and a positive aggregate supply shock moves real GDP and the price level in opposite directions. Moreover, the aggregate demand shock is associated with demand driven credit growth and an increase in loan interest rates. The house demand shock immediately increases the residential real estate prices, while it does not have an effect on real GDP within the same quarter. The assumption of no effect or negligible effect on impact on real GDP, despite new dwellings and housing investment enter the calculation of GDP, is related to relative inelasticity of housing supply, with respect to demand, where it takes time for new housing projects to filter through the regulations and development phase, and takes even longer to deliver the final product.

[27] A constraining capital requirement is assumed, which is high enough to be binding and impacts banks within a short time frame (not gradually, phased-in manner) and leads to assets side deleveraging having a negative impact on GDP.

[28] Credit supply shocks in general, instead of those specifically due to regulation, should be more present in data. Hence, an alternative empirical strategy is proposed in Behn et al. (2016): Instead of identifying capital regulation shocks directly, authors identify credit supply shocks and simulate the effects of the changes in banks' capital ratios by translating them into to credit supply shocks. The approach in Behn et al. (2016) circumvents the identification problem. However, the response of funding costs, also a proxy for perceived riskiness of the banks, have implications at the EW side of the EW-FAVAR in my application and I am attentive to this variable and to the effects of capital regulation that could be identified by the response in funding costs.

[29] Although the overall costs could increase (at least partly within a short-run, as the equity is assumed to be costlier than deposits), here the 'funding costs' refer to market funding by means of debt and borrowing from the markets. The assumption is that the banks regarded less risky (due to their increased capitalisation) can be expected to be able to borrow at lower costs from markets and can lower the deposit rates they offer to their retail customers.

Table 3.1 presents the marginal effects of the EW model variables on a bank's distress probability at three different quarterly prediction horizons[30]: 1-to-8, 5-to-12 and 9-to-16 quarters[31]. A higher leverage ratio (better capitalisation) is associated with a lower distress probability at all horizons, and the other bank level variable coefficients too have the expected and intuitive signs. There are cases where the variable becomes a statistically significant predictor at some of the horizons and not at others, and there are cases where the sign of the coefficient flips depending on the signalling horizon pointing at potential trade-offs for policy. While both the growth in household credit and GDP reduce the risks in the near term, at longer horizons, the same variables imply higher risks.

Table 3.1: Estimated coefficients for the early warning model

Variable	1 - 8 Q	5 - 12 Q	9 - 16 Q
leverage ratio	-0.013^{***}	-0.013^{**}	-0.015^{***}
RWA_TA	0.003^{***}	0.003^{***}	0.002^{***}
roe_d_4	-0.003^{**}	-0.003^{***}	*0.000*
nonIr	*-0.001*	0.001^{**}	0.003^{***}
ltd	*-0.003*	0.016^{**}	0.035^{***}
cds_proxy_d_4	*-0.004*	0.068^{***}	0.034^{**}
bs_npl_d_8	0.024^{*}	0.027^{*}	*-0.005*
bs_credit_gap_d_12	0.012^{***}	-0.002	*-0.002*
bs_loans_hh_g_8	-0.004^{*}	0.004^{*}	0.007^{*}
mf_DSR_d_8	0.049^{**}	0.022	*-0.004*
mf_pti_rre_gap_d_12	0.001	0.006^{**}	0.003
mf_gdp_g_8	-0.007^{***}	0.014^{**}	0.008
N	814	722	650

Notes: Coefficients refer to the estimates from the logit regression where the left-hand side variable is a binary distress event for individual banks and represent the average marginal effects. Extensions d and g in variable names are used to indicate cases where the variable is in growth or difference terms, over 4, 8 or 12 quarters. Stars indicate the level of significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Banking sector and macro-financial variables capture the feedback mechanisms between the banks and the rest of economy in a plausible manner. GDP growth and the debt service ratio represent the income and interest rate risks in the model. A rising NPL ratio increases the risks for the banks. The gap variables, credit-to-GDP gap and the house price-to-income ratio gap, imply that as the gaps become larger the distress probability increases.

Both longer and short horizons are used in the literature. Longer horizons can be considered as the proper horizon from the macroprudential policy implementation perspective, as it may require time for the imbalances to build up. Short horizons could have advantages in

[30] Table A.2.1 in Appendix presents the statistics regarding the overall performance of the model.

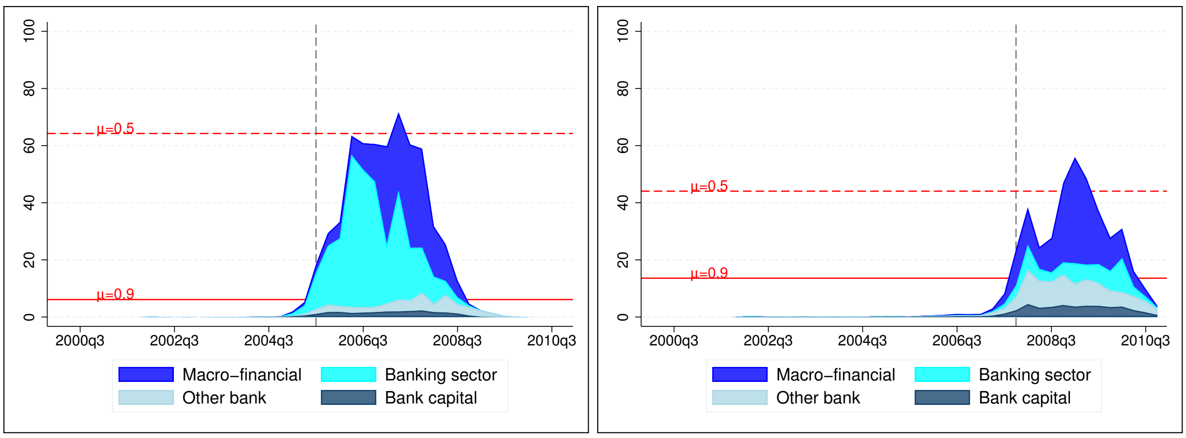
[31] I do not assign names for the horizons that could be more informative, such as micro or macro-prudential, in order to emphasize that I do not take an a-priori stance.

monitoring how large shocks translate into immediate risks. In the following analysis, I focus on and present results for 1-to-8 and 9-to-16 quarter horizons, since both horizons are relevant and can capture different dimensions of the risks. However, I contrast the policy effectiveness for the two horizons with the aim to decide on the horizon that best serves as the reference for triggering policy response. In choosing the final model, I drop the variables with non-significant coefficients. The exceptions are those that are indicated to be significant with the same signs in the middle column for the 5-to-12 quarters prediction horizon, which are kept with the aim to include a larger number of variables and to have comparable models across the prediction horizons[32].

Figure 3.1 presents the output of the EW model using historical data for the 1-to-8 and 9-to-16 quarters ahead signalling horizons. Risk probabilities are drawn in the graph with the decomposition of contributing factors and signalling thresholds. Referring to the 9-to-16 quarters signalling horizon, it can be observed that the vulnerabilities start to build up in 2005 and reach the highest level in the course of the years 2006-2007. The threshold line that result from using a μ of 0.9 flags the risks at 2005 Q3. For the same μ and using the 1-to-8 quarters prediction horizon, the risk level rises above the threshold by 2007 Q4.

Figure 3.1: Aggregate distress probabilities estimated from the historical data

a. 9-to-16 quarters horizon　　　**b.** 1-to-8 quarters horizon



Notes: Figures present the estimated distress probabilities by the EW model from historical data with the 9-to-16 and 1-to-8 quarters prediction horizons. The coloured areas illustrate the risk decomposition. Risk thresholds for $\mu = 0.9$ and $\mu = 0.5$ are drawn with red horizontal lines. The vertical dashed line indicates the quarter the risk in the banking system elevates above the threshold for the respective signalling horizon. The y-axes present the distress probability in percentages.

[32]The variables that are dropped from the model for a given horizon are in indicated in Table 3.1 in italic font.

EW output with the historical data from Slovenia show that macro-financial and banking sector variables play a significant role at both prediction horizons, while they are the dominant factors in the case of 9-to-16 quarters horizon. The role of bank-specific variables, which stand for the effect of individual banks' balance sheets and other developments at the individual bank-level, increases as risk indicators in the short-run, at the 1-to-8 quarters prediction horizon.

3.2 EW-FAVAR results from the counterfactual exercise

In this section I compare a countercyclical -early tightening and release- intervention with a *late* intervention. Simulations show that the countercyclical (*early*) intervention reduces the risks as measured by the logistic-early warning model. The *late* intervention is much less effective. The latter is initially even pro-cyclical and increases the risks in the quarters that follow the intervention.

The intervention is 2 pp higher overall capital ratio to be achieved in 1 year[33]. The first counterfactual exercise is the case of *early* intervention in 2005 Q3, where the banks start to build their capital buffers by 2005 Q4 and reach the target ratio by 2006 Q3. Banks are also required to stay above the target ratio in the following periods until 2007 Q3, and then the buffer is released. Buffer release is simulated by cancelling any positive (tightening) capital regulation shock in the data over the following six quarters until 2008 Q4. The assumption is that having built buffers, with the release, the banks would not be constrained by the capital regulation in the following periods. Appendix figure A.5.a presents the historical structural shocks identified in the data by the sign and zero restrictions and the counterfactual structural shocks.

