# CREWS: A CAMELS-BASED EARLY WARNING SYSTEM OF SYSTEMIC RISK IN THE BANKING SECTOR

2021

BANCO DE ESPAÑA
Eurosistema

Documentos Ocasionales
N.º 2132

Jorge E. Galán

# CREWS: A CAMELS-BASED EARLY WARNING SYSTEM OF SYSTEMIC RISK IN THE BANKING SECTOR

# CREWS: A CAMELS-BASED EARLY WARNING SYSTEM OF SYSTEMIC RISK IN THE BANKING SECTOR (*)

Jorge E. Galán (**)

BANCO DE ESPAÑA

(*) This paper is the sole responsibility of its author. The views represented here do not necessarily reflect those of the Banco de España or the Eurosystem.
(**) I acknowledge Ángel Estrada, Javier Mencía and Carlos Pérez for their useful comments and suggestions. I am especially grateful to Gabriel Jiménez for his work at the initial stages in the development of the CREWS.
Corresponding author. Address: Banco de España, Alcalá 48 - 28014, Madrid, Spain. E-mail: jorge.galan@bde.es. Phone: +34 913 384 221.

Documentos Ocasionales. N.º 2132
November 2021

The Occasional Paper Series seeks to disseminate work conducted at the Banco de España, in the performance of its functions, that may be of general interest.

The opinions and analyses in the Occasional Paper Series are the responsibility of the authors and, therefore, do not necessarily coincide with those of the Banco de España or the Eurosystem.

The Banco de España disseminates its main reports and most of its publications via the Internet on its website at: http://www.bde.es.



ISSN: 1696-2230 (on-line edition)

## Abstract

This document proposes an aggregate early-warning indicator of systemic risk in the banking sector. The indicator is derived from a logistic model based on the variables in the CAMELS rating system, originally developed for the US, and complemented with macroeconomic aggregate variables. The model is applied to the Spanish banking sector using bank-level data for a complete financial cycle, from 1999 to 2021. The performance of the model is assessed not only during the last global financial crisis and the subsequent sovereign crisis, but also during the recent Covid-19 shock. The proposed indicator has a macroprudential orientation, which differs from most of previous studies predicting individual bank defaults. The indicator is found to provide accurate early-warning signals of systemic risk in the banking sector within a two-year horizon. In this context, the indicator provides mid-term signals of systemic risk that complement those derived from macrofinancial indicators and from measures of the materialization of risk.



**Keywords:** banks, defaults, early-warning performance, macroprudential policy, systemic risk.

**JEL classification:** C25, E32, E58, G01, G21.

## Resumen

Este documento propone un indicador agregado de alerta temprana de riesgo sistémico en el sector bancario. El indicador se obtiene de la estimación de un modelo logístico basado en las variables del sistema americano de calificación de riesgo CAMELS, complementado con variables macroeconómicas agregadas. El modelo se aplica al sistema bancario español usando datos a nivel de entidad para un ciclo financiero completo (1999-2021). El desempeño del modelo se evalúa no solo durante la pasada crisis financiera global y la siguiente crisis soberana, sino también durante la pandemia del COVID-19. El indicador propuesto tiene una orientación macroprudencial, lo cual difiere de la mayoría de los trabajos anteriores que intentan predecir quiebras bancarias individuales. Se encuentra que el indicador propuesto genera señales precisas de alerta de riesgo sistémico en un horizonte de dos años. En este contexto, el indicador produce señales de riesgo sistémico en el medio plazo, que complementan las que se obtienen de indicadores macrofinancieros y de otras medidas de materialización de riesgos.



**Palabras clave:** alerta temprana, bancos, política macroprudencial, riesgo sistémico, quiebras.

**Códigos JEL:** C25, E32, E58, G01, G21.

## Contents

## 1 Introduction

The global financial crisis (GFC) evidenced the importance of developing early warning tools that provide banking regulators and policymakers with prompt information on the accumulation of financial risk in the economy. As a consequence, after that crisis, different approaches have been proposed in the literature and implemented by macroprudential authorities. Most of the proposals have focused on the early identification of macrofinancial imbalances through indicators of excessive credit growth, house price growth, and other key variables, which are currently closely monitored by national authorities (Schularik and Taylor, 2012; Jordà et al., 2015; Tölö et al., 2018). Nonetheless, since the channel through which most of these imbalances materialize is the banking sector, it is very plausible that these disequilibria can also be identified in banks' balance sheets. This is especially important in countries as Spain, where traditionally banks provide most of funding in the economy. Moreover, bank-level data may provide more accurate information on the accumulation of systemic risk in the sector and the concentration of risks across systemic institutions. Against this background, this study proposes a measure of risk in the banking sector based on balance sheet variables at bank-level. The proposed measure is purposed to provide mid-term signals of systemic risk that complement those derived from the usual macrofinancial indicators of the build-up of cyclical risk.

There is a wide literature on methods that use bank-level variables to predict banking failures, starting with the seminal works by Altman (1968) and Sinkey (1975). Some of those variables were proposed by the US regulator in 1979 to be part of a supervisory rating system adopted by the Federal Financial Institutions Examination Council under the name of Uniform Financial Institutions Rating System (UFIRS). The UFIRS relies on balance-sheet indicators to evaluate the soundness of financial institutions on a uniform basis and to identify those institutions requiring special supervisory attention. The outcome of the UFIRS became widely known as CAMEL rating, whose acronym stands for "Capital adequacy, Asset quality, Management, Earnings, and Liquidity", as these are the categories of the bank variables evaluated in the system. Since then, different studies have provided evidence that indicators in UFIRS have a high predictive capacity of banking failures (Thomson, 1991; Barker and Holdsworth, 1993). Later on, some studies found that the absence of market information in the rating system limited its performance (Cole and Gunter, 1995). This led the Federal Reserve Board to modify the UFIRS in 1997 to include a sixth component related to market sensitivity. This led to add an "S" to the rating acronym, which is now known as CAMELS.[1] More recently, the importance of accounting for macroeconomic variables has also been identified to improve the performance of models based on these indicators (Flannery, 1998; Jagtiani and Lemieux, 2001). In general, the literature on predicting banking failures has proposed many different approaches, but most of them share the inclusion of variables in the CAMELS rating system, which have been proved to provide accurate predictions of bank distress (Erdogan, 2008; Citterio, 2020).

1 Circular No. 10905 of the Board of Governors of the Federal Reserve System, January 1997.

Against this backdrop, this document shows how a relatively simple conditional logit model based on the variables in the CAMELS rating system can be used to construct an aggregate early-warning indicator of systemic risk in the banking sector. The proposed indicator is intended to have a macroprudential orientation, which differs from most of previous studies whose main objective is to predict individual bank defaults. In this context, the model is aimed at signalling risk within a two-years horizon, which would be appropriate for taking prompt macroprudential policy decisions. The tool intends to provide mid-term signals of systemic risk that complement those derived from macrofinancial indicators and from measures of the materialization of risk.

The model is applied to the Spanish banking sector using bank-level data for the whole last financial cycle from 1999 to 2021. This sample includes data from one of the most severe banking crises in Spain, so that the analysis learns from this dramatic experience to identify and quantify the drivers of banks' distress. Since the model requires having observed whether or not risk events have materialized within a two-years horizon, the last eight quarters of data are only used for out-of-sample predictions. This implies that the period covering the Covid-19 outbreak, which has been marked by the implementation of extraordinary public support measures, is only used to obtain out-of-sample predictions rather than for model estimations. The early-warning performance of the model is assessed not only during the last GFC and the subsequent sovereign crisis, but also during the recent Covid-19 crisis. This is of great relevance given the very different nature of the two types of events, and the different response of the public sector to them. The results of the model show high both in-sample and out-of-sample performance for the prediction of bank distress at two-year horizons. This feature is crucial for the performance of the aggregate indicator, which is identified to provide accurate early-warning signals of systemic risk in the banking sector as a whole.

This document is composed of 6 sections besides this introduction. In Section 2 a description of the variables in the CAMELS categories is presented, as well as a brief literature review of studies that include them. In Section 3 definitions of banking failures are discussed. In Section 4 the method and the aggregate indicator are presented. In Section 5 the data is described. In Section 6 the main results are presented. Finally, in Section 7, the main conclusions as well as a discussion of the usefulness of the proposed method for policy purposes are presented.

## 2 CAMELS variables as predictors of banking failures

The literature on the identification of bank failures has grown during the last decades, departing from the multivariate approach proposed by Altman (1968) to predict banking failures, and the Z-score proposed by Sinkey (1975) based on variables related to bank assets and earnings. This literature has mainly focused on the identification of key variables that may content useful information for the prediction of bank distress. In this context, different measures of the categories of the CAMELS rating system have been found not only to describe properly the current financial situation of individual banks, but also to contain useful information to predict their failure in the short-term. Thomson (1991) is one of the first studies validating the predictive ability of variables in the CAMELS system. This author finds that their inclusion leads the model to classify correctly 93% of failing banks in the US between 6 and12 months before they fail. Certainly, the use of CAMELS variables in the literature of prediction of banking failures has become quite standard. Citterio (2020) documents that 92% of studies of a sample of more than 50 papers on bank default prediction include variables in at least three of the CAMELS categories. Below, I summarize some of the main works using variables in each of the 5 CAMELS categories.

