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A framework for early-warning modeling with an application to banks

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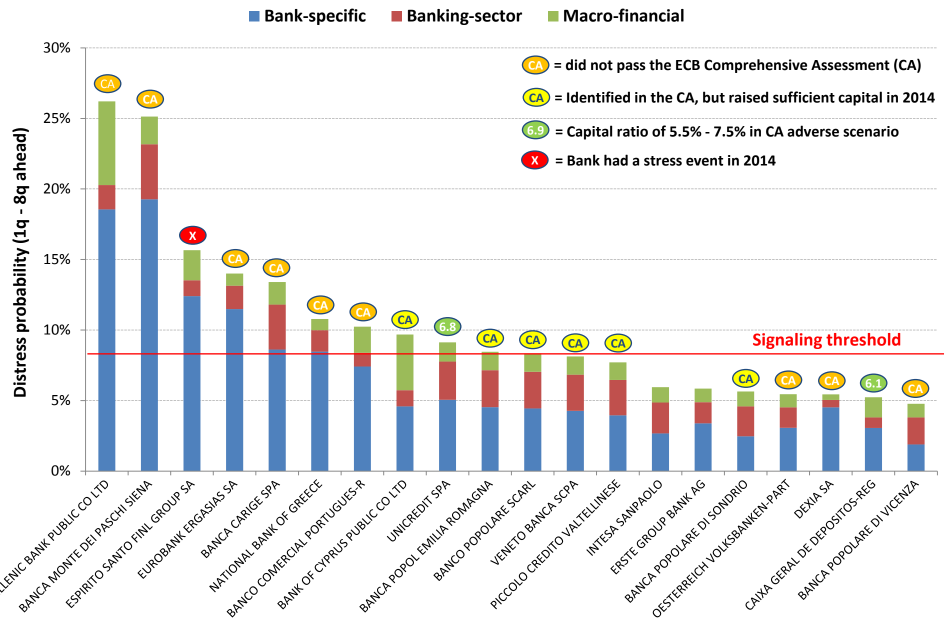
Figure 5: Most vulnerable banks in 2014Q2 for the optimal model

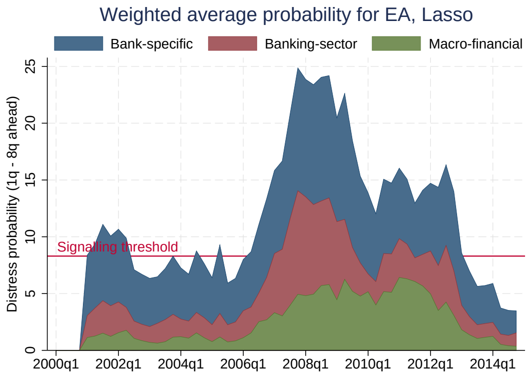


Notes: The output is chosen to illustrate the method and no policy conclusions should be drawn from the examples. The figure displays the 20 most vulnerable significant SSM banks in 2014Q2 based on the predictions of the logit model with the same specification as the logit LASSO model estimated on the full sample of available data. The signalling threshold is derived for a policy preference parameter of $\mu = 0.9$. The coloured bars illustrate the risk factor decomposition (bank-specific, banking-sector and macro-financial) as defined in Section 3.4.

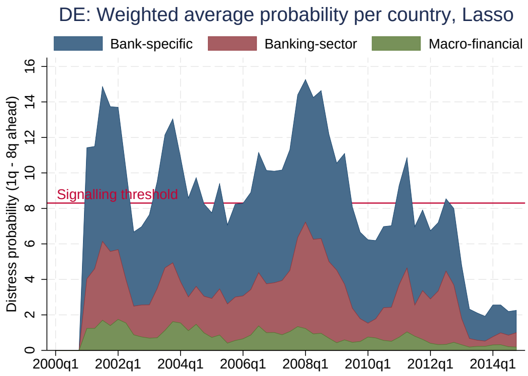
amples, it can be seen that the model captures different magnitudes of vulnerabilities across countries as well as different driving factors that are important.

