Predicting Distress in European Banks[1]

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Abstract

The paper develops an early-warning model for predicting vulnerabilities leading to distress in European banks using both bank and country-level data. As outright bank failures have been rare in Europe, we introduce a novel dataset that complements bankruptcies and defaults with state interventions and mergers in distress. The signals of the early-warning model are calibrated not only according to the policymaker's preferences between type I and II errors, but also to take into account the potential systemic relevance of each individual financial institution. The key findings of the paper are that complementing bank-specific vulnerabilities with indicators for macro-financial imbalances improves model performance and yields useful out-of-sample predictions of bank distress during the current financial crisis.

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Non-technical summary

The global financial crisis has brought a large number of European banks to the brink of collapse. Moreover, beyond the direct bailout costs and output losses, the interplay of fiscally strained sovereigns and weak banking systems that characterize the ongoing sovereign debt crisis in Europe show the important role of the euro area banking sector for the stability of the entire European Monetary Union. Thus, the motivation for an early-warning model for European banks is obvious.

To derive an early-warning model for European banks, this paper introduces a novel dataset of bank distress events. As bank defaults are rare in Europe, the data set complements bankruptcies, liquidations and defaults by also taking into account state interventions, and mergers in distress. State interventions comprise capital injections and asset reliefs (asset protection and guarantees). A distressed merger occurs if *i*) a parent receives state aid within 12 months after the merger or *ii*) if a merged entity has a coverage ratio smaller than 0 within 12 months before the merger.

The outbreak of a financial crisis is known to be difficult to predict (e.g., Rose and Spiegel, 2011). Recently, the early-warning model literature has therefore focused on detecting underlying vulnerabilities, and finding common patterns preceding financial crises (e.g., Reinhart and Rogoff, 2008; 2009). Thus, this paper focuses on predicting *vulnerable states*, where one or multiple triggers could lead to a bank distress event. The early-warning model applies a micro-macro perspective to measure bank vulnerability. Beyond bank-specific and banking-sector vulnerability indicators, the paper uses measures of macroeconomic and financial imbalances from the EU Alert Mechanism Report related to the EU Macroeconomic Imbalance Procedure (MIP).

The models derive bank-specific probabilities of being in a vulnerable state, but a policy maker has to know when to act. The paper uses the state-of-the-art methodology developed in Sarlin (2012) to evaluate the signals of the model. The approach takes into account the policymaker's preferences between type I and type II errors, the uneven frequency of tranquil and distress events, and the systemic relevance of the bank. This paper presents the first application of the evaluation framework to a bank-level model and represent a bank's systemic relevance with its size. Thus, the early-warning model is better suited to predict systemic banking crises and to analyse systemic risks.

Regarding the main findings of the paper, the estimation results provide useful insights into determinants of banking sector fragility in Europe. We find that complementing bank-specific vulnerabilities with indicators of macro-financial imbalances improves model performance. Thus, the results of the paper also confirm the usefulness of the vulnerability indicators introduced recently with respect to the

EU Macroeconomic Imbalance Procedure (MIP). Instead, indicators of imbalances in countries' banking-sectors only marginally improve model performance. Moreover, the paper shows that an early-warning exercise with the model shows that using only publicly available data yields useful out-of-sample predictions of bank distress during the current financial crisis (2007Q1-2011Q4). Finally, the results of the evaluation framework show that a policymaker has to be substantially more concerned of missing bank distress than issuing false alarms for the model to be useful. This is intuitive if we consider that an early-warning signal triggers an in-depth review of fundamentals, business model and peers of the bank predicted to be in distress. Should the analysis reveal that the signal is false, there is no loss of credibility on behalf of the policy authority. The evaluations also imply that it is important to give more emphasis to systemically important and large banks for a policymaker concerned with systemic risk.

1. Introduction

The global financial crisis has brought a large number of European banks to the brink of collapse. Data from the European Commission show that the amount of aid granted by EU states to stabilise the EU banking sector that had been used by the end of 2010 had exceeded €1.6 trillion, more than 13% of EU GDP. Though large, the immediate bailout costs account only for a moderate share of the total cost of a systemic banking crisis. As shown in Dell Arriccia *et al*. (2010) and Laeven and Valencia (2008, 2010, 2011) among others, the output losses of previous banking crises have averaged around 20-25% of GDP. In addition, the interplay of fiscally strained sovereigns and weak banking systems that characterize the ongoing sovereign debt crisis show the crucial role of the euro area banking sector for the stability of the entire European Monetary Union. The rationale behind an early-warning model for European banks is thus clear.

To derive an early-warning model for European banks, this paper introduces a novel dataset of bank distress events. As bank defaults are rare in Europe, the dataset complements bankruptcies, liquidations and defaults by also taking into account state interventions, and mergers in distress. State interventions comprise capital injections and asset reliefs (asset protection and guarantees). A distressed merger occurs if *i*) a parent receives state aid within 12 months after the merger or *ii*) if a merged entity has a coverage ratio smaller than 0 within 12 months before the merger.

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The paper is organized as follows. Section 2 provides a brief review of the related literature. Section 3 describes the data used to define bank distress events as well as the construction of the vulnerability indicators. Section 4 describes the methodological aspects of the early-warning model. Section 5 presents results on determinants of distress and predictive performance, and Section 6 discusses their robustness. Finally, Section 7 concludes the paper. Technical aspects, such as variable definitions, data sources and further robustness tests, are found in the Appendix.

2. Related literature

The present paper is linked to two strands of literature. First, it relates to papers predicting failures or distress at the bank level, and second, to studies on optimal early warning signals for policymakers.

The literature on individual bank failures draws heavily on the Uniform Financial Rating System, informally known as the CAMEL ratings system, introduced by U.S. regulators in 1979, where the letters refer to Capital adequacy, Asset quality, Management quality, Earnings, Liquidity. Since 1996 the rating system includes also Sensitivity to Market Risk (i.e., CAMELS). The CAMELS rating system is an internal supervisory tool for evaluating the soundness of financial institutions on a uniform basis and for identifying those institutions requiring special supervisory attention or concern. Several studies find that banks' balance-sheet indicators measuring capital adequacy, asset quality, and liquidity are significant in predicting bank failures in accounting-based models (e.g., Thomson (1992) and Cole and Gunther (1995, 1998)). Other studies augment the pure accounting-based models with macroeconomic indicators and asset prices. Several papers, mainly based on US bank data, suggest that both macroeconomic and market price-based indicators contain useful predictive information not contained in the CAMELS indicators (e.g., Flannery (1998), González-Hermosillo (1999), Jagtiani and Lemieux (2001), Curry *et al*. (2007), Bharath and Shumway (2008), or Campbell *et al*. (2008)). There is not, however a consensus on the findings in the US, which hinders a direct comparison to the findings on European banks in this study.

Most papers analyzing individual bank failures or distress events focus on U.S. banks or a panel of banks across countries, while there are only a few studies dealing with European banks. Data limitations set by the lack of direct failures in core Europe is illustrated by some recent works: Männasoo and Mayes (2009) focus on Eastern European banks, Ötker and Podpiera (2010) create distress events from Credit Default Swaps (CDS), and Poghosyan and Cihák (2011) create events by keyword searches in news articles. These suffer, however, from three respective limitations: no focus on the entire Europe, in particular the core, the use of CDS limits the sample to listed banks, and data from news articles are inherently noisy. The literature on country-level banking crises is also broad and has most often focused on continents, if not pursuing a fully global approach. Demirgüç-Kunt and Detragiache (2000), Davis and Karim (2008a,b) and Sun (2011) analyse banking crises with a global country coverage, whereas Hutchison (2003) and Mody and Sandri (2012) focus on European countries, where the latter study focuses on the recent crisis.

Regarding studies optimal early warning signals for a policymaker, a seminal paper by Kaminsky *et al*. (1998) introduces the so-called “signal” approach to evaluate the early-warning properties of univariate indicator signals when they exceeds a predefined threshold. The threshold is set to minimize the noise-to-signal ratio, given by the number of false alarms relative to the correct calls. Many later studies, such as Berg and Pattillo (1999a) and Edison (2003), while introducing a discrete-choice model, do not adopt a structured approach to evaluate model performance. An issue addressed by Demirgüç-Kunt and Detragiache (2000) is the introduction of a loss function of a policymaker that considers costs for preventive actions and relative preferences between missing crises (type I errors) and false alarms (type II errors). The authors show that optimising model thresholds on the basis of the noise-to-signal ratio can lead to sub-optimal results under some preference schemes.[3]

Alessi and Detken (2011) apply the loss function approach to asset price boom/bust cycles and extend it by also introducing a measure that accounts for the usefulness of

[3] If banking crises are rare events and the cost of missing a crisis is high relative to that of issuing a false alarm, minimising the noise-to-signal ratio could lead to many missed crises. As a consequence, the selected threshold could be sub-optimal from the point of view of the preferences of policymakers.

disregarding the signals of a model. Sarlin (2012) further extends the literature by amending the policymaker's loss function and usefulness measure in the framework by Alessi and Detken (2011) to include unconditional probabilities of the events, as was previously done in Demirgüç-Kunt and Detragiache (2000), and computes a measure called relative Usefulness. By computing the share of available Usefulness that a model captures, the relative Usefulness facilitates interpretation of the measure. Furthermore, the signal evaluation scheme also accounts for the systemic relevance of each individual entity, e.g., bank or country, as well as further augments the usefulness measure by focusing on the share of available usefulness that the model captures.