*Capital adequacy*. This is the most relevant category in banking failure analysis and the one where there is more apparent consensus on its usefulness. Capital has a fundamental role in explaining bank's soundness and variables regarding capital have been included in almost all previous studies. Most of these studies use capital ratios that do not account for the riskiness of assets. Among them, the most popular variable is the total equity-to-total assets ratio given the availability of this indicator and the homogeneity of its definition. Some few studies use risk-weighted measures of capital ratio, although their computation may be affected by discretionary decisions taken by bank managers as well as lack of comparability across banks and jurisdictions (Poghosyan and Čihak, 2011). Overall, most studies find a negative relation between the probability of default and capital ratios (Arena, 2008; Betz et al., 2014; Berger et al., 2016). This evidence favours regulatory arguments on the benefits of capital for strengthening bank resilience.

*Asset quality*. Asset composition is a key determinant of banks' risk profile. In fact, if the value of highly risky assets decreases rapidly, it might generate rapid losses and further reductions in capital cushions that, in turn, increase the risk of failure. Three main indicators of asset quality have been often used in this literature. The first one is the loans-to-assets ratio, which assumes that loans are a risky asset, so that a higher proportion would affect positively the probability of bank default (DeYoung, 2003; Altunbas et al., 2011). However, many studies have found this ratio to be irrelevant, unless it focuses on the riskiest loans, such as those to construction and real estate development (Berger et al., 2016). The second one is the ratio of loan provisions to total loans or total assets, which would capture how a higher coverage of expected losses reflects lower assets quality and higher expectation for losses (Betz et al., 2014). Almost all studies including this ratio have found a positive relation to default probability (Jin et al., 2011; Cipollini and Fiordelisi, 2012; Cleary and Hebb, 2016). Finally, the non-performing loans-to-total loans ratio (NPL ratio) is the most widely used indicator of asset quality. This indicator has been found to be highly reliable, since it is relatively nondiscretionary and provides timely information about loan defaults (Jin et al., 2011). Almost all studies including the NPL ratio identify a strong positive relation to bank default (Cole and White, 2012; Berger et al., 2016; Chiaramonte et al., 2016). In this regard, the more granular classification of exposures after the implementation of the International Financial Reporting Standards (IFRS) 9 in 2018, would allow a forward looking measure of assets quality to be considered, for instance by accounting for those assets in the under-performing category *(stage 2).* However, it is still too-early to get empirical evidence on the better early-warning performance of such indicator over the traditional NPL ratio as a predictor of defaults.

*Management efficiency.* This category attempts to capture the efficiency of bank's management, which would reflect in the cost structure and the ability to react to distress situations. Nonetheless, it is not easy to identify single measures capturing this aspect. This is the reason behind this category being the less represented within bank default prediction studies.[2] The most common measure in this category is the cost-to-income ratio, which intends to reflect cost efficiency and, indirectly, management quality. Ambiguous results have been found regarding this indicator. Some studies have identified a positive relation with bank's probability of default (Mayes and Stremmel, 2014; Shrivastava et al., 2020), while others have not found significant associations (Poghosyan and Čihak, 2011; Betz et al., 2014).

*Earning ability.* The ability to produce sustainable earnings and profits allow banks to foster their competitiveness, improve their solvency, and enhance their financial performance, which may prevent them from failing. The most widely used measures within this category are the Return on Assets (ROA) and the Return on Equity (ROE). A negative relation between these two measures and the banks' probability of default has been confirmed in many studies (Distinguin et al., 2006; Arena, 2008; Berger et al., 2016; Cleary and Hebb, 2016; Switzer et al., 2018). Nonetheless, some studies have found either no relation or even a positive association to bank distress (Mannaso and Mayes, 2009; Betz et al., 2014; Chiaramonte and Casu, 2017), which could be explained by aspects related to the risk-return trade-off. Other measures more related to income diversification, such as the ratio of non-interest income to total operating income, have been previously identified to be positively correlated with sustainable earnings (Stiroh, 2010; Cipollini and Fiordelisi, 2012; Altunbas et al., 2011).

*Liquidity.* Difficulties to meet liquidity demands (e.g. repay obligations to depositors or debtors) may lead to financial pressure and thereby, bank default risk. This could occur due to problems when raising funds or selling parts of their market portfolio. Although different definitions of liquid assets and levels of liquidity are considered, the general indicator used to measure liquidity is the ratio of liquid assets to total assets. This ratio has been identified to be negatively associated to bank default risk (Arena, 2008; Cipollini and Fiordelisi, 2012;

2 Just a little more than 50% of studies documented in Citterio (2020) include variables in this category.

Chiaramonte et al., 2016). Other indicator often used is the deposits-to-loans ratio. Given that deposits are considered to be a more stable and less costly source of funding, a higher ratio can be associated to lower liquidity risk, and has been found to be negatively correlated with bank distress (Altunbas et al., 2011; Berger et al., 2016). A more specific indicator of the difficulty to meet liquidity demands by financial institutions is the liquidity coverage ratio (LCR). This is a measure of highly liquid assets as a proportion of short-term obligations that is used as a base for minimum requirements in the Basel III accord. However, the recent implementation of this requirement makes that the computation of this ratio is only available from 2015, which does not allow most of distress events to be assessed, in particular those related to the GFC.

*Sensitivity to market risks.* This category was added to the CAMEL system in 1997 to reflect the ability of banks to deal with fluctuations in the financial markets. In this context, it intends to capture the risk of losses derived from changes in asset prices or interest rates. Nonetheless, this category has been widely ignored in the literature due to the difficulty on computing relevant indicators that capture this dimension. Some studies have proposed to include a ratio of volatile liabilities to assets (Mayes and Stremmel, 2014), a ratio of trading income to total income (Männasoo and Mayes 2009), and a ratio of interest bearing deposits to total assets (Kerstein and Kozberg, 2013). All these studies have found either a non-significant or a very weak relation to bank distress. A number of studies has also attempted to estimate bank default probability using market-based information. However, this type of information relies on the market efficiency assumption, which, in general, is not accomplished. Moreover, this information has been evidenced to have weak predictive performance once financial ratios such as those in CAMELS categories are included (Campbell et al., 2011). Finally, some studies have proposed to replace this category with bank size, which may capture characteristics related to the systemic importance of banks, and that can also reflect market sensitivity (Wheelock and Wilson, 2000; Avkiran and Cai, 2012). In this regard, size is usually negatively correlated to the probability of bank failure.

*Macroeconomic environment.* An important missing dimension in CAMELS-based studies is the macroeconomic environment. Since the purpose of the UFIRS is to provide ratings of banks' health and soundness from a microprudential perspective, only bank-level variables are assessed. However, macroeconomic conditions affect not only the overall performance of banks but also may have differential effects in different types of institutions. That is, although the whole banking sector faces the same macroeconomic environment, certain characteristics of banks may make them more prone to suffer or benefit from those conditions. Some studies assessing the predictive capacity of macroeconomic variables on individual banking failure have not found a strong influence of these variables by themselves (Arena, 2008; Chiaramonte and Casu, 2017). However, controlling by these conditions has effects on the predictions from financial ratios (Flannery, 1998; Jagtiani and Lemieux, 2001).

## 3 Definition of banking failure

In the literature, there are plenty of different definitions of banking failures or financial distress events. Although the choice of definition is not usually discussed, the criteria to which a bank is classified as failing may have a great influence on the performance of the models and make difficult to compare studies (Platt and Platt, 2004). In spite of the large heterogeneity in the definitions used in studies of bank defaults, two wide definitions of banking failure have been adopted most often (see Balcaen and Ooghe, 2006; for a review). The first one is legal bankruptcy, which could be the most objective definition, since it relies on a formal declaration of this situation in a court (Charitou et al., 2004). However, this definition presents several caveats. First, bankruptcy as the end-point of a distress situation may occur long time after the bank suffers a financial distress situation, which leads to misdating the events. Second, bankruptcy could also be the consequence of strategic decisions to get rid of debts, or due to unexpected events, such as natural disasters, changes in government regulations, or legal judgments. Third, and maybe the most important drawback is that bankruptcies are just one of the possible endings of bank distress. Certainly, these processes usually end on a merger or absorption by another institution. Also, a bankruptcy might be prevented by interventions from central banks and governments. These situations would lead to miss most of bank distress situations and to have a very low frequency rate of these events in the study samples, which may affect estimations.