Appendix figures A.4.1 - A.4.3 present the simulated responses of the model variables conditional on the counterfactual path of the capital ratio, where the historical path of the banks' capital ratios and the counterfactual diverge due to the capital regulation shocks introduced by 2005 Q4. 2% higher capital ratio imposed by regulation until 2007 Q3 leads to lower credit growth, as the counterfactual level of outstanding credit is 10.5% below the no-policy change level in actual data by 2007 Q4 (the outstanding volume of credit to households decreases by 9.9% compared to the no-policy case)[34]. The *early* and macroprudential intervention limits the build-up of imbalances as measured by the credit gap and house price to income ratio. These indicators are significantly lower under the counterfactual scenario than the actual peak values recorded in 2007 Q4, 5.2 and 4.9 percentage points (pps) less than the no policy case respectively. While the GDP is lower

[33] This exercise is similar to the implementation of the countercyclical capital buffer as specified in CRD IV regulation in the EU that defines a12-month implementation period.

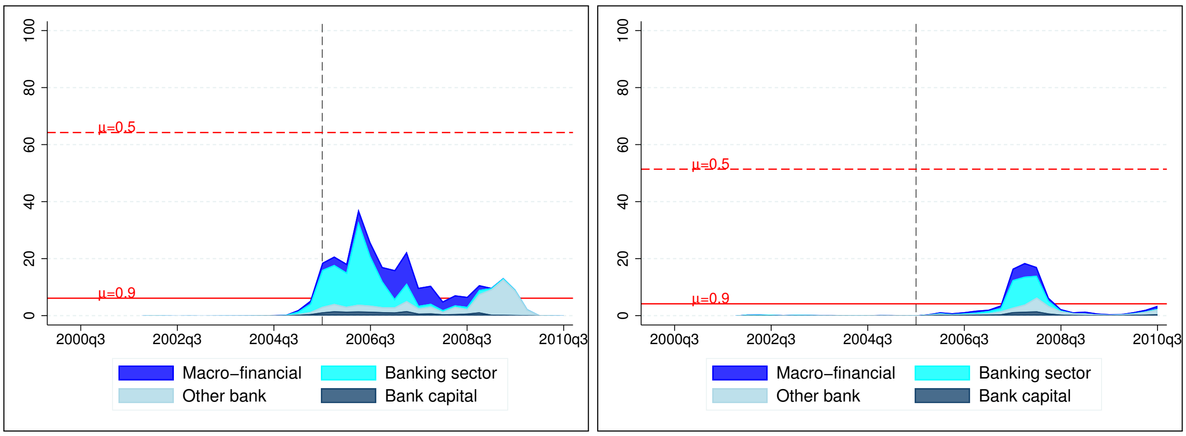
[34] The bank level variables which diverge from the historical observations under the policy counterfactual are risk weighted assets to total assets ratios, net interest margins, and the loan to deposits ratios of the banks. While the NPL ratio is initially higher under the intervention scenario, as the crisis unfolds the actual NPLs surpasses the counterfactual.

by 2.2% by the end of 2007, due to the tighter capital regulation, as the crisis unfolds the GDP drops by less and by 2008 Q4 the GDP is %2.7 higher under the counterfactual scenario (counterfactual GDP remains higher until the end of the simulation period). Debt service to income ratio is lower by 2 percentage points by 2008 Q4, implying a lower distress risk at 1-to-8 quarters horizon. The effect of the buffer release is smaller, as measured by credit gap, macro-financial ratios and with respect to key bank level variables. The relative ineffectiveness of the release on the model variables suggest the Slovenian banks were not significantly constrained by the regulatory minimum capital requirement during the period that followed the 2008 global financial crisis.

Figure 3.2 below presents the impact of the intervention on the aggregate distress probability in the case of early intervention at 1-to-8 and 9-to-16 quarters distress prediction horizons[35]. It shows that the intervention lowers the risks significantly at both prediction horizons. This finding can be interpreted as the effect of the *early* intervention that would limit the build-up of imbalances in the expansion phase and the banks, having increased their resiliencies, would be impacted by less by the financial crisis. Appendix figures A.6.1 and A.6.2 present the results at the bank level, confirming the effects are similar at the bank level.

Figure 3.2: Counterfactual aggregate distress probabilities: Intervention in 2005 Q3

a. 9-to-16 quarters horizon **b.** 1-to-8 quarters horizon



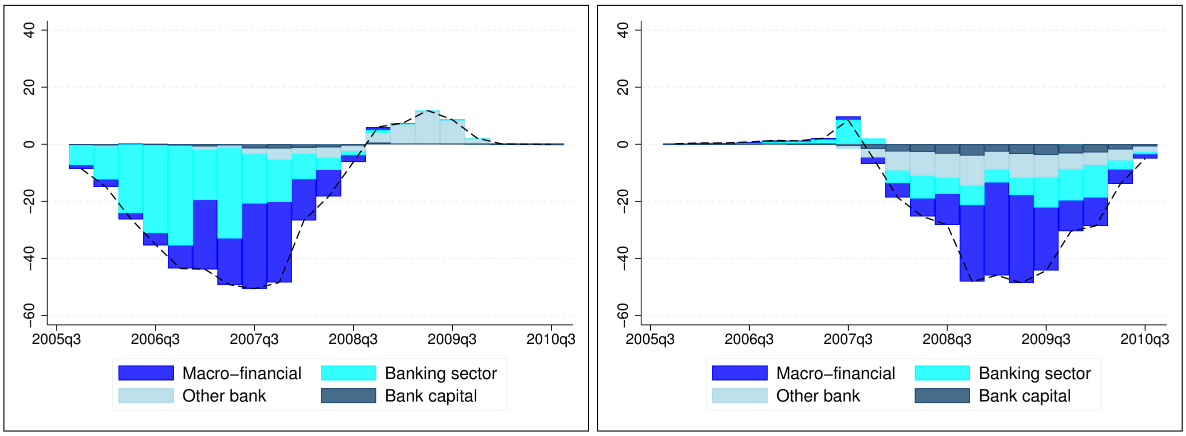
Notes: Figures present the estimated distress probabilities under the counterfactual scenario with the 9-to-16 and 1-to-8 quarters prediction horizons for the intervention in 2005 Q3. The coloured areas illustrate the risk decomposition. Risk thresholds for $\mu = 0.9$ and $\mu = 0.5$ are drawn with red horizontal lines. The vertical dashed line indicates 2005 Q3, the quarter the risk in the banking system elevates above the threshold and triggers the intervention (using 9-to-16 quarters horizon). The y-axes present the distress probability in percentages.

[35] Counterfactual EW simulations are conducted using the logistic regression coefficients estimated from the historical data and plugging in the simulated counterfactual variable values.

Figure 3.3 illustrates the transmission of the requirements by drawing the difference between policy counterfactual simulation (Fig. 3.2) and the historical benchmark (Fig. 3.1) with the breakdown of the contributing factors and helps to identify the transmission channels of the policy. It shows that the difference is larger than 40% in terms of the reduction in overall (aggregated) distress probability in the banking system. The largest contributors are macro-financial and banking sector factors, especially in the case of 9-to-16 quarters horizon. Bank-level variables, the direct effect of bank capitalisation and the other bank level factors, contribute to the reduction in the case of 1-to-8 quarters prediction horizon[36].

Figure 3.3: Contributions to the reductions of aggregate distress probabilities under the counterfactual scenario of intervention in 2005 Q3

a. 9-to-16 quarters horizon **b.** 1-to-8 quarters horizon



Notes: Figures present the difference between the counterfactual risk probabilities and the estimated probabilities from the historical data starting from the first quarter following the intervention (2005 Q4) over the simulation horizon and for (a) 9-to-16 and (b) 1-to-8 quarters prediction horizons. Negative values are reductions in distress probabilities and positive values are increases due to the factors represented by the colored areas. The dashed dark line represents the overall reduction/increase in the estimated distress probability. The y-axes presents the differences in distress probabilities in percentages.

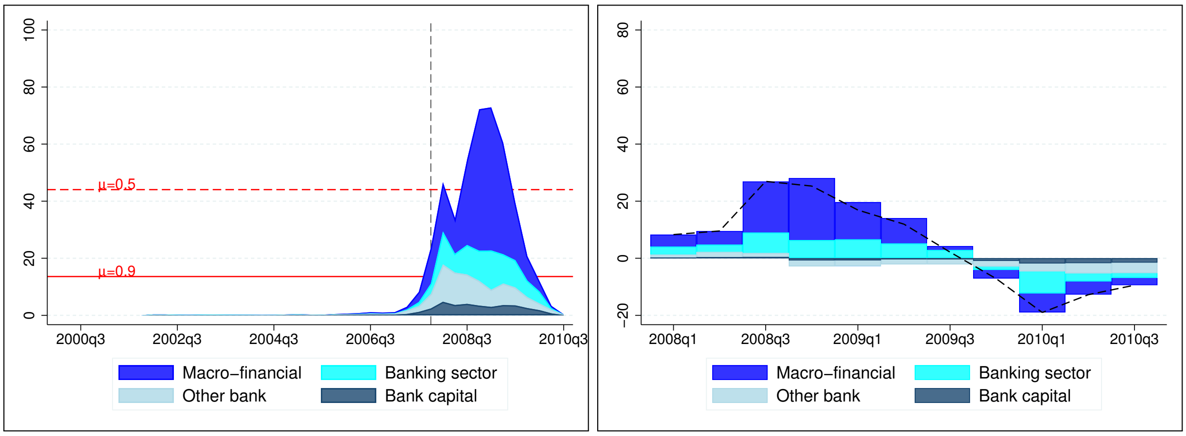
Figure 3.4 presents the results from the *late* intervention. The intervention triggered by the 1-to-8 quarters signalling horizon is not effective as the countercyclical intervention above. Figure 3.4.b. illustrates that the risks increase initially, mainly due to the channels that stand for the macro-financial feedbacks between the banks and the real economy. Risks decrease only by 2009 Q4. Appendix figure A.6.3 presents the results at the bank level that concur with the findings at the system level.