3. Data

We construct the sample based on availability of balance-sheet and income-statement data in Bloomberg. The observation period starts in Q1 2000 and ends in Q4 2011. We obtain data on 546 banks with a minimum of EUR 1bn in total assets during the period under consideration (in total 26,852 observations). By this rule, we focus on large banks with significance for system stability. The sample covers banks in all EU countries but Cyprus, Estonia, Lithuania and Romania. We do our best efforts to reconstruct the information set that would have been available to investors at each point of time. Thus, for instance, if a bank reports its accounts at annual frequency, we use this information in four subsequent quarters. The dataset consists of two parts: bank distress events and vulnerability indicators. We describe them in the following.

3.1. Identifying bank distress events

Given that actual bank failures are rare in Europe, identification of bank distress events is challenging. Thus, in addition to bankruptcies, liquidations, and defaults, the paper also takes into account state interventions and forced mergers to represent bank distress.

First, we use data on bankruptcies, liquidations and defaults to capture direct bank failures. A bankruptcy is defined to occur if the net worth of a bank falls below the country-specific guidelines, whereas liquidations occur if a bank is sold as per the guidelines of the liquidator in which case the shareholders may not receive full payment for their ownership. We define two types of defaults as follows: a default occurs *i*) if a bank has failed to pay interest or principal on at least one financial obligation beyond any grace period specified by the terms, or *ii*) if a bank completes a distressed exchange, in which at least one financial obligation is repurchased or replaced by other instruments with a diminished total value. The data on bankruptcies and liquidations are retrieved from Bankscope, while defaults are obtained from annual compendiums of corporate defaults by Moody's and Fitch. We define a distress event to start when the failure is announced and to end when the failure *de facto* occurs. This method leads to 13 distress events at the bank-quarter level, of which most are defaults.

Second, we use data on state support to detect banks in distress. A bank is defined to be in distress if it receives a capital injection by the state or participates in asset relief programmes (asset protection or asset guarantees). This definition focuses on assistance on the asset side and does hence not include liquidity support or guarantees on banks' liabilities. The state aid measures are based on data from the European Commission as well as data collected by the authors from market sources (Reuters and Bloomberg). Events in this category are defined to last from the announcement of the state support to the execution of the state support programme. This approach leads to 153 distress events, which shows the extent to which state intervention is more common than outright default.

Third, mergers in distress capture private sector solutions to bank distress. The merged entities are defined to be in distress if *i*) a parent receives state aid within 12 months after the merger or *ii*) if a merged entity has a coverage ratio smaller than 0 within 12 months before the merger. The coverage ratio is commonly used in the literature to define distressed banks (e.g., González-Hermosillo, 1999). The rationale for applying the rule only on mergers is that we want to capture banks that are forced to merge due to distress. A bank may have a negative coverage ratio, but still survive without external support. Data on mergers are obtained from Bankscope, whereas the coverage ratio is defined as the ratio of capital equity and loan reserves minus non-performing loans to total assets and computed using data from Bloomberg. While these definitions should thoroughly cover distressed mergers, the only caveat is a possible mismatch in sample coverage of the two data sources. The events identified using these definitions of distressed mergers were, however, cross-checked using market sources (Reuters and Bloomberg). We define the two types of distressed mergers to start and end as follows: *i*) to start when the merger occurs and end when the parent receives state aid and *ii*) to start when the coverage ratio falls below 0 (within 12 months before the merger) and end when the merger occurs. Based on this approach we identify 35 mergers in distress.

In total, we obtain 194 distress events at the bank-quarter level. This figure is smaller than the sum of events across categories as they are not mutually exclusive. As a bank that experiences two distress events within one year is likely to be in distress also in between those events, we modify the bank-specific time series accordingly. While being a question of interest, we do not distinguish between the different types of distress events in the sequel of this paper. The low frequency of direct failures and distressed mergers hinders robust estimations of determinants for all three categories.

Figure 1 shows the number of banks and distress events by country. Given the chosen sample and data availability, Italy is the country with the largest number of banks, followed by Spain, Germany, and France. In the case of Greece, Ireland, and Belgium, the number of distress events exceeds the number of banks, which is feasible as a bank can experience multiple distress periods. This paper focuses on vulnerable states, or pre-distress events, which can be defined from the dates of the distress events. For instance, a binary pre-distress variable takes the value 1 in 8 quarters prior to the distress events, and otherwise 0.

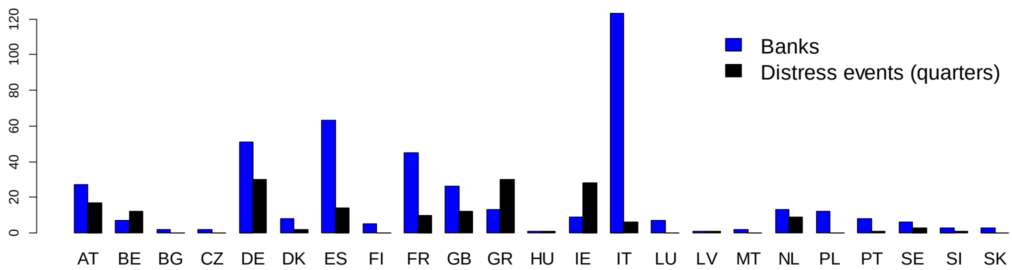

Figure 1: The number of banks and distress events by country

The number of the distress and pre-distress events per category is better illustrated in Table 1. The occurrence of the distress and pre-distress events in various categories are not mutually exclusive. Hence, the categories do not sum up. The table illustrates that most distress events, and thus also pre-distress periods, are from the category of state interventions and a large share of them are capital injections. The unconditional probabilities of the events show that distress events represent only a small share of the observations in the dataset. This imbalance in class size will be taken into account when evaluating the models.

Table 1: The number of distress and pre-distress events by category

	Distress events		**Pre-distress events**	
Distress categories	**Freq.**	**Uncond. prob.**	**Freq.**	**Uncond. prob.**
Direct failure	13	0.05 %	110	0.41 %
Bankruptcy	1	0.00 %	8	0.03 %
Liquidation	2	0.01 %	16	0.06 %
Defaulted by Moody's	11	0.04 %	75	0.28 %
Defaulted by Fitch	2	0.01 %	21	0.08 %
Distressed mergers	35	0.13 %	228	0.85 %
Merger with state intervention	28	0.10 %	179	0.67 %
Merger with coverage ratio < 0	13	0.05 %	105	0.39 %
State intervention	153	0.57 %	892	3.32 %
Capital injection	113	0.42 %	763	2.84 %
Asset protection	33	0.12 %	180	0.67 %
Asset guarantee	23	0.09 %	127	0.47 %
Total	194	0.72 %	1000	3.72 %

Notes: The statistics are derived from the entire sample with 26,852 observations and 546 banks and the pre-distress events are defined to be 8 quarters prior to the distress events.

3.2. Vulnerability indicators

The paper uses three categories of indicators in order to capture various aspects of a bank's vulnerability to distress. First, indicators from banks' income statements and balance sheets measure bank-specific vulnerabilities. Following the literature, we use indicators to account for all dimensions in the CAMELS rating system (e.g., Flannery, 1998; González-Hermosillo, 1999; Poghosyan and Cihák, 2011). The indicators to proxy the CAMELS dimensions as follows. The equity-to-assets and Tier 1 capital ratio represent Capital adequacy (C) and are used to proxy the level of bank capitalization. Asset quality (A) is represented by return on assets, size of total assets, debt-to-equity ratio, impaired assets and loan loss provisions. The cost-to-income ratio represents Management quality (M), while return on equity (ROE) and net interest margin measure Earnings (E). Liquidity (L) is represented by the share of interest expenses to total liabilities, deposits-to-funding ratio and the ratio of loans to deposits. Finally, the share of trading income represents Sensitivity to market risk (S). We do not consider market-based indicators, such as proposed by Agarwal and Taffler (2008). The key reasons are two: *i*) we aim at predicting underlying vulnerabilities 1-3 years prior to distress, whereas market-based signals tend to have a shorter horizon, and *ii*) we aim at using a broad sample of banks, rather than only listed banks.

Second, country-specific banking sector indicators represent imbalances at the level of banking systems. These indicators are often cited as key early-warning indicators for banking crises (e.g., Demirgüç-Kunt and Detragiache, 1998; 2000; Kaminsky and Reinhart, 1999). Moreover, there are currently efforts at the EU level to find a suitable vulnerability indicator for the banking/financial sector (EC, 2012). The indicators proxy the following types of imbalances: booms and rapid increases in banks' balance sheets, e.g., growth in financial liabilities and non-core liabilities; securitization, e.g., debt securities to liabilities; property booms, e.g., mortgages-to-loans ratio; banking-system leverage, e.g., debt-to-equity and loans-to-deposits ratios; and banking-system exposures to derivatives contracts, e.g., gross derivatives to capital and reserves. The indicators used in the paper are described in Appendix A.1. All indicators except credit to GDP are constructed using the ECB's statistics on the Balance Sheet Items (BSI) of the Monetary, Financial Institutions and Markets (MFI), whereas the credit-to-GDP indicator is calculated using data from Haver Analytics and the IMF International Financial Statistics database (IFS).