The second type of definition is financial distress, which may encompass several stress and failure-related situations that can be of interest, but suffers of subjectivity of the financial criteria chosen to identify those events. This may include, among others, missed dividend payments, low interest coverage ratio, low cash flow to cover current maturities of long-term debt, change in equity prices, negative earnings before interests and taxes, or sell of shares to private investors (McLeay and Omar, 2000; Platt and Platt, 2002; 2004; Bose, 2006). Definitions may also vary across jurisdictions and depend on the policy responses and types of interventions carried out in different countries. Nonetheless, in the US, most studies follow a more homogeneous definition by relying on the inclusion of a bank in the Federal Deposit Insurance Corporation's (FDIC) failed bank list, which is the authority that manages the resolution of distressed banks, and lists banks under this situation that ended-up in a bankruptcy, a merger or an acquisition by another institution. On the other hand, in Europe, studies present more heterogeneity in the definitions used, including receiving government financial aid (Momparler et al., 2016), poor results in the EU stress tests carried out by the European Banking Authority (EBA) (Kolari et al., 2019), downgrading announcements (Distinguin et al., 2006), mentions to negative keywords in global news (Poghosyan and Čihak, 2011), low value of Credit Default Swaps (Podpiera and Ötker, 2010), low shareholder value ratio (Cipollini and Fiordelisi, 2012), or being involved in non-strategic mergers (Betz et al., 2014). More recently, Lang et al. (2018) use a definition that involves state aid in the form of capital injections and asset protection measures, besides bankruptcies, and non-strategic mergers.

At aggregate level, Laeven and Valencia (2013) provide one of the most complete international crises databases. The authors define banking crisis as events where significant signs of financial distress in the system are present (i.e., significant bank runs, losses in the banking system, and/or bank liquidations), and where significant policy interventions are carried out (i.e., deposit freezes, bank nationalizations, high restructuring costs, extensive liquidity support, significant guarantees; and significant asset purchases).

Against this background, and given the nature of the proposed method to assess risk in the banking sector at aggregate level, the definition of bank distress events in this study is consistent with that in Laeven and Valencia (2013), and adapted to the experience with the bank failures observed in Spain during and after the GFC. In particular, we define bank distress events as those experienced by an institution in two situations. First, signs of financial distress that materialize either in the form of capital needs derived from the stress tests conducted by the Banco de España, or as distressed mergers and acquisitions. The latter are defined as absorptions by the holding group or takeovers by another institution, where any of the involved institutions present weaknesses that threat their short-term viability, as identified by expert judgment. Second, public interventions, which account for the six events defined as policy interventions by Laeven and Valencia (2013), including the recapitalization with public funds.

## 4 Methodology

Starting from the seminal work by Altman (1968), statistical methods such as multivariate analysis have been widely used to the prediction of banking failures. One of the most common methods is discriminant analysis, which allows to classify banks as failed or non-failed based on a set of variables that discriminate the observations in the sample according to a cut-off. Although these models may exhibit good statistical performance, they require a series of restrictive assumptions, such as the normal distribution of regressors, equal variance-covariance matrices across groups, and absence of multicollinearity (see Demyanyk and Hasan, 2010, for a review).

Binary-outcome models, such as probit and logistic regressions, are also a very common statistical approaches to predict banking failures. In these models, the coefficients of a set of predictor variables are computed using maximum likelihood techniques, which lead to the estimation of a probability of occurrence of an event from which a given cut-off can be computed to classify observations. Probit and logit models differ only in the assumed distribution of the error component of the model. The former assumes a standard normal distribution, while the latter assumes a Type-I extreme value distribution.

Besides the classical statistical tools, artificial intelligence methods have also been proposed for the prediction of bank failures. These include neural networks, support vector machines, K-nearest neighbours, and decision trees. In general, these methods provide more flexibility, mainly by avoiding assumptions on distributions, but suffer from other problems, such as computational burden, need for large amounts of data to avoid wide confidence intervals, complex structures, and difficulties to understand the mechanics and interpret the results. Another branch of recent methods, known as hybrid models, attempts to combine different clustering and classification techniques through machine learning approaches.

Overall, the performance of all these techniques is not very different. Citterio (2020) compares the predictive performance of a large number of studies using all the mentioned methodologies. The author documents that all methods may reach an accuracy of more than 90%, but that dispersion is also high within studies using the same method. In general, it seems that a single method could perform equally well or poorly in different samples depending on the characteristics of the banking sector, the variables, and the definition of bank failure employed. Nonetheless, if a method provides a good performance in a particular sample, it seems very difficult that a competing method could outperform it.

In this context, this study uses a standard logistic regression to estimate banking failure probabilities in the Spanish banking sector. Lang et al. (2018) identify that logistic models have a good performance in the issuance of early warning signals of banking failures in Europe, using similar definitions of bank distress as those used in this document. Although this approach still depends on assumptions of absence of multicollinearity and a linear functional relationship, it is not based on the assumption of normal distribution and equal covariance. It is also a relatively simple method that could be easily computed, updated, replicated and communicated. The general proposed specification is the following:

$$\log \frac{P(\gamma_{i,t+h} = 1 \mid X_{it}, Z_{it})}{P(\gamma_{i,t+h} = 0 \mid X_{it}, Z_{it})} = \alpha + X_{it}\beta + Z_{it}\delta + \varepsilon_{it} \tag{1}$$

where $\gamma_{i,t}$ is a dummy variable that takes the value of 1 if a bank i experiences at least one of the four distress situations, as defined in Section 3, during the period from t to t+h, and 0, otherwise. It is important to remark that banks classified as being under a distress situation at time t are not included in the sample in that time period. Although its inclusion may improve the model fit, from a prudential perspective the interest is to predict new distress situations in addition to those already observed in the system. P represents the probability of a bank to go into a distress situation given certain determinants in vectors $X_i$ and $Z_i$. In particular, $X_i$ represents a set of variables based on the CAMELS categories, and $Z_i$ contains some variables intended to capture the macroeconomic environment.

Regarding the time horizon, since the final purpose of the proposed indicator is to provide early-warning signals of distress in the system that may help to support macroprudential decisions, an 8-quarter horizon is defined. This is a common horizon used for the assessment of cyclical risk signals that guide macroprudential instruments (Lang et al., 2019; Galán and Mencia, 2021). It also represents an equilibrium between choosing short horizons, at which macroprudential policy may not have enough time to act effectively, and too-long horizons, at which this type of bank-level data models are usually not able to provide accurate early-warning signals.

### 4.1 Performance criterion

In the literature on early-warning models, the signalling approach has been the most common method to measure predictive performance. The idea behind this approach is that an indicator issues a signal when it is above certain threshold. The signals can be then compared in terms of their ability to issue right signals (True Positive Rate, TPR, or rate of alert signals that correctly anticipate the analysed events) and the frequency of false alarms (False Positive Rate, FPR). This is related to the statistical concepts of errors of Type I (not signalling a true event) and Type II (issue a wrong positive signal). In this regard, the signal-to-noise ratio, which represents the TPR divided by FPR, is a standard measure of predictive performance. However, this measure requires the definition of a specific threshold, leading to different results of the performance of a model depending on the chosen value. Moreover, the signal-to-noise ratio is usually maximized for high thresholds, by which few positive signals are issued (Alessi and Detken, 2011).

Against this background, the AUROC (Area Under the Receiver Operating Characteristics Curve) measure, has the key advantage of taking all possible threshold values into account. This measure has become widely used for assessing classification models in very different fields. In the economics literature, Berge and Jordà (2011) is one of the most relevant studies using AUROC as an evaluation criterion of indicators for the classification of recessions and expansions. This measure has become standard in several studies on early-warning indicators of financial crises (Detken et al., 2014; Drehmann and Juselius, 2014; Giese et al., 2014; Galán and Mencía, 2021). In particular, AUROC assesses the relation between the noise ratio (FPR) and the signal ratio (TPR) for every probability threshold. In this context, AUROC is a measure of the probability that the model predictions are correct. It can take values from 0.5 to 1, where a value of AUROC equal to 1 would indicate perfect predictions, while a value of 0.5 would indicate that the model is not able to improve the predictions coming from a random assignment.3 In this study, AUROC is used to assess both in-sample and out-of-sample performance of the model in the prediction of bank distress.