Figure 6: Aggregate vulnerability for selected countries for the optimal model

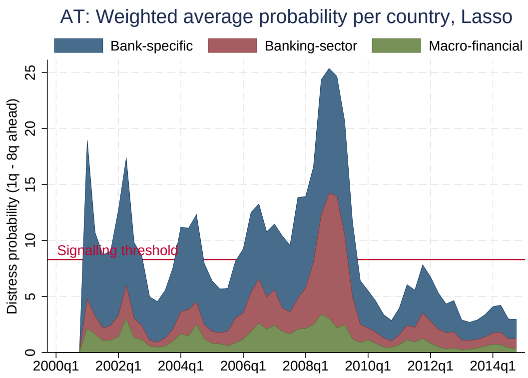
(a) Euro area



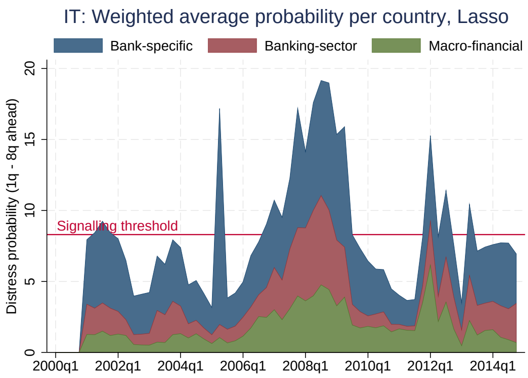
(b) Germany



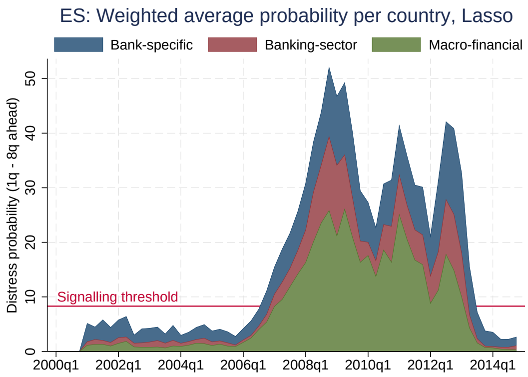
(c) Austria



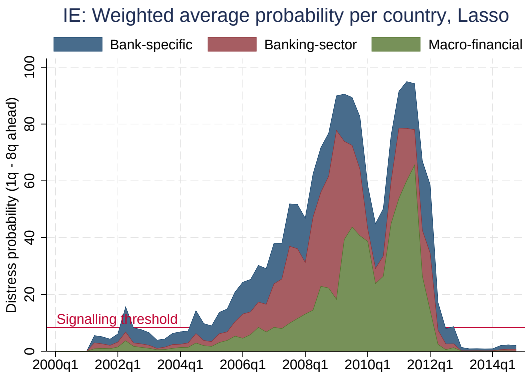
(d) Italy



(e) Spain



(f) Ireland



Notes: The countries are chosen to illustrate the method and no policy conclusions should be drawn. Aggregation is done for the logit model with the same specification as the logit LASSO model estimated on the full sample of available data. The coloured areas illustrate the risk factor decomposition (bank-specific, banking-sector and macro-financial) as defined in Section 3.4. The signalling threshold is derived for a policy preference parameter of $\mu = 0.9$.

4.5 Illustration of the flexibility of the modeling solution

The previous subsections have highlighted how the proposed modeling solution can be used to obtain an optimal early warning model specification for a given set of pre-modeling choices. However, the optimal early warning model will always depend on the specific aim it is to serve. As will be illustrated below, the proposed modeling solution is one possible way to deal with this multitude of context-specific optimal early warning models in a flexible way. The robustness exercises presented below also illustrate the importance of making the pre-modeling and modeling choices presented in section 2 explicit, as they will influence the optimal early warning model specification in a meaningful way.

Table 4 illustrates how the optimal cross-validated LASSO shrinkage parameter and therefore the optimal model complexity and specification changes when the forecast horizon, policy preference parameter and variable pre-selection are changed. Specifically, a shorter forecast horizon (1-4 quarters), a longer forecast horizon (1-12 quarters), a lower preference for not missing bank distress events ($\mu = 0.8$) and a smaller set of pre-selected variables (i.e. a larger requirement on the sample size of 10,000 observations) compared to the benchmark model are tested. In the benchmark specification a forecast horizon of 1-8 quarters before distress events, a preference parameter of $\mu = 0.9$ and a recursive variable pre-selection procedure that resulted in 5,000 observations were used.

Table 4 clearly shows that the optimal early warning model specification changes, when some key modeling choices are altered. For example, a shorter prediction horizon leads to a more complex model (15 variables) to be selected by the LASSO with cross-validation than in the baseline (11 variables), while a longer prediction horizon leads to a less complex model (8 variables). For our example, a lower preference for not missing distress events also leads to a less complex model with 7 variables, as does the case when one pre-selects fewer variables in order to cover a larger bank sample over time. Table 4 also illustrates that for the shorter prediction horizon of 1-4 quarters, more bank-specific variables get selected as relevant predictors for bank distress. These examples illustrate the need to be explicit about the modeling choices that are made, as set out in section 2, because these modeling choices will influence what type of early warning model is optimal. One benefit of our proposed modeling solution from section 3 is that it allows to derive an optimal early warning model for a given set of such choices in a straightforward way.