[36]The direct effect of bank capital, measured by the leverage ratio, occurs most likely through its contribution to the loss absorption capacity. It is worth underscoring that the effect of the capital ratio regulation on the resilience of the banks and banking system is beyond the direct effect of capital on loss absorption capacity, as the intervention influences the evolution of other variables that are drivers of risk at both bank and macro level. Bank capitalisation can also have effects that can take longer to materialise and harder to observe. The bank managers and shareholders can be expected to act prudent, invest in their capacity to monitor the borrowers and the risks, when the capitalisation is high as they have more *skin in the game*.

Figure 3.4: Counterfactual aggregate distress probabilities and the contributing factors in reductions/increases: Intervention in 2007 Q4

a. Risks predicted using 1-to-8 quarters horizon

b. Contributions to change in risk using 1-to-8 quarters prediction horizon



Notes: (a.) The graph presents the estimated distress probabilities under the counterfactual scenario with the 1-to-8 quarters prediction horizon for the intervention in 2007 Q4. Risk thresholds for $\mu = 0.9$ and $\mu = 0.5$ are drawn with red horizontal lines. The vertical dashed line indicates 2007 Q4, the quarter the risk in the banking system elevates above the threshold and triggers the intervention (using 1-to-8 quarters horizon). The y-axis presents the distress probability in percentages. (b.) The graph presents the difference between the counterfactual risk probabilities and the estimated probabilities from the historical data starting from the first quarter following the intervention (2008 Q1) over the simulation horizon. Negative values are reductions in distress probabilities and positive values are increases due to the factors represented by the colored areas. The dashed dark line represents the overall reduction/increase in the estimated distress probability. The y-axis presents the differences in distress probabilities in percentages. The coloured areas illustrate the risk decomposition.

Appendix figures A.4.4 - A.4.6 represent the historical series and the simulated responses of the variables of the model conditional on the counterfactual path of the capital ratios in the *late* intervention case[37]. Loan growth stagnates in actual data by 2008 due to the financial crisis, the GDP contracts sharply and the share of NPL ratios in overall loans start to rise. Whereas these variables are drivers of distress at the bank and system level, at 1-to-8 quarters prediction horizon, the *late* intervention is procyclical in its effect on these developments and amplify the adverse shock of the crisis. As the banks pass-on the cost of capital and contract their credit by increasing their loan interest rates, the debt service ratio surges and exacerbate the conditions of the borrowers and the banks in-turn. Moderate contributions in the direction of lowering the risks from the gap variables, which are already in the course of converging to the long-run trend in no-policy intervention case, accompany the improvements in the loss absorption capacity at the bank level due to the higher capitalisation.

[37] The counterfactual shocks that drive the outcomes in Figure 3.4 are presented in Figure A.5.b.

These results highlight the importance of the interactions between the banks' actions and real economy. In-line with the macroprudential view of risk[38], the feedback mechanisms that result from the banks' responses to regulation produce first order effects on their distress probabilities within the simulation horizon. Behn et al. (2016) similarly show the indirect effects of capital measures can be sizeable, while the overall effectiveness of capital-based measures depends on how banks move to higher capital ratios according to their analysis[39]. My findings point to the role of the timing. While both short and longer signalling horizons are used in literature, and have been shown to provide meaningful information, longer horizons need to be taken as reference for setting the signalling threshold for activating a measure by means of higher capital ratios.

4 Conclusion

The integrated approach and the EW-FAVAR model allows to go beyond monitoring the risks with an EW model, and one can explore how risks evolve at both the system level and across the banking system in response to shocks and under pre-specified scenarios in a forward-looking manner. It can aide policy in calibrating the capital-based macroprudential instruments, in particular the countercyclical capital buffer, and allows for quantifying the benefits from introducing these measures in terms of reduced distress probabilities.

The capital requirements on banks contribute to their resilience by constraining them from taking excess risks and ensuring their solvency. However, the dynamics between the banks and real economy, while the the banks adjust their capital ratios, can create sizeable feedbacks and have financial stability implications. My results are in-line with the insights and the evidence provided in the literature that emphasize the critical role of the feedback mechanisms and the macroprudential perspective.

Using the EW-FAVAR model developed in this paper, I showed that a countercyclical implementation of capital requirements in the build-up phase prior to the global financial crisis would have significantly reduced the risks in the banking sector in Slovenia in this period. Although, a late intervention by means of a tightening in the face of material risks had pro-cyclical effects and increased the distress probability in the quarters that followed the intervention. These findings point at the importance of the timing for the effective implementation of prudential policies.

[38]Macroprudential view considers the endogenous risks, as opposed to the exogenous conception with the micro-prudential view (Borio, 2010). In this view, banks' own actions amplify the shocks through feedbacks between the banks and real economy. In a downturn, for example, the banks deleverage as they absorb losses while they seek to remain above the regulatory minimum, which leads to reduced investment, employment and consumption. As households' and firms' incomes are lower, they struggle paying their outstanding loans, cut spending and amplify the downturn further. This spiral puts further stress on the banks' balance-sheets. The macroprudential view and policy complements the micro-prudential -firm-specific- prudential supervision with a view to safeguard financial system as a whole by taking into account such general equilibrium effects (Hanson et al., 2011).

[39]The empirical approach in Behn et al. (2016) allows for simulating two polar kinds of adjustments, where banks shrink their assets (holding capital constant) or add on new capital (holding debt constant) in response to the capital requirements.

References

Arias, J., D. Waggoner, and J. F. Rubio-Ramirez (2016). Inference Based on SVARs Identified with Sign and Zero Restrictions: Theory and Applications. 2016 Meeting Papers 472, Society for Economic Dynamics.

BCBS (2010, December). Guidance for National Authorities Operating the Countercyclical Capital Buffer. techreport, Bank for International Settlements, Basel Committee on Banking Supervision.

Behn, M., M. Gross, and T. Peltonen (2016). Assessing the Costs and Benefits of Capital-Based Macroprudential Policy. Working Paper Series 1935, European Central Bank.

Bernanke, B. S., J. Boivin, and P. Eliasz (2005). Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach. *The Quarterly Journal of Economics 120*(1), 387–422.

Boivin, J. and M. Giannoni (2007). Global forces and monetary policy effectiveness. In *International Dimensions of Monetary Policy*, pp. 429–478. National Bureau of Economic Research, Inc.

Borio, C. E. V. (2010). Towards a macroprudential framework for financial supervision and regulation? BIS Working Papers 128, Bank for International Settlements.

Buch, C., S. Eickmeier, and E. Prieto (2014). Macroeconomic Factors and Microlevel Bank Behavior. *Journal of Money, Credit and Banking 46*(4), 715–751.

Budnik, K., M. Affinito, G. Barbic, S. Ben Hadj, E. Chretien, H. Dewachter, C. Gonzalez, J. Hu, L. Jantunen, R. Jimborean, O. Manninen, R. Martinho, J. Mencia, E. Mousarri, L. Narusevicius, G. Nicoletti, O. Michael, S. Ozsahin, A. R. Pereira, J. Rivera-Rozo, C. Trikoupis, F. Venditti, and S. Velasco (2019). The Benefits and Costs of Adjusting Bank Capitalisation: Evidence from Euro Area Countries. Working Paper Series 2261, European Central Bank.

Budnik, K. and P. Bochmann (2017). Capital and liquidity buffers and the resilience of the banking system in the euro area. Working Paper Series 2120, European Central Bank.

Bussiere, M. and M. Fratzscher (2006). Towards a New Early Warning System of Financial Crises. *Journal of International Money and Finance 25*(6), 953–973.

Coudert, V. and J. Idier (2018). Reducing model risk in early warning systems for banking crises in the euro area. *International Economics* (156), 98–116.

Dave, C., S. J. Dressler, and L. Zhang (2013). The Bank Lending Channel: A FAVAR Analysis. *Journal of Money, Credit and Banking 45*(8), 1705–1720.

ECB (2018). Financial Stability Review. Technical report, European Central Bank. May, 2018.

Gambacorta, L. and H. S. Shin (2018). Why Bank Capital Matters for Monetary Policy. *Journal of Financial Intermediation 35*(PB), 17–29.

Gropp, R., T. Mosk, S. Ongena, and C. Wix (2019). Banks Response to Higher Capital Requirements: Evidence from a Quasi-Natural Experiment. *Review of Financial Studies 32*(1), 266–299.

Hanson, S., A. Kashyap, and J. Stein (2011). A Macroprudential Approach to Financial Regulation. *Journal of Economic Perspectives 25*(1), 3–28.

Lang, J. H., C. Izzo, S. Fahr, and J. Ruzicka (2019). Anticipating the Bust: a New Cyclical Systemic Risk Indicator to Assess the Likelihood and Severity of Financial Crises. Occasional Paper Series 219, European Central Bank.

Lang, J. H., T. A. Peltonen, and P. Sarlin (2018). A Framework for Early-Warning Modeling with an Application to Banks. Working Paper Series 2182, European Central Bank.

Lang, J. H. and P. Welz (2018). Semi-Structural Credit Gap Estimation. Working Paper Series 2194, European Central Bank.

Lo Duca, M., A. Koban, M. Basten, E. Bengtsson, B. Klaus, P. Kusmierczyk, J. H. Lang, C. Detken, and T. Peltonen (2017). A New Database for Financial Crises in European Countries. Occasional Paper Series 194, European Central Bank.

Mesonnier, J.-S. and A. Monks (2015). Did the EBA Capital Exercise Cause a Credit Crunch in the Euro Area? *International Journal of Central Banking 11*(3), 75–117.