### 4.2 Aggregate indicator of banking sector fragility

Since the purpose of the proposed early-warning model is to provide information of risk in the banking sector as a whole that could be useful from a macroprudential perspective, rather than predicting single bank default risk, an aggregation of individual predictions into an indicator of risk in the system is necessary. In this study the aggregation used weights the results by the asset size of the institutions. Certainly, size is highly correlated with systemicity and it is the most important category for classifying systemically important institutions, as recommended by the European Banking Authority (EBA) in its guidelines, while keeping calculations simple and transparent (see EBA/GL/2014/10). In particular, the aggregate indicator is the following:

$$CREWS_{t+h} = \sum_{i=1}^{N} PD_{it+h} * RS_{it}; \qquad RS_{it} = \frac{TA_{it}}{\sum_{i=1}^{N} TA_{it}}, \tag{2}$$

where $PD_{it+h}$ is the estimated individual probability of distress for bank i at time t during the following h quarters, as predicted from model in Equation (1); and, $RS_{it}$ represents the relative size of each bank, defined as the fraction of total assets ($TA_{it}$) of a bank with respect to the sum of total assets in the sector. Thus, $CREWS_{t+h}$ is a size-weighted aggregate indicator of individual probabilities of bank distress during the following h quarters, computed at each period of time. The indicator can be seen as a measure of the expected fraction of the banking system that will be at risk of default in *h*-quarters. Thus, the CREWS indicator distinguishes the distress risk of individual institutions by their relative importance within the sector. In that sense, the probability of observing a risk event in a large bank would have greater implications for risk in the banking sector that the same probability of a distress event in a small institution. However, if many small institutions present a high probability of failure, the CREWS indicator may signal an important risk for the sector, thereby highlighting the importance of the expected magnitude of distress events within the sector, rather than focusing on individual risk. In this context, the signals provided by CREWS are consistent with aggregate definitions of banking crises (see Laeven and Valencia, 2013).

3 Although it is possible to obtain values lower than 0.5, this would indicate that the model performs better than a random assignment but with opposite results. That is, by issuing negative signals when events occur, and vice-versa.

## 5 Data

The sample used for the model estimation is an unbalanced panel composed by 82 commercial and saving banks operating in Spain, with quarterly data from 1999Q1 to 2021Q2. This sample represents over 90% of the total assets of the total banking sector.[4] The CAMELS variables included in the model are the following:

a *Capital adequacy:* the capital ratio, defined as the total equity-to-total assets ratio.

b *Asset quality:* the NPL ratio, defined as the non-performing loans-to-total loans ratio, and its annual variation.

c *Management efficiency:* the cost-to-income ratio, defined as the total operating costs-to-total income ratio.

d *Earning ability:* the ROE.

e *Liquidity:* the liquidity ratio, defined as the sum of cash, net deposits in credit institutions and credit to public entities without considering public debt, divided by total assets.

f *Sensitivity*: the bank size, defined as the log of total assets of a bank.

These variables are those identified in the literature to be more related to bank defaults, as discussed in Section 2. Some of them have also been selected for improving the

Table 1
**SUMMARY STATISTICS**

| Variable | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|
| Capital ratio (%) | 8.10 | 6.82 | 5.01 | 2.09 | 19.79 |
| NPL ratio (%) | 4.60 | 3.10 | 4.34 | 0.15 | 19.67 |
| Annual variation NPL ratio (pp) | -0.08 | -0.07 | 1.21 | -3.66 | 3.70 |
| Cost-to-income ratio (%) | 58.36 | 63.21 | 15.25 | 37.92 | 91.06 |
| ROE (%) | 11.87 | 9.40 | 14.23 | -19.10 | 35.83 |
| Liquidity ratio (%) | 31.51 | 23.97 | 24.15 | 4.63 | 77.87 |
| Total assets (ln) | 14.63 | 14.79 | 2.23 | 9.68 | 18.89 |
| Annual GDP growth rate (%) | 0.81 | 2.59 | 4.86 | -21.60 | 5.71 |
| Quarterly change in interest rates (pp) | -0.04 | -0.02 | 0.29 | -2.13 | 0.62 |
| Bank distress events (distress=1) | 0.05 | 0.00 | 0.22 | 0.00 | 1.00 |

**SOURCE:** Banco de España.
NOTE: Ratios are expressed in percentages. Total assets are expressed in logarithms. The quarterly change in interest rates is expressed in percentage points. Bank distress events is a binary variable taking the value equal to 1 if a bank is classified as presenting a distress event during the sample period, and 0 otherwise.

4 The sample does include neither foreign branches nor cooperatives.

most the early-warning performance of the model (see Table A1 in Annex 1 for a comparison of the results using alternative variables). As mentioned in Section 2, although some alternative variables derived from recent banking regulation could also be good candidates to be included in the model, the lack of long series for these variables impedes to account for them (i.e. the solvency ratio and the LCR). Nonetheless, the evolution and variability of some of these series in recent years is very similar to the one exhibited by the variables included in the model.[5] Finally, two variables are included to capture the macroeconomic environment: the annual GDP growth rate and the interest rate quarterly change.

For the CAMELS variables, the sources of information are the financial statements reported by banks to the Banco de España. Regarding macroeconomic data, the Spanish National Statistical Office (INE) is used for data on GDP growth, and the Statistical Bulletin of the Banco de España is used for interest rates. A summary statistics of the variables included in the model is presented in Table 1. High dispersion is observed in most of the variables included, given that the sample covers the whole last financial cycle, including the boom and bust periods.

5 A comparison between the liquidity and capital ratios included in the model, and the LCR and the solvency ratio, respectively, is showed in Chart A1.1 in Annex 1.

## 6 Results

### 6.1 Estimation results

The model in Equation (1) is estimated with data up to 2019Q2. This is because the proposed horizon of evaluation requires information on the occurrence of risk events in the following two years, which implies that the last eight quarters of data are only used for out-of-sample predictions. Results are presented in Table 2. It is observed that all the coefficients have the expected signs and are statistically significant. In particular, more capitalization reduces the probability of bank distress at an 8-quarter horizon. That is because capital reflects banks solvency and their resilience to adverse events. In fact, under the materialization of a negative shock, low capitalized banks would be in a more fragile situation to face losses and to meet regulatory requirements. This may lead them to restrict dividends, to suffer stigma from markets, and to face the need of raising capital in an environment of high cost of equity. These results are in line with previous studies finding that higher capital ratios lower the probability of losses that cause bank default (Arena, 2008; Betz et al., 2014; Berger et al., 2016).

Regarding asset quality, it is observed that a higher share of low quality assets is positively correlated to the probability of distress. Managing problematic loans is costly and high shares of these loans indicate problems on its resolution. This is reflected into banks' balance sheets, impeding banks to operate normally and affecting profitability. Results also show that the rate of NPL deterioration is highly significant as a factor determining banks' distress. Moreover, compared to the level of the NPL ratio, its variation seems to be more significant, both statistically and economically.[6] Given that the realization of adverse macrofinancial shocks is transmitted into loan losses, these indicators of assets quality would reflect the size of a shock and the speed of its materialization in the banks' balance sheet. These results are consistent with previous studies that identify a strong positive association between the NPL ratio and bank default (Cole and White, 2012; Berger et al., 2016; Chiaramonte et al., 2016).

Management efficiency is also identified as a key factor explaining probability of bank distress in a two-year horizon. Certainly, banks' cost efficiency has been found to be a key factor related to profitability, risk, productivity and M&A processes (Berger and DeYoung, 1997; Sarmiento and Galán, 2017; Castro and Galán, 2019). In this regard, a higher cost-to-income ratio implies a less cost efficient structure, which can affect the risk of bank distress. On the one hand, it may reflect low managerial efficiency, which would imply a suboptimal mix of resources and a less agile response to adverse events. On the other hand, banks with a high cost structure with respect to income may suffer more from unexpected events that increase their costs even further and reduce the needed income to cover them. These results are consistent with previous studies that have identified a positive relation between the cost-to-income ratio and bank's probability of default (Mayes and Stremmel, 2014; Shrivastava et al., 2020).

6 Departing from average values, a one standard deviation increase in the NPL ratio produces an increase of 4pp in the probability of distress, while the same variation in the NPL growth rate, implies an increase of around 10pp.

Table 2
**ESTIMATION RESULTS**

| Variable | Coefficients |
|---|---|
| Capital ratio | -31.3136 *** |
| NPL | 0.6989 * |
| Δ NPL | 35.2478 *** |
| Cost-to-income | 0.4142 ** |
| ROE | -0.0014 ** |
| Liquidity ratio | -7.4280 *** |
| Size (ln Assets) | -0.1856 *** |
| Δ GDP | -0.5809 *** |
| Δ Interest rates | 0.8676 *** |
| AUROC in-sample | 93.5% |
| AUROC out-of-sample | 85.1% |

**SOURCE:** Author's calculations.
NOTE: Estimations with data up to 2019Q2. ***, ** and * represent the significance of the estimated coefficients at 1%, 5% and 10%, respectively. Standard errors are clustered at bank-level. AUROC stands for Area under the ROC (Receiver Operating Characteristics Curve). It measures the probability that the model prediction is correct by comparing the false positive rate with the true positive rate. AUROC values ranges from 0.5 to 1, where a value equal to 1 indicates a perfect prediction model, and a value equal to 0.5 indicates predictions equivalent to those obtained randomly. The out-of-sample AUROC is obtained by estimating the model until 2009Q1 and predicting from 2009Q2 to 2019Q2.