Finally, country-specific macro-financial indicators identify macro-economic imbalances and control for conjunctural variation in asset prices and business cycles. To control for macro-economic imbalances, the paper uses the internal and external indicators from the EU Macroeconomic Imbalance Procedure (MIP), such as current account imbalances, unit labour costs, unemployment rate, and general government debt. Moreover, asset prices (stock and house price gaps) and business cycle indicators (real GDP growth and CPI inflation) capture conjunctural variation.

Appendix A.1 provides a more detailed description of the indicators. Most of the macro-financial indicators are retrieved from Eurostat and Bloomberg.

Tables A and B in the Appendix describe the indicators used and their definitions and transformations, as well as their summary statistics. The statistical tests show that the data are non-normally distributed and exhibit most often a positive skew with a leptokurtic distribution. Table C in the Appendix shows the discriminatory power of the indicators through mean-comparison tests. The *t*-test results indicate that most variables are good candidates for discriminating between tranquil and vulnerable periods. Among bank-specific indicators, the cost-to-income ratio, share of trading income and loans to assets do not hold a promise to discriminate between the classes. Financial liabilities and gross derivatives are the poorest discriminators among banking-sector indicators, whereas inflation and stock-price gap are the poorest among macro-financial indicators.

4. Methodology

The methodology presented in this section consists of two building blocks: *i*) a framework for evaluating signals of early-warning models, and *ii*) the estimation and prediction methods.

4.1. Evaluation of model signals

Early-warning models require evaluation criteria that account for the nature of the underlying problem. Distress events are oftentimes outliers in three aspects: the dynamics of the economy differ significantly from tranquil times, they are often costly, and they occur rarely. Given these properties, an evaluation framework that resembles the decision problem faced by a policymaker is of central importance. Designing a comprehensive evaluation framework for early-warning model signals is challenging as there are several political economy aspects to be taken into account. For instance, the frequency and optimal timing when the policymaker should signal a crisis might depend on potential inconsistencies between the maximisation of the policymaker's own utility vs. social welfare. While important, these types of considerations are beyond the scope of this study. Thus, the signal evaluation framework focuses only on a policymaker with relative preferences between type I and II errors and the usefulness that she gets by using a model vs. not using it.

As the focus is on detecting vulnerabilities and risks prior to distress, the ideal leading indicator can be represented by a binary state variable $C_j(h) \in \{0,1\}$ for observation *j* (where *j*=1,2,…,*N*) with a specified forecast horizon *h*. Let $C_j(h)$ be a binary indicator that is one during pre-crisis periods and zero otherwise. For detecting events C_j using information from indicators, discrete-choice models can be used for estimating probabilities of occurrence of crisis $p_j \in [0,1]$. To mimic the ideal leading indicator, the probability p is transformed into a binary prediction P_j that is one if p_j exceeds a specified threshold $\lambda \in [0,1]$ and zero otherwise. The correspondence between the prediction P_j and the ideal leading indicator C_j can be summarized into a so-called contingency matrix.

		Actual class C_j	
		1	0
Predicted class P_j	1	*True positive (TP)*	*False positive (FP)*
	0	*False negative (FN)*	*True negative (TN)*

While the elements of the matrix (frequencies of prediction-realization combinations) can be used for computing a wide range of measures[4], a policymaker can be thought of mainly being concerned about two types of errors: giving false alarms and missing crises. The evaluation framework in this paper follows Sarlin (2012) for turning policymakers' preferences into a loss function, where the policymaker has relative preferences between type I and II errors. Type I errors represent the proportion of missed crises relative to the number of crises in the sample ($T_1 \in [0,1] = FN/(TP+FN)$), and type II errors the proportion of false alarms relative to the number of tranquil periods in the sample ($T_2 \in [0,1] = FP/(FP+TN)$). Given probabilities p of a model, the policymaker should choose a threshold λ such that her loss is minimized. The loss of a policymaker consists of T_1 and T_2, weighted according to her relative preferences between missing crises (μ) and giving false alarms $(1-\mu)$. By accounting for unconditional probabilities of crises $P_1 = P(D=1)$ and tranquil periods $P_2 = P(D=0) = 1 - P_1$, the loss function is as follows:

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

where $\mu \in [0,1]$ represents the relative preferences of missing events and $1-\mu$ the relative preferences of giving false alarms, T_1 the type I errors and T_1 the type II errors. P_1 refers to the size of the crisis class and P_2 to the size of the tranquil class. Using the loss function $L(\mu)$, the Usefulness of a model can be defined in two ways. First, the absolute Usefulness (U_a) is given by:

[4] Some of the commonly used simple evaluation measures are as follows. Recall positives (or TP rate) = TP/(TP+FN), Recall negatives (or TN rate) = TN/(TN+FP), Precision positives = TP/(TP+FP), Precision negatives = TN/(TN+FN), Accuracy = (TP+TN)/(TP+TN+FP+FN), FP rate = FP/(FP+TN), and FN rate = FN/(FN+TP).

$$U_a = \min(\mu P_1, P_2(1-\mu)) - L(\mu), \tag{2}$$

which computes the extent to which a model performs better than no model at all. As the unconditional probabilities are commonly unbalanced and the policymaker may be more concerned about one class, a policymaker could achieve a loss of $\min(\mu P_1, P_2(1-\mu))$ by either always or never signalling an event. It is thus worth noting that already an attempt to build an early-warning model for events with unbalanced events implicitly assumes a policymaker to be more concerned about the rare class. With a non-perfectly performing model, it would otherwise easily pay-off for the policymaker to always signal the high-frequency class.
Second, relative Usefulness U_r is computed as follows:

$$U_r = \frac{U_a}{\min(\mu P_1, P_2(1-\mu))}, \tag{3}$$

where the absolute Usefulness U_a of the model is compared with the maximum possible usefulness of the model, i.e., the loss of disregarding the model. That is, U_r reports U_a as a percentage of the usefulness that a policymaker would gain with a perfectly performing model.

A policymaker may further want to enhance the representation of preferences by accounting for observation-specific differences in costs. In bank early-warning models, the bank-specific misclassification costs are highly related to the systemic or contagious relevance of an entity for the policymaker. While this relevance can be measured with network measures such as centrality, a simplified measure of relevance for the system in general is the size of the entity relative to the system's size (e.g., assets of a financial institution). Let w_j be a bank-specific weight that approximates the importance of correctly classifying observation *j*. Also, let TP_j, FP_j, FN_j and TN_j be binary vectors of combinations of predictions and realizations rather than only their sums. By multiplying each binary element of the contingency matrix by w_j, we can derive a policymaker's loss function with bank and class-specific misclassification costs. Let T_1 and T_2 be weighted by w_j to have weighted type I and II errors:

$$T_{w1} \in [0,1] = \sum_{j=1}^{N} w_j FN_j \Big/ \left(\sum_{j=1}^{N} w_j TP_j + \sum_{j=1}^{N} w_j FN_j\right)$$
$$T_{w2} \in [0,1] = \sum_{j=1}^{N} w_j FP_j \Big/ \left(\sum_{j=1}^{N} w_j FP_j + \sum_{j=1}^{N} w_j TN_j\right).$$

As T_{w1} and T_{w2} are ratios of weights rather than ratios of binary values, the errors T_{w1} and T_{w2} can replace T_1 and T_2 in Equations 1-3, the loss function $L(\mu)$, and absolute and relative utilities U_a and U_r for given preferences can be derived.

Receiver operating characteristics (ROC) curves and the area under the ROC curve (AUC) are also viable measures for comparing performance of early warning models. The ROC curve shows the trade-off between the benefits and costs of a certain λ. When two models are compared, the better model has a higher benefit (TP rate on the vertical axis) at the same cost (FP rate on the horizontal axis).[5] Thus, as each FP rate is associated with a threshold, the measure shows performance over all thresholds. In this paper, the size of the AUC is computed using trapezoidal approximations. The AUC measures the probability that a randomly chosen distress event is ranked higher than a tranquil period. A perfect ranking has an AUC equal to 1, whereas a coin toss has an expected AUC of 0.5.

4.2. Estimation and prediction

The early-warning model literature has utilized a wide range of conventional statistical methods for estimating distress probabilities. The obvious problem with most statistical methods (e.g., discriminant analysis and discrete-choice models) is that all assumptions on data properties are seldom met. By contrast, the signal approach is univariate in nature. We turn to discrete-choice models, as methods from the generalized linear model family have less restrictive assumptions (e.g., normality of the indicators). Logit analysis is preferred over probit analysis as its assumption of more fat-tailed error distribution corresponds better to the frequency of banking crises and bank distress events (van den Berg *et al*., 2008). Hazard models would hold promise for these inherently problematic data by not having assumptions about distributional properties, such as shown in Whalen (1991) in a banking context. However, the focus of hazard models is on predicting the timing of distress, whereas we aim at predicting vulnerable states, where one or multiple triggers could lead to a bank distress event.