Mian, A. and A. Sufi (2018). Finance and business cycles: The credit-driven household demand channel. *Journal of Economic Perspectives 32*(3), 31–58.

Sarlin, P. (2013). On Policymakers' Loss Functions and the Evaluation of Early Warning Systems. *Economics Letters 119*(1), 1–7.

Suarez, J. and A. S. Serrano (2018). Approaching non-performing loans from a macroprudential angle. Report of the Advisory Scientific Committee 7, European Systemic Risk Board.

Volk, M. (2017). Predicting Distress in Slovenian Banks. Mpra paper, Unpublished.

A Appendix

A.1 Visualisation of the EW output

This section presents the methods for the decomposition of risk to driving factors and the aggregation of bank level risks to system level risk as described in Lang et al. (2018).

The respective contributions of risk factors to overall distress probability of a bank is calculated in three steps:

i. The counterfactual probability for each factor is calculated by setting other factors at their means.

ii. Probability share of each factor is calculated as the ratio of each factor's counterfactual probability to the sum of the counterfactual probabilities of all the factors.

iii. Probability shares obtained in the second step are multiplied with the distress probability of the respective bank from the model to arrive at the factors' probability contributions.

Where f is the logit function determining the distress probability, as defined in (1), the probability contribution of factor m for entity i at time t is expressed in the following way:

$$P^c(x_{i,t}^m) = \frac{f(x_{i,t}^m \mid x_{i,t}^{-m} = E_{i,t}(x_{i,t}^{-m}))}{\sum_m f(x_{i,t}^m \mid x_{i,t}^{-m} = E_{i,t}(x_{i,t}^{-m}))} f(x_{i,t}) \tag{A.1}$$

The aggregation of distress probabilities at system level use the following approach:

$$ADP_t = \sum_{i=1}^{N} f(x_{i,t}) \frac{a_{i,t}}{\sum_i a_{i,t}} \tag{A.2}$$

ADP is aggregate distress probability in time t expressed as the weighted average of distress probabilities $f(x_{i,t})$ across N entities. The weights are the share of total assets of bank i at time t in overall banking system assets. a is bank size measured by the total assets and bank size is considered as the proxy for systemic importance.

A.2 Early warning model performance

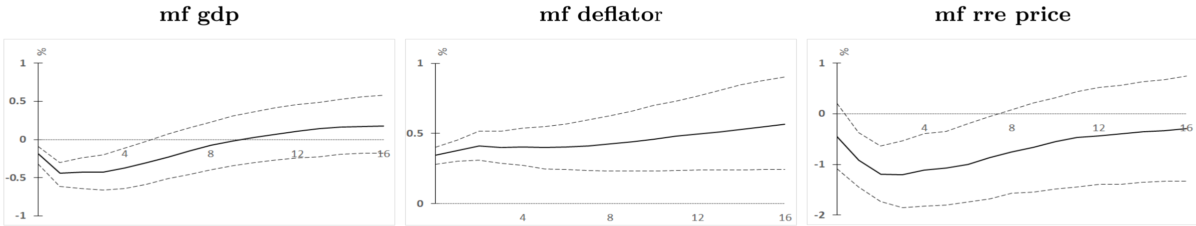
Table A.2.1: In-sample performance of the early warning model

	Prediction horizon	
	1-to-8 quarters	**9-to-16 quarters**
Signaling threshold	0.061	0.056
AUROC	0.957	0.954
Noise-2-Signal ratio	0.149	0.202
Type I Error rate	0.031	0.000
Type II Error rate	0.144	0.202
TP rate	0.073	0.093
FP rate	0.134	0.183
TN rate	0.791	0.724
FN rate	0.002	0.000

Notes: Signalling thresholds are computed minimizing the loss function given in section 2.1. AUROC stands for Area Under the Receiver Operating Characteristics Curve. The noise-to-signal ratio measures the ratio of false alarms to the share of distress events that are correctly predicted. Abbreviations TP, FP, TN and FN stand for true positives, negatives positives, true negatives and false negatives respectively. Type I and II error rates are calculated as following: $Type\,I\,error\,rate\ = \frac{FN}{TP+FN}$ and $Type\,II\,error\,rate\ = \frac{FP}{FP+TN}$. TP rate, FP rate, TN rate and FN rate are expressed as shares in the total number of observations.

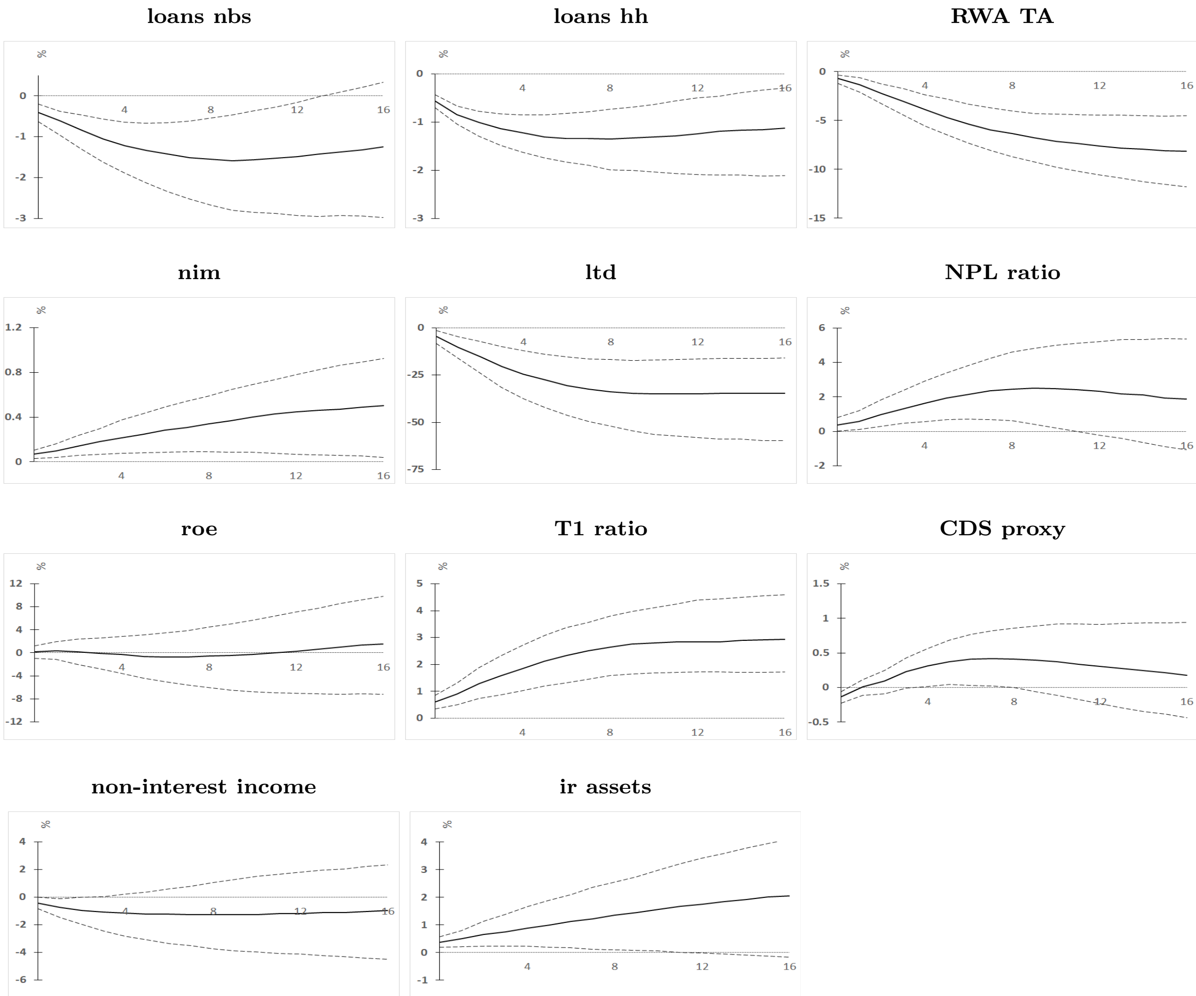
A.3 Impulse response functions for the capital requirement shock

Figure A.3.1: Impulse response functions of the macro variables for the capital requirement shock



Notes: Impulse response functions of macro variables to a one standard deviation capital requirement shock are given with 50% confidence intervals.