Regarding earnings, ROE has a negative and significant relation with the probability of bank distress in a two-year horizon. Low profitability implies low market valuation and high sensitivity of market reactions to unexpected events. It also implies low margin to react to adverse events, thereby increasing the probability of capital needs and restrictions to dividend payments. This situation can also affect banks' liquidity and reflect structural problems in the structure of income and expenses. A negative relation between profitability and the banks' probability of default has also been confirmed in several previous studies (Distinguin et al., 2006; Arena, 2008; Berger et al., 2016; Cleary and Hebb, 2016; Switzer et al., 2018).

Liquidity is also found to be negatively correlated with the probability of bank distress. A low fraction of liquid assets may translate into difficulties to accomplish short-term obligations with debtors, and compromises with stock holders, that may affect the operational viability of the bank. A weak position in terms of liquidity increases the vulnerability of the bank to negative shocks. In this regard, the liquid assets-to-total assets ratio has also been identified to be negatively associated to bank default risk in other studies (Arena, 2008; Cipollini and Fiordelisi, 2012; Chiaramonte et al., 2016).

Size is also found to be an important determinant of banks' distress risk. In particular, large banks would be subject to lower default risk, *ceteris paribus.* This can be related to the fact that large institutions are usually more diversified in terms of income sources and less sensitive to market uncertainty. Other studies including size as a driver of bank default risk have also identified a negative and significant relation of this factor to the probability of bank failure (Wheelock and Wilson, 2000; Avkiran and Cai, 2012).

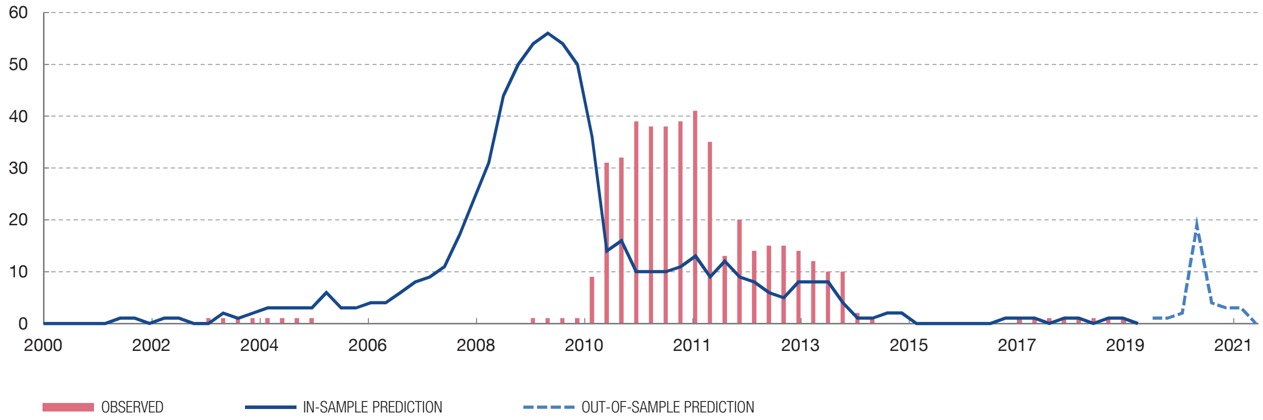
Finally, macroeconomic variables are found to play a very relevant role in explaining banks' distress risk. A deterioration of the economic situation, as measured by GDP growth, would translate into a lower loan demand, a higher delinquency rate of borrowers, and a decrease in assets valuations, that reduce bank revenues and increase the need of provisions. This affects the overall banks' solvency, liquidity and profitability. A decrease in interest rates is also found to be significantly associated to a higher probability of bank distress. Although empirical evidence has identified mixed effects of interest rates on bank profits (Claessens et al., 2017; Pérez and Ferrer, 2018), low interest rates can reduce margins and affect revenues, which tend to decrease at a faster speed than costs, thereby diminishing profitability. On the other hand, a reduction of reference interest rates can identify the reaction of monetary authorities to macroeconomic crisis, marking an adverse macro financial environment. Certainly, controlling by macroeconomic conditions has been previously found to improve the performance of bank default models (Flannery, 1998; Jagtiani and Lemieux, 2001).

### 6.2 Predictive performance

The predictive performance of the proposed model at a two-year horizon is found to be fairly high. The in-sample AUROC value is 0.94, which indicates that the model predicts very accurately bank distress events at the defined horizon. This is the highest value across some alternative specifications described in Annex 1. Nonetheless, it is possible that the high predictive capacity of the model might be influenced by the events occurred during the GFC and the subsequent sovereign crisis, when both financial ratios of banks and macroeconomic conditions deteriorated rapidly and deeply. The specific and abnormal conditions observed during those years may influence the performance of the model and potentially it might not signal equally well situations where imbalances are not comparable to those presented in that period. Thus, assessing the out-of-sample performance of the model is of interest. For this purpose, the sample is split into two sub-samples: one for the estimation of the model from 1999Q1 to 2009Q1, which corresponds to the last expansionary phase of the financial cycle in Spain, where large imbalances were cumulated, and that ends just previous to the start of the banking crisis in Spain (see Lo Duca et al., 2017, for systemic crises dates). The date of the onset of the banking systemic crisis in Spain was marked by the first relevant banking failure *(Caja Castilla La Mancha)*. The second sample from 2009Q2 to 2019Q2 is used for the out-of-sample assessment of the predictions. The AUROC value in this case is also high (0.85) indicating that the model also features a high out-of-sample predictive performance.

These results give an idea of the good performance of the model in predicting individual bank distress situations in an 8-quarter horizon at all possible thresholds. However, if a threshold for the estimated probability of distress is chosen based on the relation between false and true positives, it is possible to compute the number of institutions that the model predicts to be in a distress situation in a two-year horizon. In particular, a *pareto* optimal threshold, defined as that where it is not possible to improve either the TFP or the FPR without worsening the other, is found to correspond to an approximate estimated probability

Chart 1
**NUMBER OF BANKS WITH RISK EVENTS AT A TWO-YEAR HORIZON**




**SOURCE:** Author's calculations.
NOTE: Predictions correspond to the number of banks with estimated probabilities of distress over the following eight quarters above the 14% optimal threshold. This threshold optimizes the relationship between false positives and true positives. The continuous line represents in-sample predictions at each quarter from 2000Q1 to 2019Q2. The dotted line represents out-of-sample predictions from 2019Q3 to 2021Q2. The bars represent, at each quarter, the observed number of banks in distress during the previous two years.

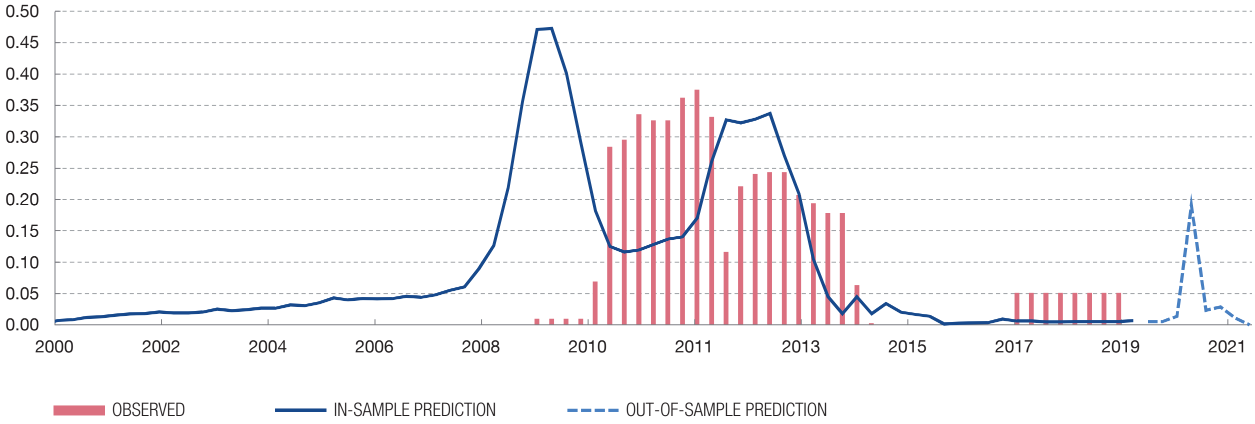
of distress of 14% to classify a bank in a distress situation (see Annex 2 for a comparison of results using other thresholds). Following this criterion, Chart 1 compares the observed number of banks in distress in the last 8 quarters with the number of banks predicted to be under this situation (with an estimated probability of distress above the threshold) in an 8-quarter horizon. It is observed that the model predicts fairly well the distress events occurred during the GFC and the sovereign crisis, by issuing signals of these situations up to two years before their materialization. During the recovery phase, only a couple of banks is predicted to face a distress situation, which materializes at the end of the sample considered in the model. Since the model requires to observe the occurrence of distress events 8-quarters ahead, predictions for the last two years of data corresponds to out-of-sample predictions of distress events that might not yet materialized. This period coincides with the Covid-19 pandemic, when the model predicts an increase in future bank distress events. The specific characteristics of this recent period are further analysed in Section 6.3.