Typically, the literature has preferred the choice of a pooled logit model (e.g., Fuertes and Kalotychou, 2007; Kumar *et al*., 2003; Davis and Karim, 2008b; Sarlin and Peltonen, 2011). Fuertes and Kalotychou (2006) show that accounting for time- and country-specific effects leads to better in-sample fit, while decreasing the predictive performance on out-of-sample data. Further motivations of pooling are the relatively small number of crises in individual countries and the strive to capture a wide variety

[5] In general, the ROC curve plots, for the whole range of measures, the conditional probability of positives to the conditional probability of negatives: $ROC = \frac{P(P=1|C=1)}{1-P(P=0|C=0)}$.

of vulnerable states. Country-specific effects are, to some extent, still taken into account as country-level explanatory variables are included in the model. Rather than using lagged explanatory variables, the dependent variable is defined as a specified number of quarters prior to the event (8 quarters in the benchmark case). The early-warning model is a recursive logit model that makes a prediction at each quarter t=1,2,…,T with an estimation sample that grows in an increasing-window fashion and functions according to the following steps:

1. Estimate the model on in-sample data using the information that would have been available from the beginning of the sample up to quarter t-1 (in-sample period).
2. Collect the probabilities p of the model for the in-sample period and compute the Usefulness for all thresholds $\lambda \in [0,1]$.
3. Choose the λ that maximizes in-sample Usefulness, estimate distress probabilities p for the out-of-sample data (quarter t) and apply λ to the out-of-sample data.
4. Set t=t+1 and recursively re-estimate the model starting from Step 1 at each quarter t while $t \leq T$.

In practice, we estimate a model at each quarter t with all available information up to that point, evaluate the signals to set an optimal threshold, and provide an estimate of the current vulnerability of each bank with the same threshold as in sample. Hence, the estimation samples change as increasing windows and the out-of-samples as rolling windows (one quarter). As the time frequency is quarters and parts of the bank-specific data are annual, due to data limitations, an assumption in those cases is then that changes in vulnerability of banks derives from country-specific factors. These recursive changes in in-sample and out-of-sample data enable testing the performance of the model in real-time use.

The estimation strategy accounts for post-crisis and crisis bias, as proposed by Bussiere and Fratzscher (2006), by not including periods when a bank distress event occurs or the 4 quarters thereafter. However, post-distress periods are included in the sample if they are also pre-distress periods. The excluded observations are not informative regarding the transition from tranquil times to distress events, as they can neither be considered "normal" periods nor vulnerabilities prior to distress. While the above recursive estimation includes only the Usefulness measure for optimizing the models, all measures introduced in Section 4.1 are computed for evaluating model performance.

5. An early-warning model for bank distress

This section presents the results of our early-warning model for bank distress in Europe. First, the section discusses determinants of bank vulnerability in terms of explanatory power. Second, the section discusses the predictive performance of the early-warning model.

5.1 Predicting Distress in European Banks

We are interested in two key issues: what are the main sources of bank vulnerabilities and to what extent do indicators, or groups of them, predict bank vulnerabilities? Table 2 presents the estimates of the benchmark logit model, which predicts bank vulnerability 8 quarters ahead of distress. The coefficients refer to the estimation sample (2000Q1-2010Q1). The ending date is chosen as per the availability of full information on bank vulnerabilities. Yet, the predictions use recursive increasing windows for the in-sample data (2000Q1-2011Q4) and rolling windows for the out-of-sample data (2007Q1-2011Q4).

The benchmark model (Model 1) contains vulnerability indicators that are drawn from the three groups introduced in Section 3: bank-level indicators, country-specific banking sector indicators and country-level macro-financial indicators. The model is chosen based on two considerations. On the one hand, the model should be encompassing and contain a wide-range of potential vulnerabilities. On the other hand, bank-specific items that have a comparatively short history in available data sources limit the number of observations. Model 2 (Benchmark+) in Table 2 presents results based on a trade-off between the number of observations and the number of indicators. Including the Tier 1 capital ratio, impaired assets, reserves to impaired assets and loan loss provisions reduces the number of available banks from 403 to 214 and the observations from 10,898 to 4,541, but does not improve the predictive usefulness of the model.

Table 2 shows that most of the coefficients in the benchmark model are statistically significant. Among the bank-specific indicators, a high capital ratio and a high return on assets are associated with lower distress probabilities. High interest expenses and a high ratio of deposits-to-funding, on the other hand, increase the probability of distress. Generally, the signs of the coefficients follow economic intuition and findings in the literature, such as higher levels of bank capitalization decreasing distress probabilities, larger banks being more vulnerable, higher returns on equity lowering distress probabilities and larger funding costs increasing bank vulnerability. The positive sign of the deposits-to-funding ratio is the only somewhat counterintuitive estimate, as bank deposits are normally considered a more stable source of funding compared to wholesale funding sources (interbank borrowing or borrowing from capital markets).

Table 2: Logit estimates on bank distress and their predictive performance

		Estimates	(1) Benchmark	(2) Benchmark +
		Intercept	-10.76 ***	-19.23 ***
	C[a]	Equity to assets	-13.32 ***	6.23
		Tier 1 ratio		11.10 **
		Impaired assets		18.18 ***
		Reserves to impaired assets		0.00
	A[a]	Loan loss provisions		21.80 .
		Size (total assets)	0.47 ***	0.60 ***
Bank-specific indicators		Debt to equity	0.00	0.04 **
		ROA	-36.07 **	-32.73
	M[a]	Cost to income	0.00	0.00
	E[a]	ROE	-1.03 .	-0.29
		Net interest margin		16.42
		Interest expenses to liabilities	1.86 ***	22.53 ***
	L[a]	Deposits to funding	24.43 ***	1.39 *
		Loans to deposits		0.03
	S[a]	Share of trading income	-0.05	0.01
		Loans to assets		1.06
Country-specific banking sector indicators		Financial liabilities (annual growth rate)	8.50 ***	6.53 .
		Non-core liabilities (annual growth rate)	10.07 *	0.39
		Debt securities to liabilities	2.49 *	-0.75
		Mortgages to loans	2.51 *	0.12 ***
		Debt to equity	0.07 ***	-1.61 .
		Loans to deposits	0.34 ***	1.60 ***
		Gross derivatives to capital and reserves (annual growth rate)	-0.56	16.51 **
Country-specific macro-financial indicators		GDP (annual growth rate)	-5.94 .	-15.59 **
		Inflation (annual growth rate)	19.58 ***	0.17 ***
		House price gap	0.13 ***	30.28 ***
		Stock price gap	0.00 **	0.00 .
		10-year bund spread	12.77	-33.63 .
		Current account balance to GDP (3-year average)	5.79 **	-1.50
		Government debt to GDP	1.13 ***	2.43 ***
		Private sector credit flow to GDP	-3.79 ***	-3.14 ***
		Private sector credit to GDP gap	6.98 ***	-14.61 ***
		Unemployment rate (3-year average)	9.45 ***	0.26
		International investment position to GDP	-2.59 ***	9.92 ***
		Real effective exchange rate (3-year % change)	4.80 ***	6.89 ***
		Export market share (3-year % change)	-1.90 ***	1.31
		Unit labour cost (3-year % change)	0.13	11.54 *
		R2[b]	0.32	0.39
		No. of banks	403	214
		No. of observations	10898	4541

	Predictive performance	(1) $U_a(\mu)$	(1) $U_r(\mu)$	(2) $U_a(\mu)$	(2) $U_r(\mu)$
Usefulness for a policymaker[c]	μ=0.6	0.00	2 %	0.01	16 %
	μ=0.7	0.01	12 %	0.03	26 %
	μ=0.8	0.02	23 %	0.04	38 %
	μ=0.9	**0.03**	**37 %**	**0.02**	**28 %**
$P(I_j(h)=1)$[d]		0.07		0.09	

Notes:

Signif. codes: '***', 0.001; '**', 0.01; '*', 0.05; '.', 0.10

[a] The letters of CAMELS refer to Capital adequacy, Asset quality, Management, Earnings, Liquidity and Sensitivity to market risk.

[b] R2 refers to the Nagelkerke's pseudo R-squared.

[c] The Usefulness for a policymaker is computed with absolute and relative usefulness $U_a(\mu)$ and $U_r(\mu)$ as described in Section 4.1.

[d] $P(I_j(h)=1)$ refers to the unconditional probability of pre-distress events.

Among the country-level banking-sector indicators, almost all are estimated to be statistically significant. As expected, rapid growth in both financial liabilities and non-core liabilities is associated with higher probabilities of distress. The same applies to the ratio of debt securities to liabilities, a measure of securitization, and the share of mortgages among loans, a proxy for property booms. Likewise, high banking system leverage and a high loans-to-deposits ratio increase bank vulnerability.