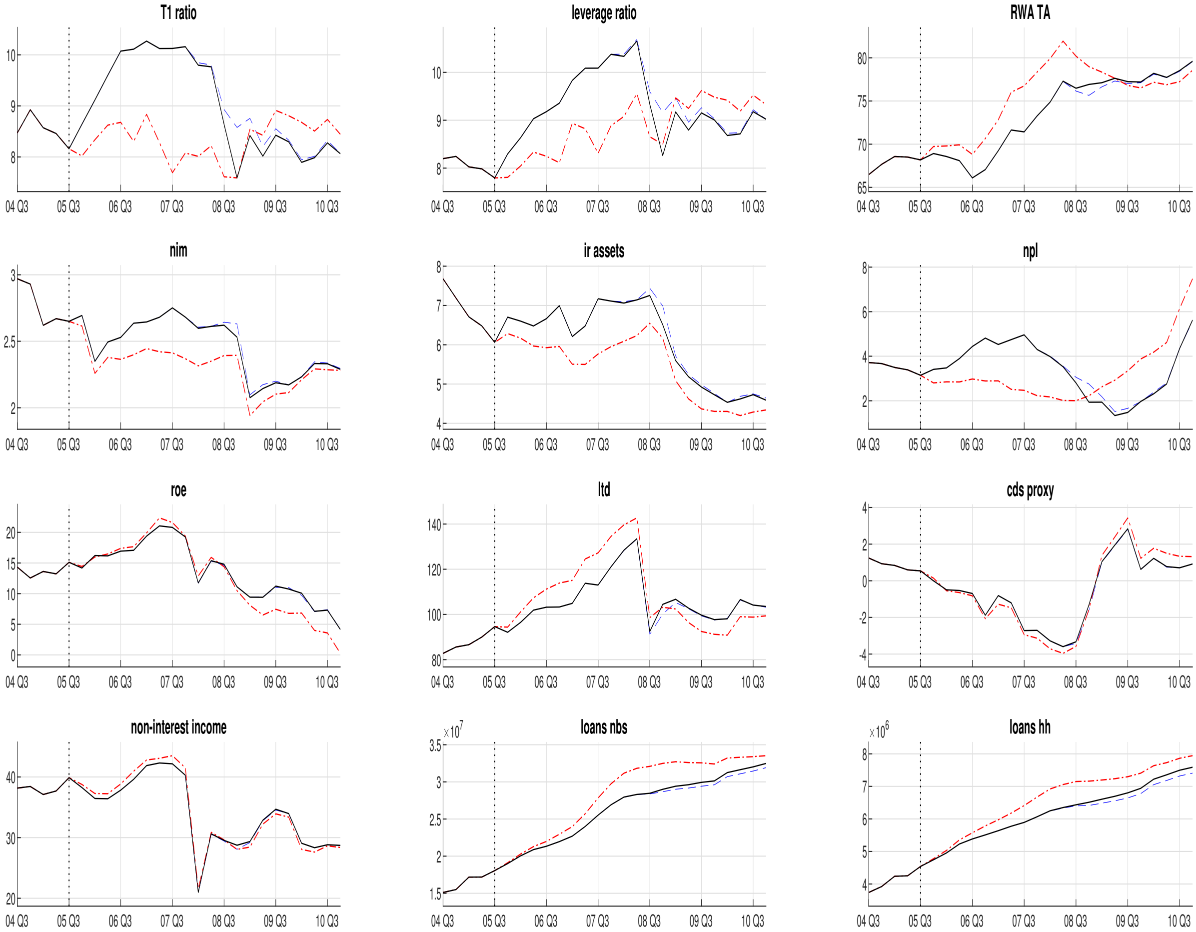
Figure A.3.2: Aggregated impulse response functions of the bank level variables for the capital requirement shock



Notes: Impulse response functions to a one standard deviation capital requirement shock are given with 50% confidence intervals. Responses of bank-level variables are aggregated to the sector level by weighting banks's responses with the share of their assets in total banking assets in 2008 Q1.

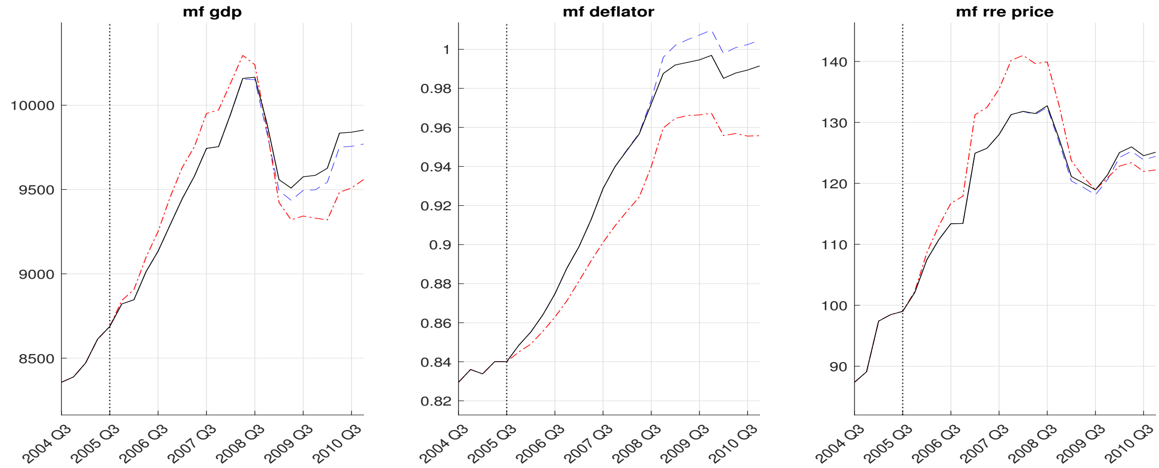
A.4 Historical and counterfactual series of the model variables

Figure A.4.1: Simulated evolution of aggregated bank-level variables under the counterfactual scenario introduced in 2005 Q3 and the historical series



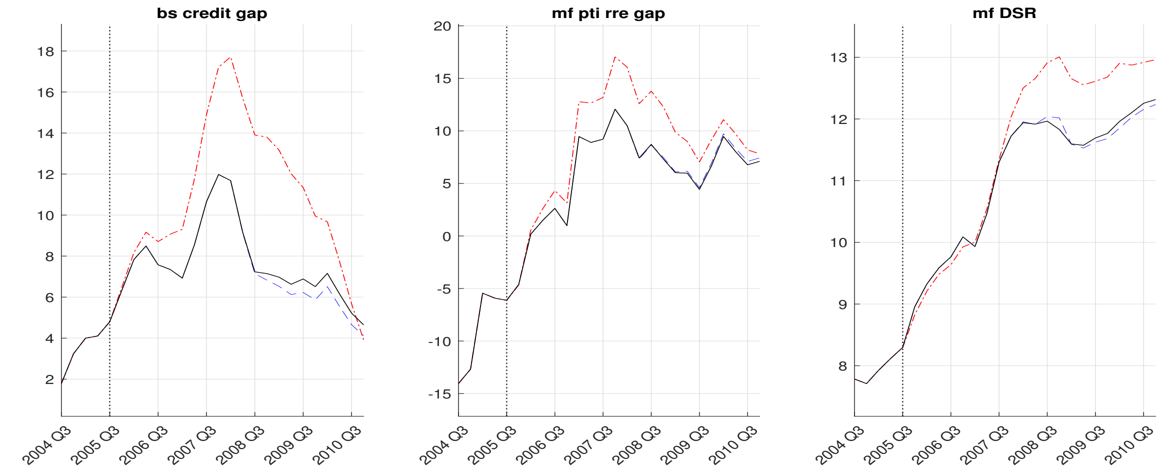
Notes: The graphs present the historical and the counterfactual series for the bank variables of the model that are aggregated from bank level series (banks are weighted by their shares in total banking assets in Slovenia in 2008 Q1). The historical series are represented by the red dashed lines. Dark solid lines stand for the median estimates under the counterfactual, where at the system level banks' T1 capital ratios rise by 2pp by 2006 Q3 due to the intervention at 2005 Q3. Banks overall preserve at least a 2pp higher T1 ratio until 2007 Q3. The counterfactual includes a release condition, where any positive capital shock is cancelled for the following six quarters. The blue dashed line represents the counterfactual without the release condition.

Figure A.4.2: Simulated evolution of the macro variables under the counterfactual scenario introduced in 2005 Q3 and the historical series



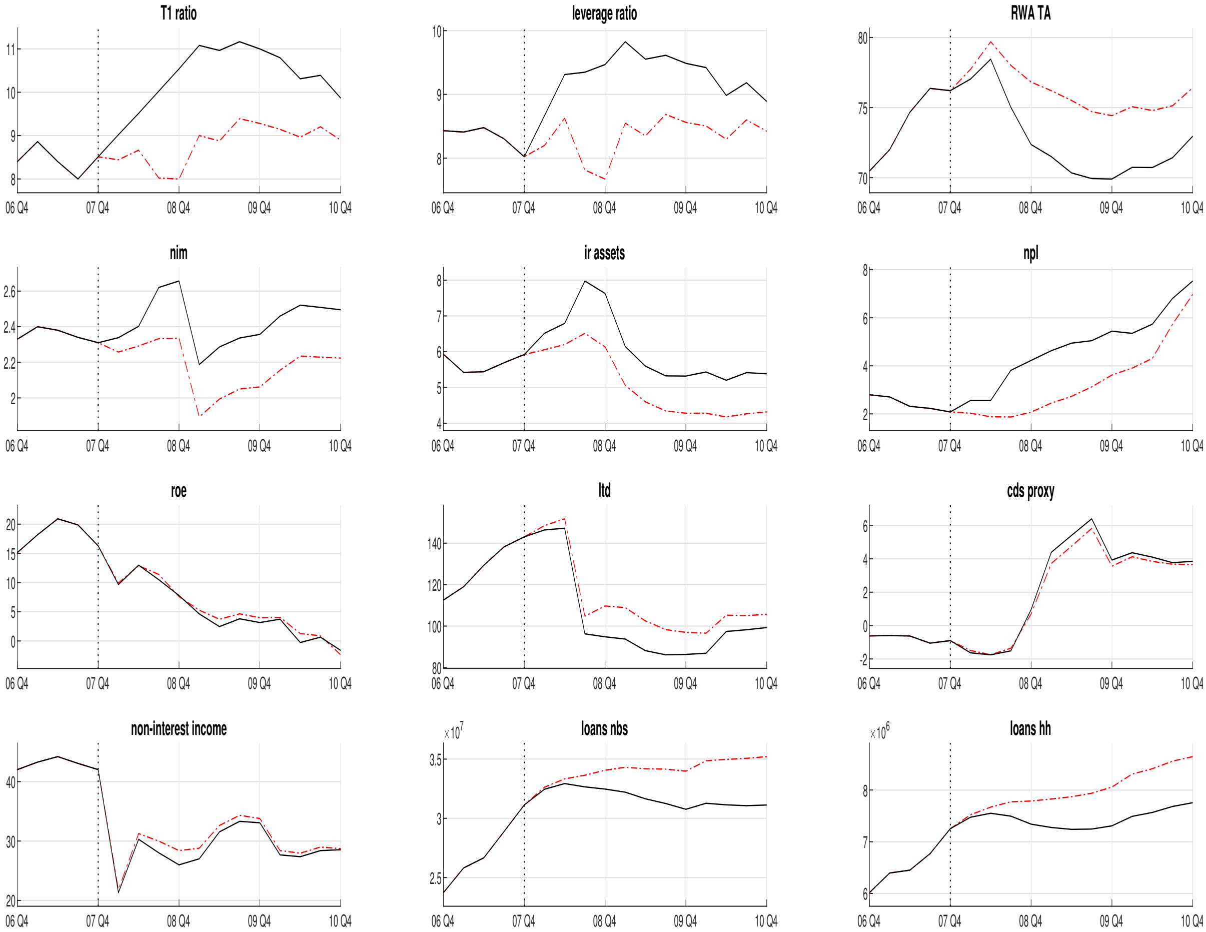
Notes: Graphs present the historical and the counterfactual series for the macro variables of the model. The historical series are represented by the red dashed lines. Dark solid lines stand for the median estimates under the counterfactual, where at system level banks' T1 capital ratios rise by 2pp by 2006 Q3 due to the intervention at 2005 Q3, and the banks overall preserve at least a 2pp higher T1 ratio until 2007 Q3. The counterfactual includes a release condition, where any positive capital shock is cancelled for the following six quarters. The blue dashed line represents the counterfactual without the release condition.