## 6.3 The CREWS indicator

Although, the number of institutions in distress is indicative of the banking sector health, the most important information from a macroprudential perspective is whether or not these distress events can be considered as systemic. Thus, a measure of the importance of the predicted banks in distress within the whole system is a better approximation to the situation of the whole banking sector. In this regard, the aggregate CREWS indicator presented in Equation (2), which accounts for the relative importance of each institution in terms of its size, is computed.

Chart 2

**CREWS INDICATOR OF BANKING SECTOR ASSETS UNDER DISTRESS AT A TWO-YEAR HORIZON VS THE OBSERVED PROPORTION OF THE SECTOR EXPERIENCING DISTRESS EVENTS**




**SOURCE:** Author's calculations.
NOTE: The CREWS indicator is computed as the sum of the probability of distress events at every individual bank weighted by their assets. The continuous line represents, at each quarter, in-sample predictions from 2000Q1 to 2019Q2. The dotted line represents out-of-sample predictions from 2019Q3 to 2021Q2. The bars represent, at each quarter, the observed proportion of banking sector assets under distress during the previous two years.

Chart 2 plots this indicator along with the observed fraction of the system in distress, also in terms of size. It is observed that the CREWS indicator predicts well the magnitude of the banking system in distress during the GFC, which reached almost 40% of the sector in terms of assets. This indicator is not only more informative than the predicted number of institutions, but also shows a different picture of the situation during the period corresponding to the sovereign crisis. While the number of banks in distress holds relatively stable and exhibits a decreasing trend starting in 2010, the CREWS indicator exhibits a second peak that evidences the magnitude of that second wave of the crisis, which affected around 25% of the system. After the crisis, the indicator does not show warning signals until the recent Covid-19 crisis, which is analysed in more detail below. It is important to remark that the observed distress events after 2017 correspond to the failure of Banco Popular, which represented almost 5% of the total assets of the sector. As it can be noticed, the CREWS indicator does not issue strong signals of this event, which reflects the fact that the indicator is not designed to issue individual signals of distress, but warnings of situations that may represent risk for an important fraction of the system.

A confirmation of the good early-warning performance of these indicators is provided by the AUROC. For that purpose, the observed cumulated share of the banking sector assets at risk is transformed into binary variables based on thresholds around some of the observed values during the last GFC that could confirm the occurrence of a systemic crisis (i.e. between 10% and 20%). Then, the prediction performance of the CREWS indicator is assessed. Table 3 shows these results, where very high AUROC values are obtained from the early signals issued by the indicator within an 8-quarters horizon.

Table 3

**AUROC VALUES FOR THE CREWS INDICATOR AT DIFFERENT THRESHOLDS OF THE OBSERVED PROPORTION OF THE BANKING SECTOR UNDER DISTRESS**

| Threshold | 10% | 15% | 20% |
|---|---|---|---|
| AUROC | 0.9608 | 0.9506 | 0.9242 |

**SOURCE:** Author's calculations.
NOTE: The thresholds to evaluate the probability of distress correspond to those used to transform the observed proportion of the banking sector under distress into binary variables. The occurrence of systemic crises is signaled when that proportion is greater than the threshold. The AUROC is assessed for the period 2000Q1-2019Q2.

### 6.4 Impact of the GFC vs the COVID-19 crisis

Although it did not reach the values observed during the GFC and the sovereign crisis, the results presented above show that the pandemic increased the probability of bank distress. This was especially evident during the second quarter of 2020, when the negative effects of the lockdown materialized. Nonetheless, besides magnitude, there are important differences in the effects of the Covid-19 crisis with respect to the GFC in terms of distress risk in the banking sector. The first one is the duration of the shock on the probability of distress. During the GFC, the probability of risk in the banking sector increased continuously for more than 5 quarters, and it took around 7 years to go back to pre-crisis values. However, during the Covid-19 crisis, risk of distress in the banking sector only peaked suddenly during the second quarter of 2020 and decreased quickly again to pre-crisis values (see Chart 2).

A second relevant difference regards the drivers of risk, which are quite different in the two crises. Chart 3 evidences this situation by showing a decomposition of the contribution of the main factors in the model to the predicted probability for an average bank over time (Panel 1) and focusing in the pre-GFC period and the Covid-19 shock (Panel 2). It is observed that during the two years before the onset of the GFC, banks' balances started to evidence signals of a gradual accumulation of vulnerabilities that explained nearly 90% of the predicted probability of distress. During that period, capital adequacy and liquidity increased notably their importance as drivers of risk. This indicates that vulnerabilities of banks regarding solvency and liquidity became evident during that period, while macroeconomic conditions still held relatively stable. Once the crisis materialized, macroeconomic conditions gained some importance, but mainly factors related to assets quality became the most relevant drivers of distress risk. Certainly, during that period credit losses started to emerge very quickly. In the subsequent years this factor as well as earnings maintained a relatively high importance.[7]

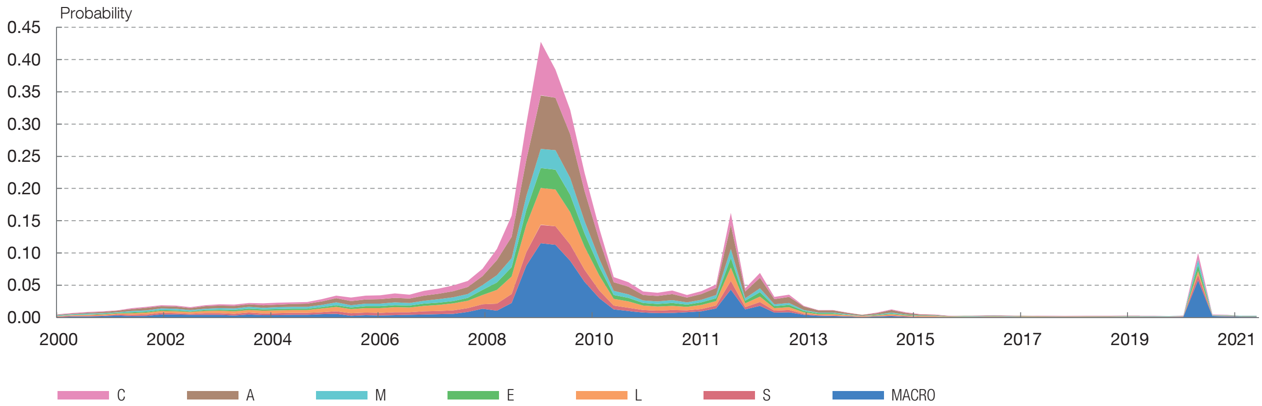
On the other hand, the increase in risk during the Covid-19 shock has been mostly explained by the macroeconomic deterioration, which explained half of the peak observed

7 The contribution of each factor during periods of low predicted probability can be observed in more detail in Annex 3.

Chart 3

**DECOMPOSITION OF THE FACTORS CONTRIBUTING TO THE PREDICTED PROBABILITY OF BANK DISTRESS IN A TWO-YEAR HORIZON**

1 EVOLUTION OF THE DETERMINANTS OF THE PROBABILITY OF BANK DISTRESS OVER TIME



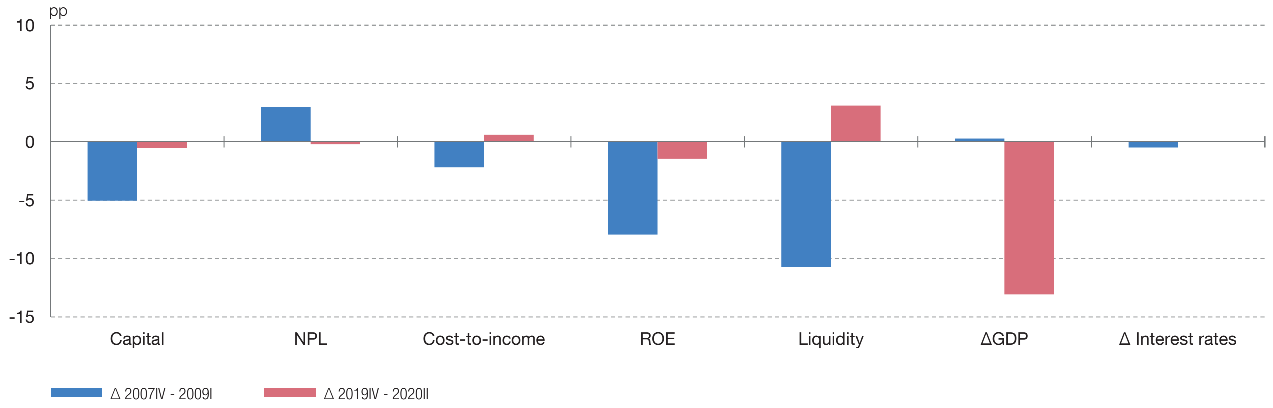

2 SHARE OF FACTORS PREDICTING BANK DISTRESS PROBABILITY


**SOURCE:** Author's calculations.
NOTE: The colored areas represent the contribution of each of the CAMELS categories and macroeoconomic conditions to the predicted probability of bank distress at a two-year horizon for a bank with average values of all the included variables at each period, where C stands for capital adequacy, A for assets quality, M for management efficiency, E for earnings ability, L for liquidity, and S for sensitivity to market. Macro includes GDP growth and interest rate change. In Panel 1, the values from 2019Q3 to 2021Q2 correspond to out-of-sample predictions. In Panel 2, the left figure shows the average of the contribution of each factor during the 8 quarters prior to the onset of the systemic crisis in Spain, and the right figure shows the share of these factors during the second quarter of 2020.