Among the country-specific macro-financial indicators, all estimates have the expected sign. High inflation and low real GDP growth increase bank vulnerability. Likewise, positive stock and house price gaps that proxy for overvaluation of assets, increase distress probabilities. Regarding indicators of internal imbalances, the estimated coefficient for government debt is positive, whereas the estimated coefficient for private sector credit flow is negative and the coefficient for private sector credit-to-GDP gap is positive. This could be interpreted as an indication of bank vulnerability being increased when there is an ongoing credit contraction or credit crunch or when there are accumulated imbalances through a credit boom (credit-to-GDP gap). Higher levels of unemployment increase bank vulnerability. Finally, regarding external competitiveness, high net external borrowing of a country increases bank vulnerability, whereas a higher current account balance lowers bank vulnerability. This could be interpreted as the current account surplus proxying for a boom in an economy that increases the vulnerability of a bank. An increase in the real effective exchange rate and a decrease in export market share positively affect bank vulnerability through a loss of competitiveness.

Table 2 also evaluates the predictive performance of the models based upon the recursive estimation procedure presented in Section 4.2 for each quarter in 2007Q1-2011Q4 (out-of-sample) conditional on the policymaker's preference parameter $(\mu = 0.6, 0.7, \ldots, 0.9)$. Given that the threshold λ for classifying signals is a time-varying parameter that is chosen to optimize in-sample usefulness at each t, the table does not report the applied λ. As discussed above, we assume that the policymaker is substantially more interested in correctly calling bank distress events than tranquil periods. This is intuitive if we consider that an early-warning signal triggers an in-depth review of fundamentals, business model and peers of the bank predicted to be in distress. Should the analysis reveal that the signal is false, there is no loss of credibility on behalf of the policy authority. Hence, in the benchmark case, preferences are set to $\mu = 0.9$. Table 2 reports both the absolute and the relative Usefulness measures as well as the unconditional probability of pre-distress events (0.07). The benchmark model's absolute Usefulness U_a equals 0.03 (U_a) which translates into a relative Usefulness U_r equal to 37%, in contrast to U_r equals to 28% for Model 2 which includes a larger sample of bank-specific indicators.

Table 3 provides information on the predictive power of the three indicator groups. Conditional on a preference parameter $\mu = 0.9$, Model 4 based on macro-financial indicators clearly outperforms the other models by achieving a U_r of 24%. The specification in column 2, which includes only bank-specific indicators, achieves a

U_r of 16% compared to 2% for the banking-sector model. The comparison of U_r may be performed in terms of percentage points. That is, Model 2 generates 14 percentage points and Model 4 generates 22 percentage points more useful predictions than those of Model 3. It is, indeed, an interesting finding that macro-financial indicators turn out to be more useful for predicting vulnerabilities at the bank level than bank-specific indicators. However, the latest crisis clearly evolved along national borders. While the macro-financial indicators consist of those featured in the MIP, and have been chosen to mimic imbalances prior to this crisis, they follow the earlier literature on country-level imbalances (e.g., Demirgüç-Kunt and Detragiache, 1998; Kaminsky and Reinhart, 1999; Borio and Lowe, 2002).

Models 5-6 not only confirm that combining the bank-level data with country-specific banking sector indicators generates little added value, but also the fact that combining bank-level data and macro-financial indicators produces a model that clearly outperforms a model with only bank-level data. As the benchmark model still improves predictive performance compared to that of Model 6, it is justified to use all three groups of indicators, also from a statistical point of view. Finally, Table 3 confirms the overall relative stability of the estimates and that in addition to the highest usefulness, the benchmark model also obtains the highest R2 (0.32).

Table 4 shows the predictive performance of the benchmark model for different policymaker preferences between type I and II errors. The models are calibrated with respect to non-weighted absolute Usefulness $U_a(\mu)$, but we also compute weighted absolute Usefulness $U_a(\mu, w_j)$ for each preferences, where weights w_j represent bank size.[6] The rationale for using absolute size, rather than bank size to the size of the country-specific banking sector, is the focus on systemically important financial institutions (SIFIs) in general, not domestic SIFIs. When focusing on non-weighted $U_a(\mu)$, the results indicate that it is optimal to disregard the model for $\mu \leq 0.5$. The model derives negative $U_a(\mu)$ for $\mu = \{0.4, 0.5\}$ as signalling for a tiny fraction of bank-quarter observations yields $U_a(\mu)$ in sample but not out of sample. For $\mu \leq 0.3$, the policymaker is better off by not signalling at all. In addition, Table 4 shows that model performance decreases slightly for $\mu = 0.9$ when augmenting the Usefulness measure with bank-specific weights ($U_a(\mu, w_j)$). This would confirm the expected effect as vulnerabilities and risks of large financial institutions are oftentimes more complex than those of smaller ones. However, $U_a(\mu, w_j)$ is larger than non-weighted for $\mu = [0.3, 0.8]$. This is somewhat counterintuitive as the estimates in Table 2 show that larger entities are more vulnerable to distress.

6 Systemic relevance of a bank is approximated by computing its share of total assets to total assets in the sample at quarter *t*. A possible amendment is to derive the systemic relevance from the systemic risk contributions of banks from, e.g., tail dependence networks.

Table 3: Logit estimates on bank distress and their predictive performance – models using different set of indicators

		Estimates	(1) Benchmark	(2) BS Model	(3) BSI Model	(4) MF Model	(5) BS & BSI Model	(6) BS & MF Model
Bank-specific indicators		Intercept	-10.76 ***	-4.65 ***	-5.35 ***	-3.36 ***	-6.02 ***	-6.57 ***
	C[a]	Equity to assets	-13.32 ***	-15.47 ***			-13.68 ***	-13.60 ***
		Size (total assets)	0.47 ***	0.38 ***			0.40 ***	0.47 ***
	A[a]	Debt to equity	0.00	-0.01 .			-0.01	0.00
		ROA	-36.07 **	-16.34			-28.94 *	-41.35 **
	M[a]	Cost to income	0.00	-0.01			0.00	0.00
	E[a]	ROE	-1.03 .	-2.53 ***			-2.15 ***	-1.07 .
	L[a]	Interest expenses to liabilities	1.86 ***	2.61 ***			2.11 ***	1.53 ***
		Deposits to funding	24.43 ***	21.14 ***			20.80 ***	23.88 ***
	S[a]	Share of trading income	-0.05	-0.07 .			-0.07 .	-0.05
Country-specific banking sector indicators		Financial liabilities (annual growth rate)	8.50 ***		0.62		3.75 .	
		Non-core liabilities (annual growth rate)	10.07 *		14.40 ***		12.47 ***	
		Debt securities to liabilities	2.49 *		-3.62 ***		-2.04 **	
		Mortgages to loans	2.51 *		7.56 ***		6.48 ***	
		Debt to equity	0.07 ***		0.08 ***		-0.03 *	
		Loans to deposits	0.34 ***		0.26 ***		0.36 ***	
		Gross derivatives to capital and reserves (annual growth rate)	-0.56		-0.51		-1.06 *	
Country-specific macro-financial indicators		GDP (annual growth rate)	-5.94 .			-7.82 **		-5.77 .
		Inflation (annual growth rate)	19.58 ***			24.51 ***		18.87 ***
		House price gap	0.13 ***			0.10 ***		0.12 ***
		Stock price gap	0.00 **			0.00 *		0.00 ***
		10-year bund spread	12.77			3.92		4.35
		Government debt to GDP	1.13 ***			-0.61 *		0.26
		Private sector credit flow to GDP	-3.79 ***			-1.63 *		-2.68 ***
		Private sector credit to GDP gap	6.98 ***			10.92 ***		7.76 ***
		Unemployment rate (3-year average)	9.45 ***			2.74		2.67
		Current account balance to GDP (3-year average)	5.79 **			5.33 **		8.51 ***
		International investment position to GDP	-2.59 ***			-1.41 ***		-2.49 ***
		Real effective exchange rate (3-year % change)	4.80 ***			4.99 ***		4.88 ***
		Export market share (3-year % change)	-1.90 ***			-3.23 ***		-2.53 ***
		Unit labour cost (3-year % change)	0.13			-4.57 **		0.16
		R2[b]	0.32	0.17	0.06	0.14	0.21	0.31
		No. of banks	403	403	403	403	403	403

	Predictive performance	(1) $U_a(\mu)$	(1) $U_r(\mu)$	(2) $U_a(\mu)$	(2) $U_r(\mu)$	(3) $U_a(\mu)$	(3) $U_r(\mu)$	(4) $U_a(\mu)$	(4) $U_r(\mu)$	(5) $U_a(\mu)$	(5) $U_r(\mu)$	(6) $U_a(\mu)$	(6) $U_r(\mu)$
Usefulness for a policymaker[c]	μ=0.6	0.00	2 %	0.00	0 %	0.00	0 %	0.00	0 %	0.00	0 %	0.00	2 %
	μ=0.7	0.01	12 %	0.00	2 %	0.00	-1 %	0.00	-1 %	0.00	5 %	0.01	11 %
	μ=0.8	0.02	23 %	0.00	5 %	0.00	1 %	0.01	10 %	0.01	12 %	0.02	23 %
	μ=0.9	**0.03**	**37 %**	**0.01**	**16 %**	**0.00**	**2 %**	**0.02**	**24 %**	**0.01**	**16 %**	**0.03**	**36 %**
$P(I_j(h)=1)$[d]		0.07		0.07		0.07		0.07		0.07		0.07	

Notes:
Signif. codes: '***', 0.001; '**', 0.01; '*', 0.05; '.', 0.10

[a] The letters of CAMELS refer to Capital adequacy, Asset quality, Management, Earnings, Liquidity and Sensitivity to market risk.