Table 4: Optimal model specifications for different early warning choices

Variable	(1) Baseline specification	(2) Different horizon (shorter)	(3) Different horizon (longer)	(4) Different preferences	(5) Different pre-selection
Intercept	-3.111***	-3.928***	-2.528***	-2.906***	-3.144***
Bank-specific variables					
Tangible equity / Total assets, lag 2	-0.296***	-0.286***	-0.183	-0.227***	
Interest expenses / Total liabilities, lag 2	0.256***	0.226***	0.216***	0.213**	0.075*
Reserves for NPLs / Total assets, lag 2	0.349***	0.267**			
Non-operating losses / Net revenue, lag 2		0.001			
Other income / Net revenue (1-year change), lag 2		0.016**			
Common equity / Total assets, lag 2			-0.064		-0.235***
Banking-sector variables					
Financial assets / GDP, lag 2	0.003***	0.0004	0.001	0.003***	
Loans / Deposits (1-year change), lag 1	0.015	0.01			
Mortgages / Loans (1-year change), lag 1	-0.261*	-0.308*			-0.472***
Issued debt / Total liabilities (1-year change), lag 1	-0.136*	-0.160			
Financial liabilities / GDP, lag 2		0.002			
Total assets / GDP, lag 2			0.012*		
Macro-financial variables					
Total credit / GDP (3-year change), lag 2	0.017**		0.019*	0.019*	0.021***
House price gap (lambda = 1,600), lag 2	-0.053**	-0.093***		-0.084***	-0.039**
MIP International Investment Position, lag 2	-0.007	-0.009*			
10-year yield (1-year change), lag 1	0.402*	0.201*	0.566***	0.534**	0.412***
Stock prices (1-quarter growth), lag 1		-0.013*			
Stock prices (4-quarter growth), lag 1		-0.009**			
MIP Private sector debt, lag 2			0.003		
Total credit / GDP, lag 2				-0.002	
MIP Current account balance, lag 2					-0.061***
Preference parameter	0.9	0.9	0.9	0.8	0.9
Pre-crisis period	1 - 8	1 - 4	1 - 12	1 - 8	1 - 8
Variable pre-selection	5,000	5,000	5,000	5,000	10,000
LASSO penalty parameter	0.029	0.013	0.037	0.035	0.024
Number of variables	11	15	8	7	7
Pseudo R2	0.260	0.270	0.209	0.211	0.194
AUROC	0.850	0.874	0.810	0.831	0.820
Signalling Threshold	8.906	7.704	9.500	19.30	8.299
Relative Usefulness	0.515	0.467	0.422	0.281	0.442

Notes: Coefficient estimates refer to the logit model with the same specification as the optimal logit LASSO model estimated on the pre-selected sample for the cross-validation. Stars indicate the level of significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

As the examples provided above have illustrated, building an early warning model is a complex task with several choices that need to be made. Most importantly, decisions about the specific purpose of the early warning model should influence its optimal specification in a meaningful way. This highlights the need for a conceptual framework as presented in section 1 to guide the model building process and to make certain modeling choices explicit rather than implicit. Based on these explicit modeling choices, the proposed modeling solution presented in section 3 provides one possible way to easily obtain a model specification that suits the specific early warning purpose at hand.

5 Conclusion

The large economic costs brought about by severe financial crises have again become apparent in recent years. In order to avoid or at least mitigate the impact of future financial crises it is necessary to gain a deeper understanding of the driving factors that cause such crisis episodes and to devise models that help to identify the build-up of financial imbalances and systemic risk early on. The work on early-warning models has therefore gained prominence in recent years, both in the academic and policy sphere. However, the numerous complex choices that are involved in building such models and the various approaches that have been employed in the literature call for a structured modeling approach.

This paper has put forward a general-purpose framework for deriving early-warning models and has applied it to predicting distress in European banks. The paper therefore contributes to the existing literature in three main ways. First, the paper has introduced a conceptual framework to guide the process of building early-warning models, which highlights and structures the numerous complex choices that the modeler needs to make. Second, the paper has provided a flexible modeling solution to the conceptual framework that supports model selection in real-time. Specifically, our proposed solution combines the loss function approach to evaluate early-warning models with regularized logistic regression and cross-validation to find a model specification with optimal real-time out-of-sample forecasting properties. Finally, the paper has illustrated how the modeling framework can be used in analysis supporting both micro- and macro-prudential policy by applying it to a large dataset of EU banks and showing some examples of early-warning model visualizations.

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