in the second quarter of 2020. It is also behind the subsequent improvement in the last quarters. The nature of the shock, which is unexpected and unrelated to the accumulation of financial vulnerabilities makes that bank variables did not reflect signals of imbalances with anticipation to the shock. This situation is also evident when comparing changes in the values of the variables in the model during the period before the onset of the GFC and the pandemic. In Chart 4, it can be observed that capital, ROE and liquidity decreased importantly, while the NPL ratio increased between 2007 and the onset of the systemic crisis in the first quarter of 2009. However, these variables have been quite stable during the pandemic, when, as mentioned above, the large drop in GDP growth has driven the most important changes.

Chart 4

**VARIATION OF THE MAIN VARIABLES IN THE MODEL. THE GFC VS THE COVID-19 CRISIS**




**SOURCE:** Author's calculations.
NOTE: The bars represent the change in the observed values of the selected CAMELS and macroeconomic variables. The orange bars show the changes in the period 2007Q4-2009Q1, and the blue bars show the changes in the period 2019Q4-2020Q2.

This leads to a very different picture of the signals issued after the onset of the pandemic with respect to those observed before the GFC. The greater resilience of banks before the pandemic, as a consequence of higher capital ratios, and the continuous improvement of NPL ratios in the years before the Covid-19 outbreak have helped the banking system to face the Covid-19 crisis in a much more solid position with favourable perspectives for the moment. Moreover, the large public support measures implemented as a response to the pandemic have also helped to contain risks in the banking sector. In this regard, the fact that the model does not account for these measures may suggest that the increase in risk predicted by the model reflects, at some extent, a counterfactual in terms of impact of what could have happened in the absence of the decisive public policy response. Nonetheless, the challenges that represent the phase-out of the public support measures and the uncertainty regarding a potentially longer than expected recovery phase may translate into credit losses in the short-run. This could in turn affect the risk of the banking sector in the following quarters.

### 6.5 Predictive margins of CAMELS variables

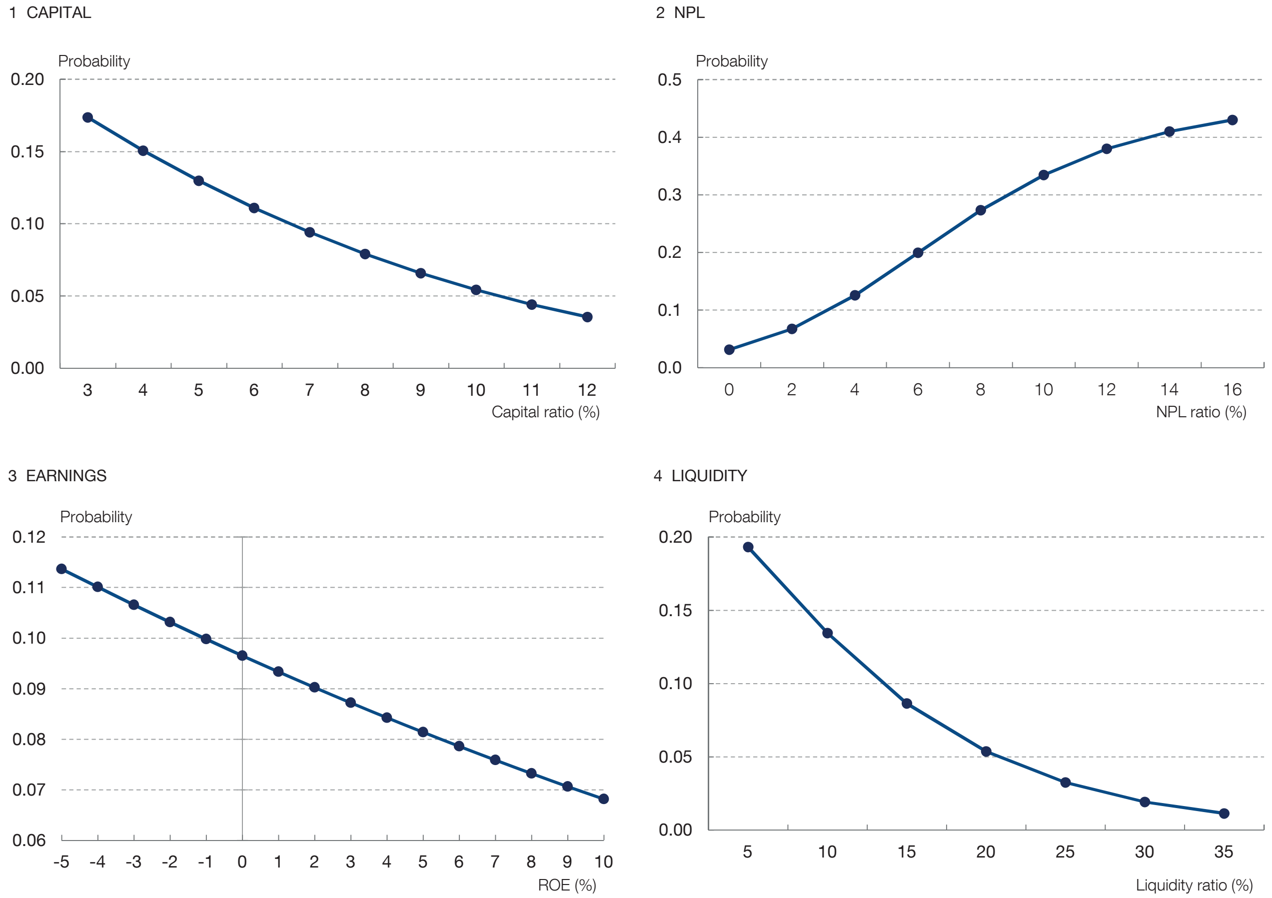
Another interesting result that can be derived from the presented model is the computation of the predictive margins. This allows identifying how the marginal effects on the probability of distress change at different values of the most relevant variables.

Chart 5 shows these values for the most important variables under each category.[8] It can be observed that for values of the capital ratio between 3% and 8%, an increase of 1pp reduces the probability of distress in around 2.5 pp (Panel 1). The effect is

8 Predictive margins are computed as the average predicted probability if every observation were treated as having the specified values of the selected variables, while holding their observed values for the rest of variables.

Chart 5

**PREDICTIVE MARGINS AT RELEVANT VALUES OF BANK VARIABLES**




**SOURCE:** Author's calculations.
NOTE: The vertical axis represents the average predictive margin. That is, the average predicted probability of bank distress (in a 0-1 scale) if every observation were treated as having the specific value in the horizontal axis of the selected variables, while holding their observed values for the rest of variables.

decreasing, and after this threshold, reductions start to be very small (about 1pp). Regarding asset quality, the negative effect on risk is very relevant, especially when moving within the range between 2% and 10%, where a 1pp increase could represent an increase of up to 5pp in the probability of distress (Panel 2). This indicates that banks' risk is very sensitive to the quality of their assets. In terms of profitability, marginal effects are quite linear for relevant values of ROE (Panel 3). They are only somewhat higher for negative ROE when a 1pp increase implies a reduction of around 0.5pp in the probability of distress. For positive values, this marginal effect is of about 0.2pp. Regarding liquidity, the reduction in risk is more relevant for liquidity ratios up to 25; while, beyond that threshold, the positive effect starts to decrease rapidly (Panel 4). Although this analysis provides an interesting overview of the effects of key bank variables on risk, it is important to notice that it is static and it does not account for the benefits of prudential measures, such as capital buffers, over the banking system and the economy as a whole.

## 7 Conclusions

This document proposes the use of a simple conditional logit model to derive out-of-sample predictions of the build-up of systemic risk in the banking sector. The model is based on the variables in the CAMELS rating system, which have been proved to provide useful early information on the probability of distress of individual banks (Erdogan, 2008; Citterio, 2020), and is complemented with macrofinancial variables. The model is used to derive an aggregate measure of risk in the banking system rather than only to compute individual probabilities of bank failure. In this context, the proposed CREWS indicator has a macroprudential orientation, which is different from most of previous studies, whose main objective is to predict individual bank defaults.