[b] R2 refers to the Nagelkerke's pseudo R-squared.

[c] The Usefulness for a policymaker is computed with absolute and relative usefulness $U_a(\mu)$ and $U_r(\mu)$ as described in Section 4.1.

[d] $P(I_j(h)=1)$ refers to the unconditional probability of pre-distress events.

Table 4: The predictive performance of the benchmark specification for different policymakers' preferences

					Positives		Negatives									
Preferences	TP	FP	TN	FN	Precision	Recall	Precision	Recall	Accuracy	FP rate	FN rate	$U_a(\mu)$	$U_r(\mu)$	$U_a(\mu,w_j$	$U_r(\mu,w_j$	AUC
μ=0.0	0	0	5025	605	NA	0.00	0.89	1.00	0.89	0.00	1.00	0.00	NA	0.00	NA	0.80
μ=0.1	0	0	5025	605	NA	0.00	0.89	1.00	0.89	0.00	1.00	0.00	0 %	0.00	0 %	0.80
μ=0.2	0	0	5025	605	NA	0.00	0.89	1.00	0.89	0.00	1.00	0.00	0 %	0.00	0 %	0.80
μ=0.3	0	0	5025	605	NA	0.00	0.89	1.00	0.89	0.00	1.00	0.00	0 %	0.00	1 %	0.80
μ=0.4	20	26	4999	585	0.43	0.03	0.90	0.99	0.89	0.01	0.97	0.00	-3 %	0.01	6 %	0.80
μ=0.5	78	91	4934	527	0.46	0.13	0.90	0.98	0.89	0.02	0.87	0.00	-2 %	0.01	11 %	0.80
μ=0.6	119	161	4864	486	0.43	0.20	0.91	0.97	0.89	0.03	0.80	0.00	2 %	0.03	19 %	0.80
μ=0.7	187	262	4763	418	0.42	0.31	0.92	0.95	0.88	0.05	0.69	0.01	12 %	0.06	32 %	0.80
μ=0.8	243	414	4611	362	0.37	0.40	0.93	0.92	0.86	0.08	0.60	0.02	23 %	0.04	26 %	0.80
μ=0.9	**336**	**746**	**4279**	**269**	**0.31**	**0.56**	**0.94**	**0.85**	**0.82**	**0.15**	**0.44**	**0.03**	**37 %**	**0.01**	**16 %**	**0.80**
μ=1.0	605	5025	0	0	0.11	1.00	NA	0.00	0.11	1.00	0.00	0.00	NA	0.00	NA	0.80

Notes: The table reports results for real-time out-of-sample predictions of a logit model with optimal thresholds w.r.t. Usefulness with given preferences. Bold entries correspond to the benchmark preferences. Thresholds are calculated for μ={0.0,0.1,...,1.0} and the forecast horizon is 8 quarters. The table also reports in columns the following measures to assess the overall performance of the models: TP = True positives, FP = False positives, TN= True negatives, FN = False negatives, Precision positives = TP/(TP+FP), Recall positives = TP/(TP+FN), Precision negatives = TN/(TN+FN), Recall negatives = TN/(TN+FP), Accuracy = (TP+TN)/(TP+TN+FP+FN), absolute and relative usefulness U_a and U_r (see formulae 1-3), and AUC = area under the ROC curve (TP rate to FP rate). See Section 4.1 for further details on the measures.

Figure 2 shows how the benchmark model would have performed out of sample in the case of Dexia from 2007Q1-2011Q4. The figure shows blue and green lines for absolute and percentile distress probabilities and highlights in grey the periods when the model signals. The black lines on top of the *x*-axis represent the distress events and the red lines the vulnerable states (or pre-distress) that the model aims to correctly call. In the run up to the first distress event in 2008, the model signals early on and consistently ranks Dexia as one of the most risky banks in the sample (as shown by the percentile probabilities). Later, the model is not quite as successful, though it correctly signals the first quarters of vulnerability and a couple of quarters before the second distress event. Figure 3 shows a similar case study on Bank of Ireland. The model signals vulnerability in 2007Q4, when the distress event occurs in 2009Q1, and throughout the pre-distress period before the distress event that started in 2010Q2.

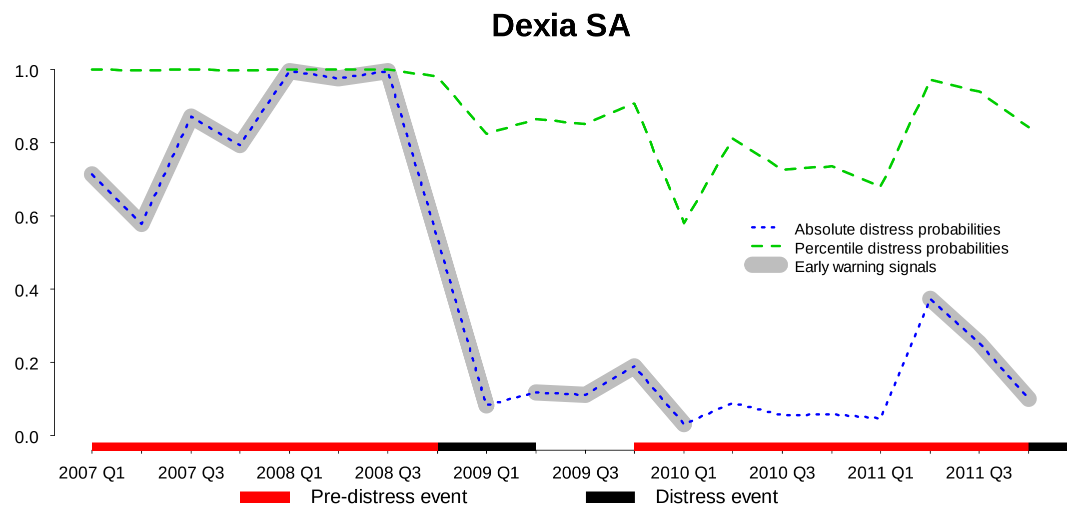

Figure 2: A case study of the early-warning model on Dexia. Out-of-sample prediction of bank distress (8 quarters ahead) from 2007Q1-2011Q4.

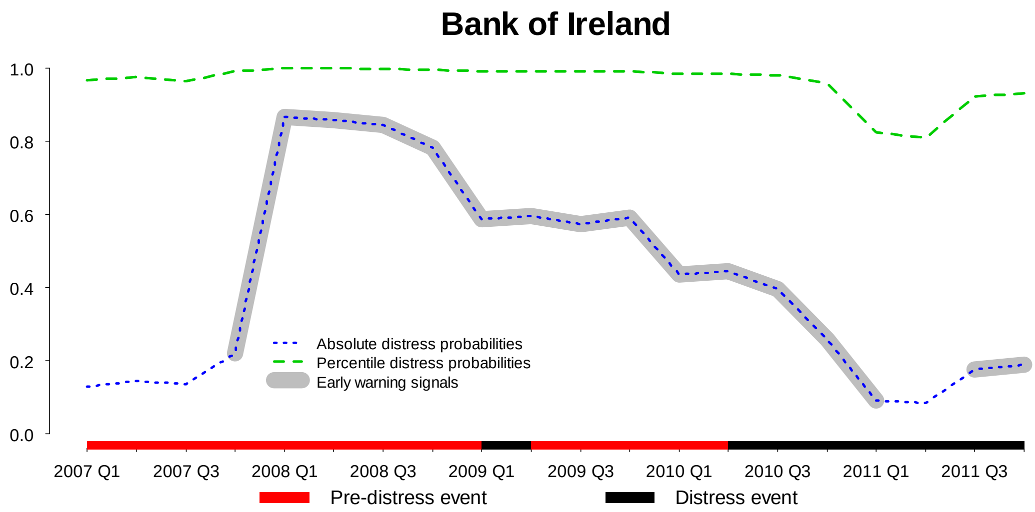

Figure 3: A case study of the early-warning model on Bank of Ireland. Out-of-sample prediction of bank distress (8 quarters ahead) from 2007Q1-2011Q4.

6. Robustness

We test the robustness of the early-warning model in several ways. As Table 2 shows, the results are, in a broad sense, robust to omitting some key CAMELS indicators with weak data coverage, such as Tier 1 capital ratio, loan loss provisions and impaired assets. Similarly, Table 3 showed that complementing bank-specific vulnerabilities with indicators of macro-financial imbalances is crucial for model performance, while the predictive performance is not sensitive to excluding indicators of imbalances in countries' banking-sectors. Further, as partly discussed in the Section 5 (Tables 2,3 and 4), the out-of-sample performance of the model is sensitive to the policymaker's preferences due to the unbalanced frequencies of distress events and tranquil periods. For a model to be useful, this motivates preferences of $\mu > 0.5$.