Figure A.4.3: Simulated evolution of the macro financial ratios and gap variables under the counterfactual scenario introduced in 2005 Q3 and the historical series



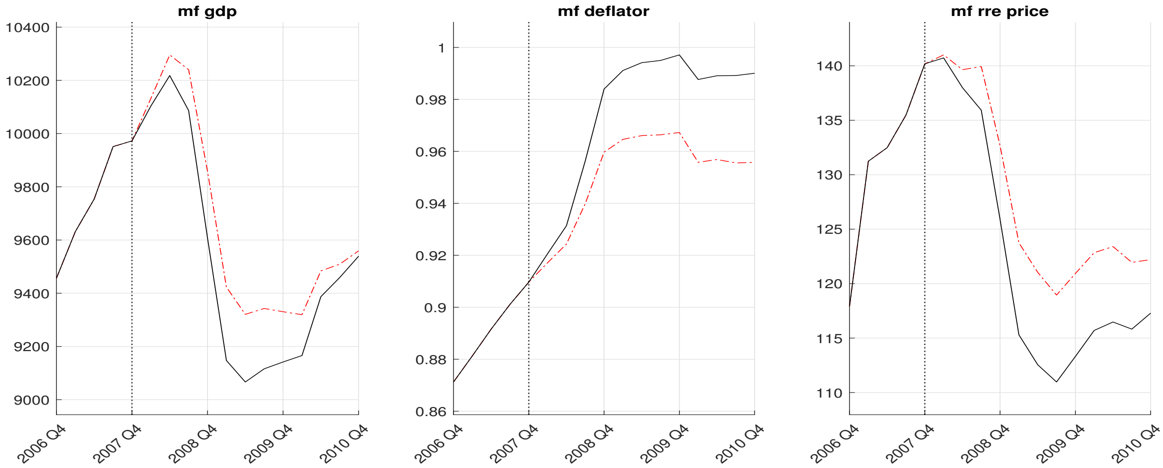
Notes: The graphs present the historical and the counterfactual series for the macro-financial ratios and gap variables of the EW model. The historical series are represented by the red dashed lines. The dark solid lines stand for the median estimates under the counterfactual, where at system level banks' T1 capital ratios rise by 2pp by 2006 Q3 due to the intervention at 2005 Q3, and the banks overall preserve at least a 2pp higher T1 ratio until 2007 Q3. The counterfactual includes a release condition, where any positive capital shock is cancelled for the following six quarters. The blue dashed line represents the counterfactual without the release condition.

Figure A.4.4: Simulated evolution of aggregated bank-level variables under the counterfactual scenario introduced in 2007 Q4 and the historical series



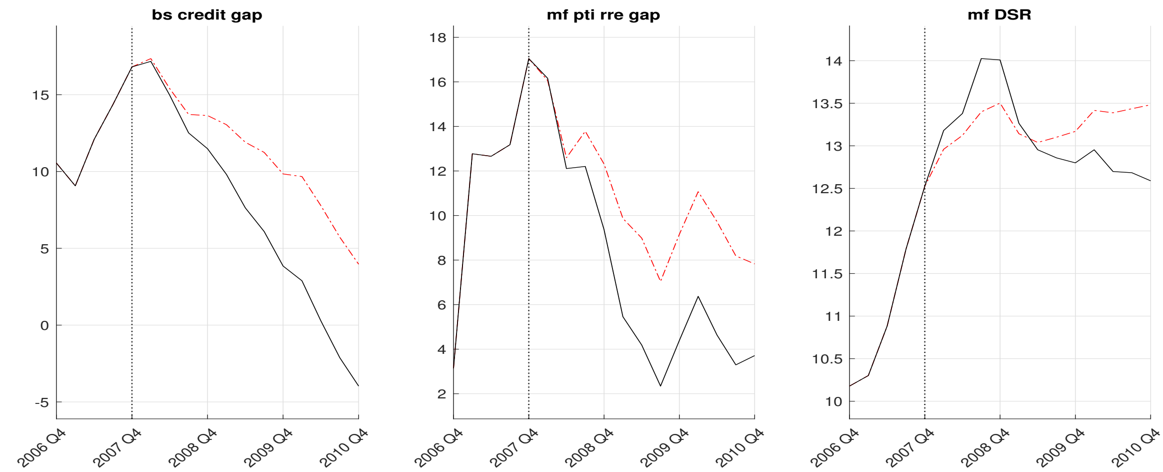
Notes: The graphs present the historical and the counterfactual series for the bank variables of the model that are aggregated from bank level series (banks are weighted by their shares in total banking assets in Slovenia in 2008 Q1). The historical series are represented by the red dashed lines. The dark solid lines stand for the median estimates under the counterfactual, where at system level banks' T1 capital ratios rise by 2pp by 2008 Q4 due to the intervention at 2007 Q4. Banks overall preserve at least a 2pp higher T1 ratio until 2009 Q4.

Figure A.4.5: Simulated evolution of the macro variables under the counterfactual scenario introduced in 2007 Q4 and the historical series



Notes: The graphs present the historical and the counterfactual series for the macro variables of the model. The historical series are represented by the red dashed lines. The dark solid lines stand for the median estimates under the counterfactual, where at system level banks' T1 capital ratios rise by 2pp by 2008 Q4 due to the intervention at 2007 Q4. Banks overall preserve at least a 2pp higher T1 ratio until 2009 Q4.

Figure A.4.6: Simulated evolution of the macro financial ratios and gap variables under the counterfactual scenario introduced in 2007 Q4 and the historical series

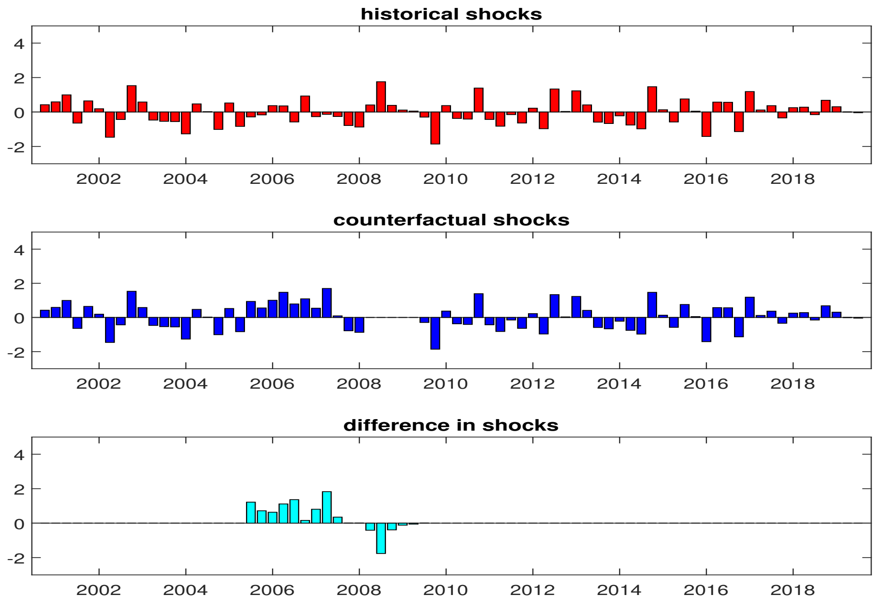


Notes: The graphs present the historical and the counterfactual series for the macro-financial ratios and gap variables of the EW model. The historical series are represented by the red dashed lines. The dark solid lines stand for the median estimates under the counterfactual, where at system level banks' T1 capital ratios rise by 2pp by 2008 Q4 due to the intervention at 2007 Q4. Banks overall preserve at least a 2pp higher T1 ratio until 2009 Q4.

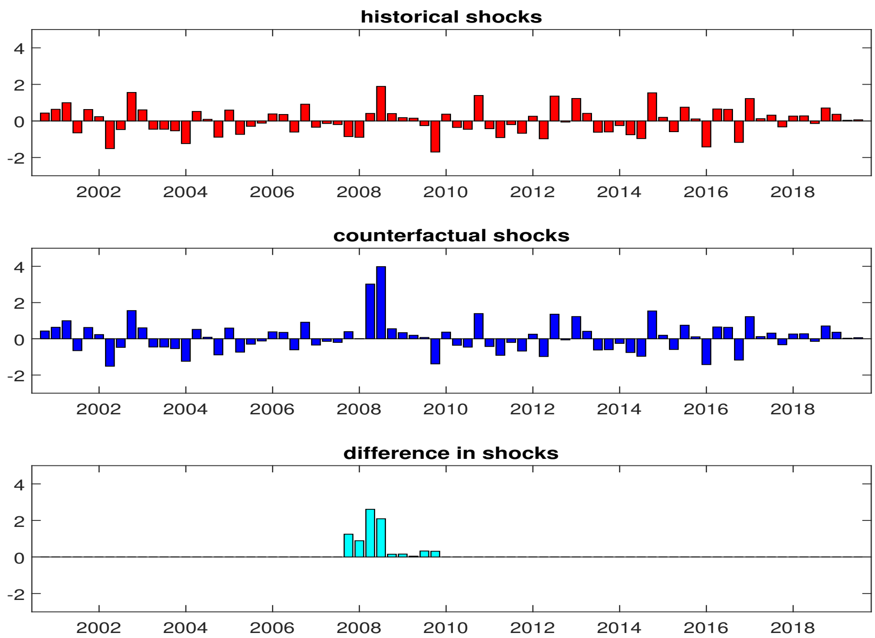
A.5 Capital regulation shocks

Figure A.5.1: Structural shocks: Identified capital regulation shocks in data and the counterfactual capital regulation shocks

a. Counterfactual scenario: Intervention in 2005 Q3



b. Counterfactual scenario: Intervention in 2007 Q4

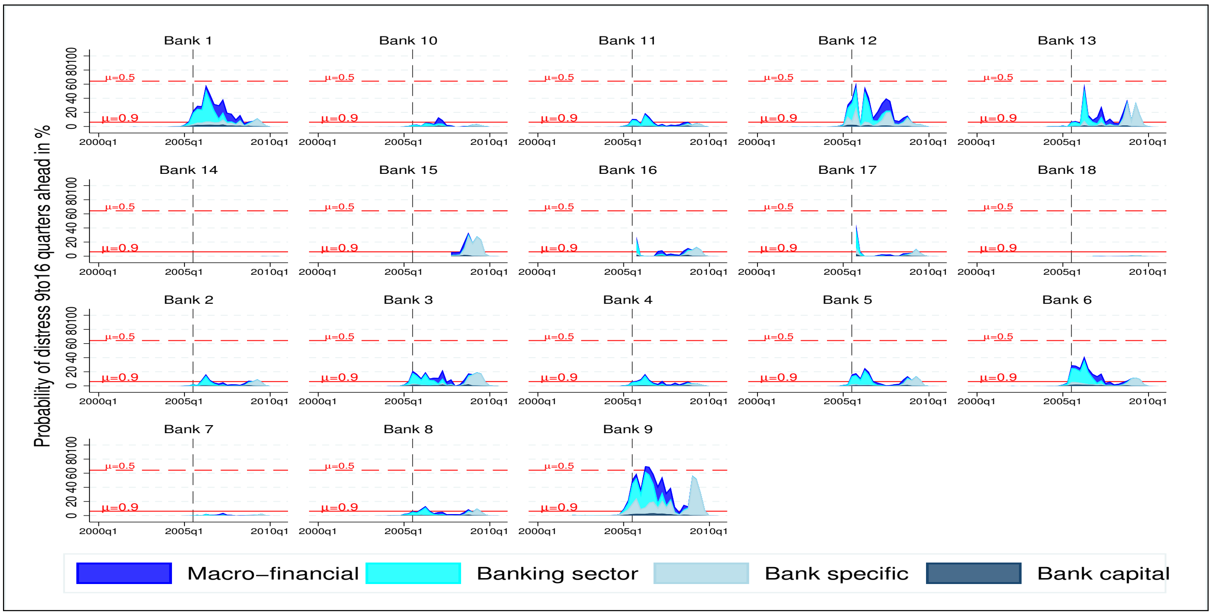


Notes: The graphs in the top rows with the red bars represent the median capital regulation shocks from the distribution of shocks identified in the data using the sign and zero restrictions that are presented in Table 2.3. The graphs in the middle rows and the dark blue bars represent the shocks under the respective counterfactual scenarios. The bottom rows and the light blue bars present the differences in structural shocks between the counterfactual and historical cases.

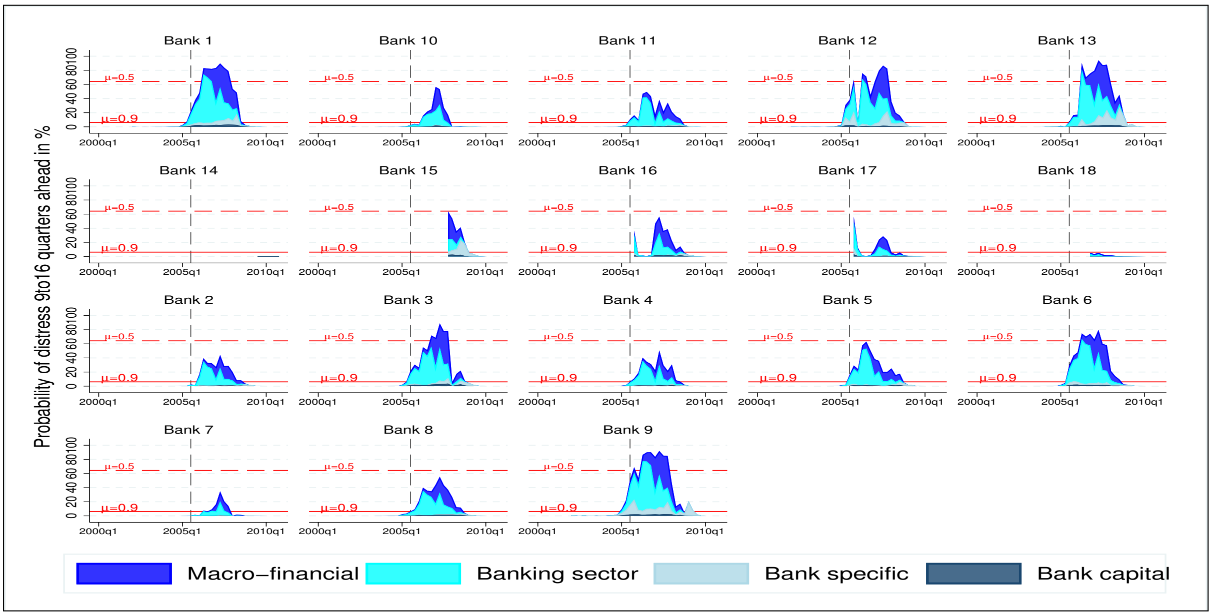
A.6 Risks estimated at the bank level and the simulations

Figure A.6.1: Bank-level distress probabilities estimated from historical data and under the counterfactual scenario of intervention in 2005 Q3 with 9-to-16 quarters prediction horizon

a. Bank-level risks under the counterfactual



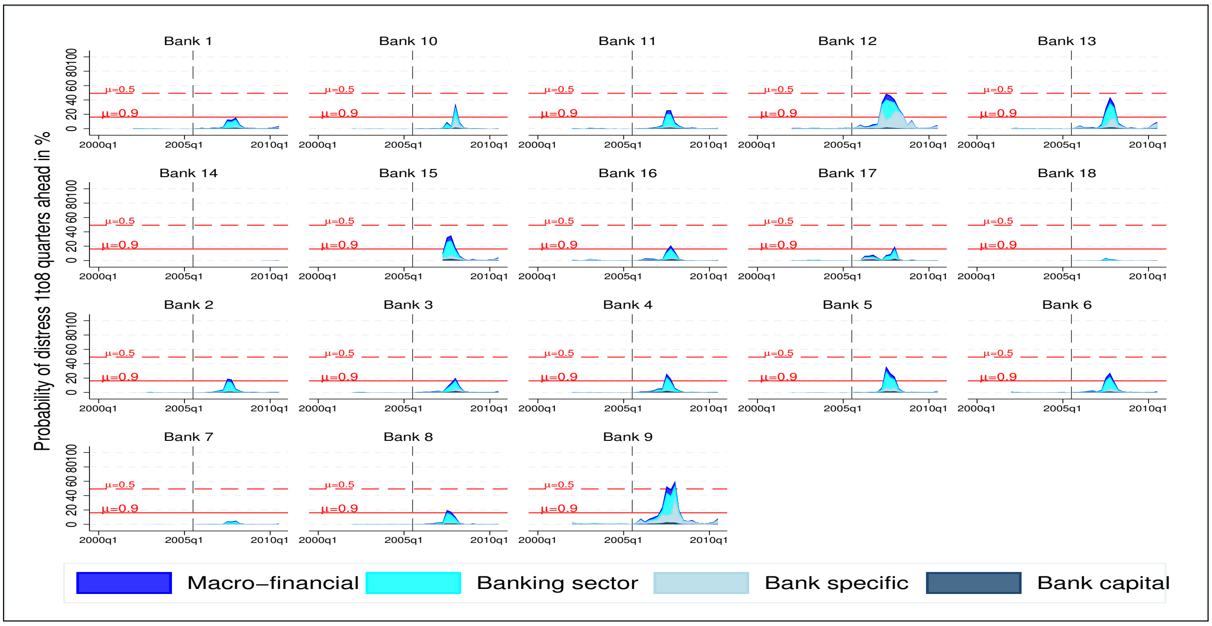
b. Bank-level risks estimated from historical data