In addition, we study the out-of-sample performance for different forecast horizons. As shown in Table 5, the absolute Usefulness of the model improves when the out-of-sample forecast horizon increases from 12 months to 24 months, whereas the performance for horizons of 24 and 36 months is similar. The models' relative Usefulness is, however, similar for different horizons. This is mainly due to the fact that increases in unconditional probabilities of pre-distress events also raise the Usefulness of the models, as the loss of disregarding a model increases.

Table 5: Robustness of the model with respect to out-of-sample forecast horizon

Forecast Horizon	TP	FP	TN	FN	Positives Precision	Positives Recall	Negatives Precision	Negatives Recall	Accuracy	FP rate	FN rate	$U_a(\mu)$	$U_r(\mu)$	$U_a(\mu, w_j$	$U_r(\mu, w_j$	AUC
12 months	94	193	1871	67	0.33	0.58	0.97	0.91	0.88	0.09	0.42	0.03	45 %	0.02	31 %	0.76
24 months	**336**	**746**	**4279**	**269**	**0.31**	**0.56**	**0.94**	**0.85**	**0.82**	**0.15**	**0.44**	**0.03**	**37 %**	**0.02**	**29 %**	**0.80**
36 months	237	527	1376	85	0.31	0.74	0.94	0.72	0.72	0.28	0.26	0.03	32 %	0.03	31 %	0.86

Notes: The table reports results for real-time out-of-sample predictions of a logit model with optimal thresholds w.r.t. Usefulness with given preferences. Bold entries correspond to the benchmark horizon and thresholds are calculated for μ={0.0,0.1,...,1.0}. The table also reports in columns the following measures to assess the overall performance of the models: TP = True positives, FP = False positives, TN= True negatives, FN = False negatives, Precision positives = TP/(TP+FP), Recall positives = TP/(TP+FN), Precision negatives = TN/(TN+FN), Recall negatives = TN/(TN+FP), Accuracy = (TP+TN)/(TP+TN+FP+FN), absolute and relative usefulness U_a and U_r (see formulae 1-3), and AUC = area under the ROC curve (TP rate to FP rate). See Section 4.1 for further details on the measures.

Finally, we show the sensitivity of the early-warning model to variation of the thresholds with an ROC curve. The curve plots the benefit (true positive rate) to the cost (false positive rate) of a certain model for each threshold λ, as noted in Section 4.1. While not accounting for imbalanced data and misclassification costs, the ROC curve's area above the diagonal line represents the benefit of a model in relation to a coin toss. Figure 4 not only shows that the ROC curves are above those of a coin toss, but also that curves of 24 and 36-month horizons are similar, while that of a 12-month horizon is somewhat poorer. This exercise is, however, somewhat imprecise. While the models issue signals based upon time-varying thresholds such that in-sample Usefulness is optimized, the ROC statistics treat all probabilities as similar. Another common limitation of the ROC curve, especially the AUC, is that parts of it, which are not policy relevant, are included in the computed area.

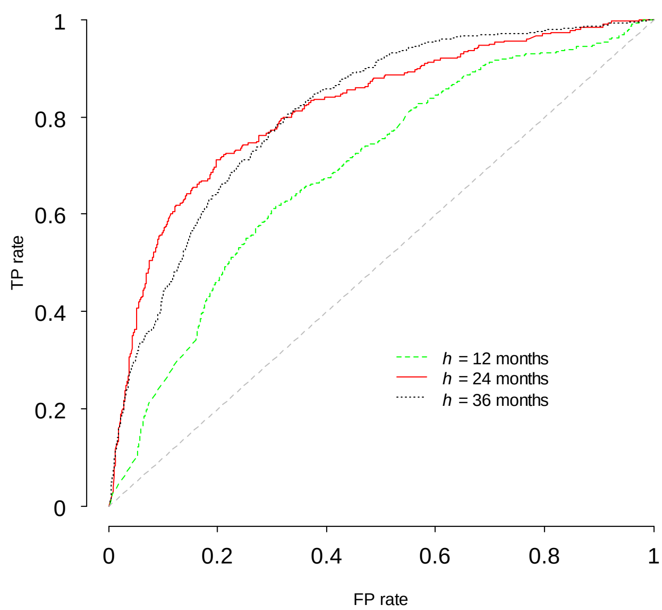

Figure 4: Robustness of the model with respect to λ for different forecast horizons

7. Conclusions

The paper presents an early-warning model for predicting bank distress in the European banking sector, using both bank-level and country-level indicators of vulnerabilities, and introduces a novel dataset of bank distress events. As outright bank failures have been rare in Europe, we introduce a novel dataset that complements bankruptcies, liquidations and defaults by also taking into account state interventions, and mergers in distress. Moreover, the signals of the early-warning model are calibrated not only according to policymakers' preferences between type I and II errors, but also accounting for the potential systemic relevance of each individual financial institution, proxied by its size.

The paper finds that complementing bank-specific vulnerabilities with indicators for macro-financial imbalances improves model performance. Thus, the results in this paper confirm the usefulness of the vulnerability indicators introduced recently via the EU Macroeconomic Imbalance Procedure (MIP). In addition, the results show that an early-warning model based on publicly available data yields useful out-of-sample predictions of bank distress during the current financial crisis (2007Q1-2011Q4). Finally, the results of the evaluation framework show that a policymaker has to be substantially more concerned of missing bank distress than issuing false alarms for the model to be useful. This is intuitive if we consider that an early-warning signal triggers an in-depth review of fundamentals, business model and peers of the bank predicted to be in distress. Should the analysis reveal that the signal is false, there is no loss of credibility on behalf of the policy authority. The evaluations also imply that it is important to give more emphasis to systemically important and large banks for a policymaker concerned with systemic risk.

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Appendices

Table A: Indicators, definitions, transformations and data sources

		Variable	Definition and transformation	Source
Bank-specific balance-sheet variables		Intercept		
	C	Equity to assets	Total Equity / Total Assets	Bloomberg
	C	Tier 1 ratio	Tier 1 Capital Ratio	Bloomberg
	A	Impaired assets	Non Performing Assets / Total Assets	Bloomberg
	A	Reserves to impaired assets	Reserves for Loan Losses / Non Performing Assets	Bloomberg
	A	Loan loss provisions	Provisions for Loan Losses / Total Average Loans	Bloomberg
	A	Size (total assets)	Natural logarithm of Total Assets	Bloomberg
	A	Debt to equity	Total Liabilities / Total Equity	Bloomberg
	M	ROA	Return on Assets	Bloomberg
	M	Cost to income	Operating Costs / Operating Income	Bloomberg
	E	ROE	Return on Equity	Bloomberg
	E	Net interest margin	Net Interest Margin	Bloomberg
	L	Interest expenses to liabilities	Interest Expenses / Total Liabilities	Bloomberg
	L	Deposits to funding	Deposits / Funding	Bloomberg
	L	Loans to deposits	Total Loans / Customer Deposits	Bloomberg
	S	Share of trading income	Trading Income / Operating Income	Bloomberg
	S	Loans to assets	Total Loans / Total Assets	Bloomberg
Country-specific banking sector variables		Financial liabilities (annual growth rate)	Growth rate of (Total Assets - Capital and Reserves)	ECB MFI statistics
		Non-core liabilities (annual growth rate)	Growth rate of (Total Liabilities - Capital and Reserves - Deposits)	ECB MFI statistics
		Debt securities to liabilities	Debt securities to liabilities	ECB MFI statistics
		Mortgages to loans	Mortgages to Total Loans	ECB MFI statistics
		Debt to equity	(Total Liabilities - Capital and Reserves) / Capital and Reserves	ECB MFI statistics
		Loans to deposits	Total Loans / Deposits	ECB MFI statistics
		Gross derivatives to capital and reserves (annual growth rate)	Growth rate of ((Positive Derivatives + Negative Derivatives) / Capital and Rese	ECB MFI statistics
Country-specific macro-financial variables		GDP (annual growth rate)	Growth rate of real GDP	Eurostat
		Inflation (annual growth rate)	Growth rate of HICP index	Eurostat
		House price gap	House price index - HP filtered trend	ECB
		Stock price gap	Stock price index - HP filtered trend	Bloomberg
		10-year bond spread	Long-term government bond yield - German long-term government bond yield	Bloomberg
		Government debt to GDP	General government debt as % of GDP	Eurostat / Alert Mechanism Report
		Private sector credit flow to GDP	Private sector credit flow as % of GDP	Eurostat / Alert Mechanism Report
		Private sector credit to GDP gap	Moving sum of 4 quarters of private sector credit / GDP - HP filtered trend	Haver Analytics / IMF IFS
		Unemployment rate (3-year average)	3 year average of unemployment rate	Eurostat / Alert Mechanism Report
		Current account balance to GDP (3-year average)	3 year average of current account balance as a % of GDP	Eurostat / Alert Mechanism Report
		International investment position to GDP	Net International Investment Position as a % of GDP	Eurostat / Alert Mechanism Report
		Real effective exchange rate (3-year % change)	% change (3 years) of Real Effective Exchange Rate, HICP deflators relative	Eurostat / Alert Mechanism Report
		Export market share (3-year % change)	% change (5 years) in export market shares	Eurostat / Alert Mechanism Report
		Unit labour cost (3-year % change)	% change (3 years) in nominal unit labour cost	Eurostat / Alert Mechanism Report

Table B: Summary statistics

		Variables	Obs	Min	Max	Mean	Std. Dev.	Skew	Kurt
Bank-specific indicators	C[a]	Equity to assets	15773	0.01	0.35	0.07	0.05	3.01	14.38
		Tier 1 ratio	8759	0.05	0.31	0.10	0.04	2.28	7.35
	A[a]	Impaired assets	9111	0.00	0.14	0.02	0.03	2.10	5.11
		Reserves to impaired assets	8672	0.00	48.59	1.96	5.83	7.29	54.08
		Loan loss provisions	12040	0.00	0.07	0.01	0.01	3.63	16.55
		Size (total assets)	15962	-0.15	7.14	3.02	1.82	0.44	-0.70
		Debt to equity	15718	0.44	74.40	18.10	12.51	2.12	5.86
		ROA	15886	-0.04	0.03	0.01	0.01	-1.25	8.75
	M[a]	Cost to income	15452	-32.08	38.78	2.50	6.85	0.13	15.62
	E[a]	ROE	15646	-0.78	0.36	0.07	0.14	-3.48	18.53
		Net interest margin	12466	0.00	0.07	0.02	0.01	1.19	2.77
		Interest expenses to liabilities	15139	0.00	0.11	0.03	0.02	2.03	5.78
	L[a]	Deposits to funding	14880	0.00	0.97	0.54	0.24	-0.34	-0.55
		Loans to deposits	13408	0.06	19.41	1.92	2.55	5.23	30.10
	S[a]	Share of trading income	15078	-5.46	5.44	0.23	1.05	-0.48	15.79
		Loans to assets	13868	0.00	0.93	0.61	0.21	-1.01	0.70
Country-specific banking sector indicators		Financial liabilities (annual growth rate)	24706	-0.14	0.22	0.02	0.03	0.39	3.41
		Non-core liabilities (annual growth rate)	24706	-0.25	0.11	0.00	0.01	-0.23	22.96
		Debt securities to liabilities	24767	0.00	0.51	0.17	0.09	0.68	2.03
		Mortgages to loans	24627	0.01	0.41	0.17	0.07	0.62	0.16
		Debt to equity	24767	3.87	28.12	14.50	4.17	0.59	-0.48
		Loans to deposits	24767	1.00	7.42	2.42	0.78	1.84	6.25
		Gross derivatives to capital and reserves (annual growth rate)	24566	-0.50	1.70	0.01	0.12	3.51	29.80
Country-specific macro-financial indicators		GDP (annual growth rate)	25449	-0.18	0.16	0.02	0.03	-0.95	2.68
		Inflation (annual growth rate)	25529	-0.07	0.54	0.02	0.02	8.44	179.89
		House price gap	22620	-26.59	34.09	0.00	3.63	0.77	14.40
		Stock price gap	25399	-18825.03	24098.27	41.28	3187.38	0.48	6.94
		10-year bund spread	25082	-0.01	0.32	0.01	0.02	9.77	145.20
		Current account balance to GDP (3-year average)	25529	-0.22	0.11	-0.01	0.04	-0.17	0.36
		Government debt to GDP	25529	0.04	1.65	0.71	0.28	0.30	-0.57
		Private sector credit flow to GDP	25529	-0.59	1.62	0.09	0.11	2.91	48.03
		Private sector credit to GDP gap	26098	-0.27	0.33	0.00	0.04	1.34	6.83
		Unemployment rate (3-year average)	25529	0.02	0.20	0.08	0.03	1.19	2.65
		International investment position to GDP	25529	-1.48	1.40	-0.19	0.36	0.02	1.62
		Real effective exchange rate (3-year % change)	25529	-0.20	0.38	0.01	0.06	-0.10	2.37
		Export market share (3-year % change)	25529	-0.24	0.78	-0.05	0.15	2.11	5.83
		Unit labour cost (3-year % change)	25529	-0.17	1.39	0.07	0.06	5.28	93.74

Notes: The statistics are derived from the entire sample with 26,852 observations.

[a] The letters refer to Capital Adequacy (C), Asset Quality (A), Management (M), Earnings (E), Liquidity (L), and Sensitivity to Market Risk (S)

Table C: Mean-comparison tests

			$C = 0$			$C = 1$			Mean t-test	
		Variables	**Obs**	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**	t	**Prob**
Bank-specific indicators	C[a]	Equity to assets	14987	0.07	0.05	786	0.05	0.03	16.42	0.00
		Tier 1 ratio	8226	0.10	0.04	533	0.09	0.02	14.78	0.00
	A[a]	Impaired assets	8585	0.02	0.03	526	0.03	0.03	3.55	0.00
		Reserves to impaired assets	8170	2.02	5.97	502	1.01	2.74	7.33	0.00
		Loan loss provisions	11404	0.01	0.01	636	0.01	0.01	6.40	0.00
		Size (total assets)	15176	2.96	1.81	786	4.11	1.69	18.58	0.00
		Debt to equity	14932	17.76	12.25	786	24.64	15.35	12.36	0.00
		ROA	15101	0.01	0.01	785	0.00	0.01	10.99	0.00
	M[a]	Cost to income	14675	2.51	6.85	777	2.28	6.85	0.91	0.36
	E[a]	ROE	14861	0.07	0.13	785	0.00	0.25	8.30	0.00
		Net interest margin	11806	0.02	0.01	660	0.02	0.01	2.29	0.02
	L[a]	Interest expenses to liabilities	14390	0.03	0.02	749	0.04	0.02	10.41	0.00
		Deposits to funding	14133	0.54	0.24	747	0.53	0.23	1.76	0.08
		Loans to deposits	12711	1.92	2.57	697	1.91	2.21	0.17	0.00
	S[a]	Share of trading income	14330	0.23	1.03	748	0.23	1.40	0.05	0.87
		Loans to assets	13151	0.61	0.21	717	0.59	0.19	3.51	0.96
Country-specific banking sector indicators		Financial liabilities (annual growth rate)	23714	0.02	0.03	992	0.02	0.03	1.05	0.29
		Non-core liabilities (annual growth rate)	23714	0.00	0.01	992	0.00	0.01	3.32	0.00
		Debt securities to liabilities	23775	0.17	0.09	992	0.16	0.10	4.58	0.00
		Mortgages to loans	23635	0.17	0.07	992	0.20	0.07	15.52	0.00
		Debt to equity	23775	14.48	4.18	992	14.86	3.85	2.99	0.00
		Loans to deposits	23775	2.42	0.77	992	2.43	1.04	0.45	0.65
		Gross derivatives to capital and reserves (annual growth rate)	23574	0.01	0.12	992	0.01	0.11	0.71	0.48
Country-specific macro-financial indicators		GDP (annual growth rate)	24449	0.02	0.03	1000	0.00	0.03	13.06	0.00
		Inflation (annual growth rate)	24529	0.02	0.02	1000	0.02	0.02	0.51	0.61
		House price gap	21703	-0.07	3.59	917	1.57	4.15	11.79	0.00
		Stock price gap	24399	43.49	3232.20	1000	-12.73	1772.05	0.94	0.35
		10-year bund spread	24106	0.01	0.02	976	0.01	0.02	3.09	0.00
		Current account balance to GDP (3-year average)	24529	-0.01	0.04	1000	-0.03	0.06	12.78	0.00
		Government debt to GDP	24529	0.71	0.28	1000	0.64	0.26	8.63	0.00
		Private sector credit flow to GDP	24529	0.09	0.11	1000	0.10	0.11	2.29	0.02
		Private sector credit to GDP gap	25109	0.00	0.04	989	0.04	0.07	15.36	0.00
		Unemployment rate (3-year average)	24529	0.08	0.03	1000	0.09	0.04	2.66	0.01
		International investment position to GDP	24529	-0.18	0.35	1000	-0.43	0.47	16.50	0.00
		Real effective exchange rate (3-year % change)	24529	0.01	0.06	1000	0.02	0.05	5.96	0.00
		Export market share (3-year % change)	24529	-0.05	0.16	1000	-0.08	0.10	12.07	0.00
		Unit labour cost (3-year % change)	24529	0.06	0.06	1000	0.08	0.08	6.17	0.00

Notes: The statistics are derived from the entire sample with 26,852 observations. $C = 0$ refers to tranquil periods and $C = 1$to vulnerable states (pre-distress periods).

[a] The letters refer to Capital Adequacy (C), Asset Quality (A), Management (M), Earnings (E), Liquidity (L), and Sensitivity to Market Risk (S)