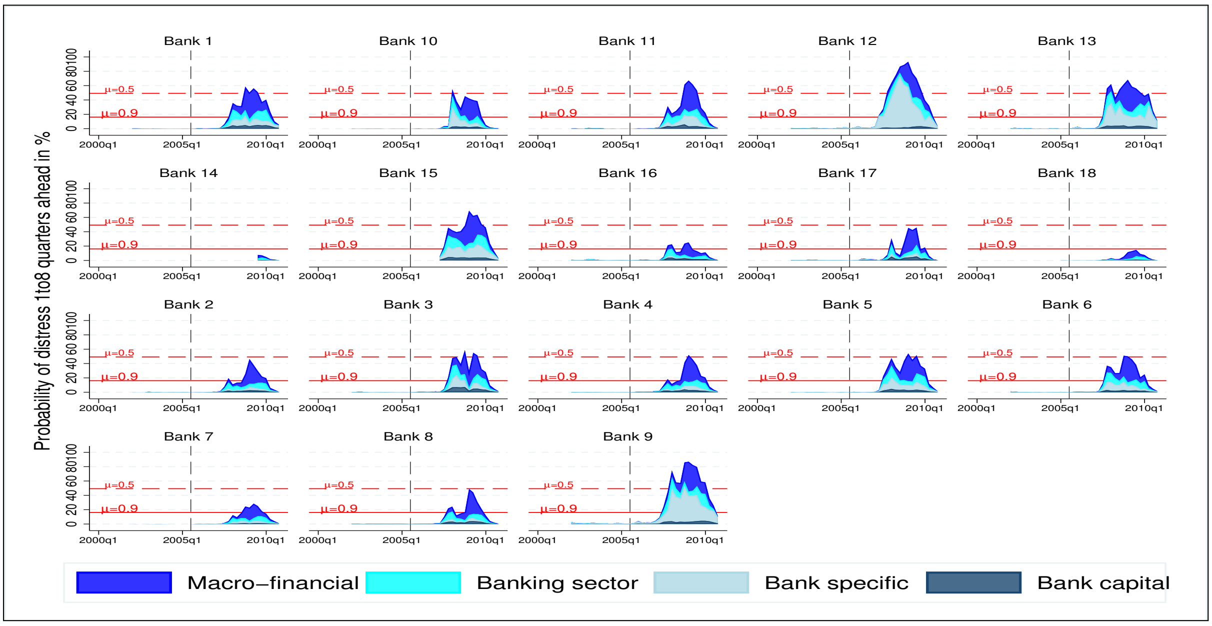
Notes: The figures present the estimated distress probabilities at the bank level (a) under the counterfactual scenario with the 9-to-16 quarters prediction horizon for the case of intervention at 2005 Q3 and (b) from the historical data. The coloured areas illustrate the risk decomposition. Risk thresholds for $\mu = 0.9$ and $\mu = 0.5$ are drawn with red horizontal lines. The vertical dashed line indicates 2005 Q3, the quarter the risk in the banking system elevates above the threshold and triggers the intervention (using 9-to-16 quarters horizon). The y-axes present the distress probability in percentages.

Figure A.6.2: Bank-level distress probabilities estimated from historical data and under the counterfactual scenario of intervention in 2005 Q3 with 1-to-8 quarters prediction horizon

a. Bank-level risks under the counterfactual



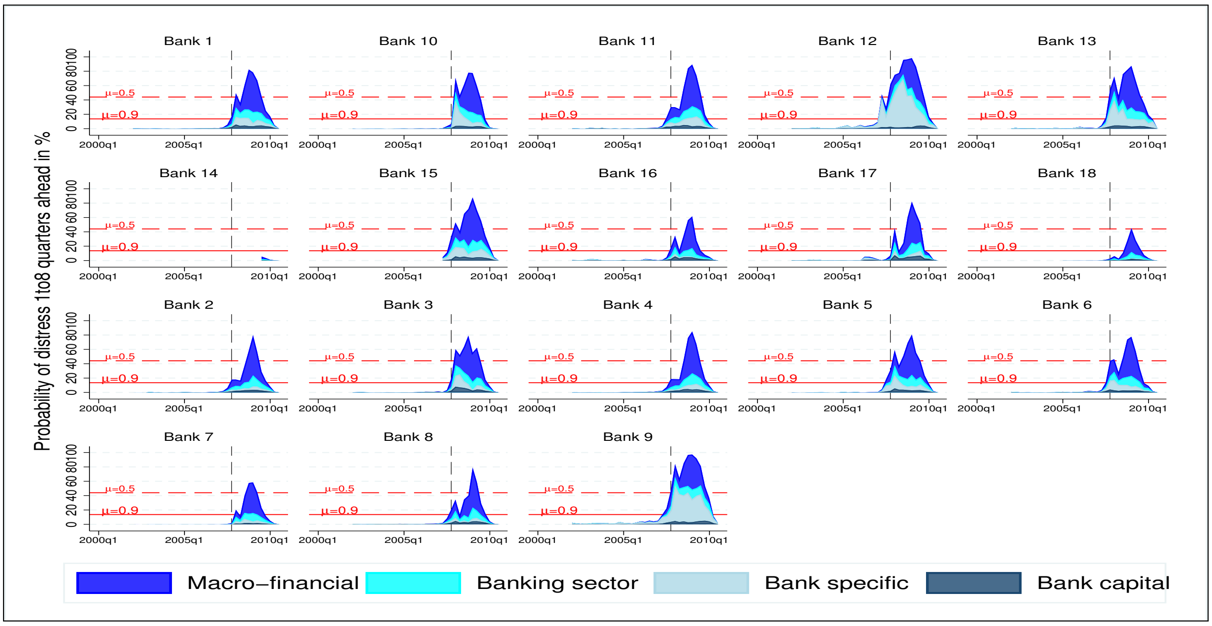
b. Bank-level risks estimated from historical data



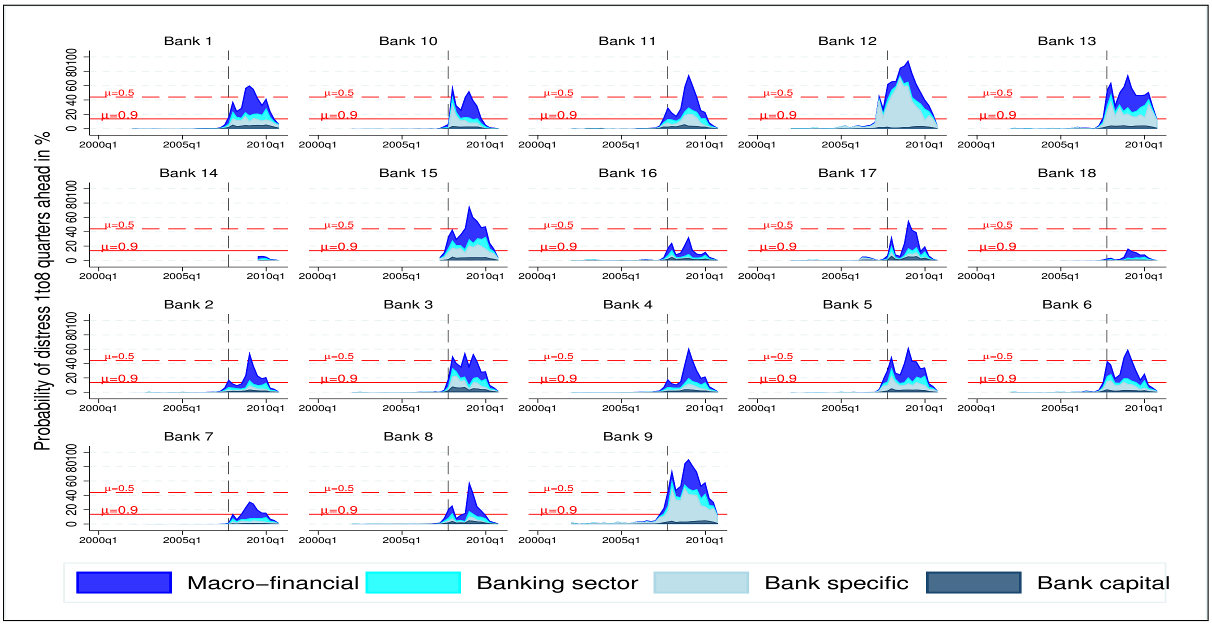
Notes: The figures present the estimated distress probabilities at the bank level (a) under the counterfactual scenario with the 1-to-8 quarters prediction horizons for the case of intervention at 2005 Q3 and (b) from the historical data. The coloured areas illustrate the risk decomposition. Risk thresholds for $\mu = 0.9$ and $\mu = 0.5$ are drawn with red horizontal lines. The vertical dashed line indicates 2005 Q3, the quarter the risk in the banking system elevates above the threshold and triggers the intervention (using 9-to-16 quarters horizon). The y-axes present the distress probability in percentages.

Figure A.6.3: Bank-level distress probabilities estimated from historical data and under the counterfactual scenario of intervention in 2007 Q4 with 1-to-8 quarters prediction horizon

a. Bank-level risks under the counterfactual



b. Bank-level risks estimated from historical data



Notes: The figures present the estimated distress probabilities at the bank level (a) under the counterfactual scenario with the 1-to-8 quarters prediction horizons for the case of intervention at 2007 Q4 and (b) from the historical data. The coloured areas illustrate the risk decomposition. Risk thresholds for $\mu = 0.9$ and $\mu = 0.5$ are drawn with red horizontal lines. The vertical dashed line indicates 2007 Q4, the quarter the risk in the banking system elevates above the threshold and triggers the intervention (using 1-to-8 quarters horizon). The y-axes present the distress probability in percentages.