Results evidence both high in-sample and out-of-sample performance for the prediction of banking crises at a two-year horizon, showing high accuracy in the prediction of individual bank failures. The CREWS indicator exhibits a good performance in predicting the systemic character of the last GFC and the subsequent sovereign crisis up to two-years before their materialization. This shows the usefulness of the aggregate indicator for the early identification of systemic risk and the prompt support of macroprudential policy decisions. The model also allows to identify the main drivers of banks' risk of distress and distinguishes the main factors behind variations in the aggregate CREWS indicator. These distinctions were made evident during the recent Covid-19 crisis, where the drivers behind the signals captured by the CREWS indicator have been mainly associated to the macroeconomic environment rather than to a deterioration of bank's balance sheets. This is very different from the factors driving the risk signals before and during the GFC, when the deterioration of balance sheet variables was evident. In this regard, the more resilient position of banks at the beginning of the pandemic as a consequence of the changes in the regulatory framework after the GFC, as well as the public support measures implemented as a response to Covid-19, could help banks to face the shock of the pandemic without suffering a major deterioration of their balance sheets.

Overall, the tool offers mid-term signals that complement both long-term indications of the build-up of cyclical risk derived from macrofinancial indicators, and contemporaneous measures of the materialization of financial risks. In this context, the CREWS indicator provides simple and accurate measures of risk in the banking sector that are useful for assessing macroprudential stance and for taking prompt prudential policy decisions.

## References


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

Altman, E. I. (1968). "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy", *The Journal of Finance,* 23(4), pp. 589-609.

Altunbas, Y., S. Manganelli and D. Marques-Ibanez (2011). *Bank risk during the financial crisis: do business models matter?,* European Central Bank Working Paper Series, No. 1394.

Arena, M. (2008). "Bank failures and bank fundamentals: a comparative analysis of Latin America and East Asia during the nineties using bank-level data", *Journal of Banking & Finance,* 32(2), pp. 299-310.

Avkiran, N. K., and L. C. Cai (2012). "Predicting bank financial distress prior to crises", in *New Zealand Finance Colloquium,* Working Paper.

Balcaen, S., and H. Ooghe (2006). "35 years of studies on business failure: an overview of the classic statistical methodologies and their related problems", *The British Accounting Review,* 38(1), pp. 63-93.

Barker, D., and D. Holdsworth (1993). *The causes of bank failures in the 1980s,* Research Paper No. 9325, Federal Reserve Bank of New York.

Berge, T. J., and Ò. Jordà (2011). "Evaluating the Classification of Economic Activity into Recessions and Expansions", *American Economic Journal: Macroeconomics,* 3, pp. 246-277.

Berger, A., and R. DeYoung (1997). "Problem loans and cost efficiency in commercial banks", Journal of Banking and Finance, 2(6), pp. 849-870.

Berger, A. N., B. Imbierowicz and C. Rauch (2016). "The roles of corporate governance in bank failures during the recent financial crisis", *Journal of Money, Credit and Banking,* 48(4), pp. 729-770.

Betz, F., S. Oprică, T. A. Peltonen and P. Sarlin (2014). "Predicting distress in European banks", *Journal of Banking & Finance,* 45, pp. 225-241.

Bose, I. (2006). "Deciding the financial health of dot-coms using rough sets", *Information & Management,* 43(7), pp. 835-846.

Campbell, J. Y., J. D. Hilscher and J. Szilagyi (2011). "Predicting financial distress and the performance of distressed stocks", *Journal of Investment Management,* 9(2), pp. 14-34.

Castro, C., and J. E. Galán (2019). "Drivers of Productivity in the Spanish Banking Sector: Recent Evidence", *Journal of Financial Services Research,* 55, pp. 115-141.

Charitou, A., E. Neophytou and C. Charalambous (2004). "Predicting corporate failure: empirical evidence for the UK", *European Accounting Review,* 13(3), pp. 465-497.

Chiaramonte, L., H. Liu, F. Poli and M. Zhou (2016). "How accurately can Z-score predict bank failure?", *Financial Markets, Institutions & Instruments,* 25(5), pp. 333-360.

Cipollini, A., and F. Fiordelisi (2012). "Economic value, competition and financial distress in the European banking system", *Journal of Banking & Finance,* 36(11), pp. 3101-3109.

Citterio, A. (2020). *Bank failures: review and comparison of prediction models,* SSRN Network Papers, 3719997.

Claessens, S., N. Coleman and M. Donnelly (2017). "'Low-For-Long' Interest Rates and Banks' Interest Margins and Profitability: Cross-Country Evidence", *Journal of Financial Intermediation,* 35(A), pp. 1-16.

Cleary, S., and G. Hebb (2016). "An efficient and functional model for predicting bank distress: in and out of sample evidence", *Journal of Banking & Finance,* 64, pp. 101-111.

Cole, R. A., and J. Gunther (1995). "A CAMEL rating's shelf life", *Federal Reserve Bank of Dallas Review,* December, pp. 13-20.

Cole, R. A., and L. J. White (2012). "Déjà vu all over again: the causes of US commercial bank failures this time around", *Journal of Financial Services Research,* 42, pp. 5-29.

Demyanyk, Y., and I. Hasan (2010). "Financial crises and bank failures: a review of prediction methods", *Omega,* 38(5), pp. 315-324.

Detken, C., O. Weeken, L. Alessi, D. Bonfim, M. Bouchina, C. Castro, S. Frontczak, G. Giordana, J. Giese, N. Jahn, J. Kakes, B. Klaus, J. H. Lang, N. Puzanova and P. Welz (2014). *Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options,* ESRB Occasional Paper Series No. 5, June.

DeYoung, R. (2003). "De novo bank exit", *Journal of Money, Credit and Banking,* 35(5), pp. 711-728.

Distinguin, I., P. Rous and A. Tarazi (2006). "Market discipline and the use of stock market data to predict bank financial distress", *Journal of Financial Services Research,* 30(2), pp. 151-176.

Drehmann, M., and M. Juselius (2014). "Evaluating early warning indicators of banking crises: satisfying policy requirements", *International Journal of Forecasting,* 30(3), pp. 759-780.

Erdogan, B. E. (2008). "Bankruptcy Prediction of Turkish Commercial Banks Using Financial Ratios", *Applied Mathematical Sciences,* 2(60), pp. 2973-2982.

Flannery, M. J. (1998). “Using market information in prudential bank supervision: a review of the US empirical evidence”, *Journal of Money, Credit and Banking,* 30(3), pp. 273-305.

Galán, J. E., and J. Mencía (2021). “Model-based indicators for the identification of cyclical systemic risk”, *Empirical Economics,* in press.

Giese, J., H. Adersen., O. Bush, C. Castro, M. Farag and S. Kapadia (2014). “The credit-to-gdp gap and complementary indicators for macroprudential policy: evidence from the UK”, *International Journal of Finance and Economics,* 19, pp. 25-47.

Jagtiani, J., and C. Lemieux (2001). “Market discipline prior to bank failure”, *Journal of Economics and Business,* 53(2-3), pp. 313-324.

Jin, J. Y., K. Kanagaretnam and G. J. Lobo (2011). “Ability of accounting and audit quality variables to predict bank failure during the financial crisis”, *Journal of Banking & Finance,* 35(11), pp. 2811-2819.

Jordà, O., M. Schularick and A. M. Taylor (2015). “Leveraged bubbles”, *Journal of Monetary Economics,* 76, pp. 1-20.

Kerstein, J., and A. Kozberg (2013). “Using accounting proxies of proprietary FDIC ratings to predict bank failures and enforcement actions during the recent financial crisis”, *Journal of Accounting, Auditing & Finance,* 28(2), pp. 128-151.

Kolari, J., D. Glennon, H. Shin and M. Caputo (2002). “Predicting large US commercial bank failures”, *Journal of Economics and Business,* 54(4), pp. 361-387.

Laeven, L., and F. Valencia (2013). “Systemic Banking Crises Database”, *IMF Economic Review,* 61(2), pp. 225-270.

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,* ECB Working Paper Series No. 2182, October.

Lo Duca, M., A. Koban, M. Basten, E. Bengtsson, B. Klaus and P. Kusmierczyk (2017). *A new database for financial crises in European countries ECB/ESRB EU crises database,* ESRB Occasional Paper Series No. 13, July.

Männasoo, K., and D. G. Mayes (2009). “Explaining bank distress in Eastern European transition economies”, *Journal of Banking & Finance,* 33(2), pp. 244-253.

Mayes, D. G., and H. Stremmel (2014). *The effectiveness of capital adequacy measures in predicting bank distress,* SUERF Study 2014/1, Brussels, Larcier.

McLeay, S., and A. Omar (2000). “The sensitivity of prediction models to the non-normality of bounded and unbounded financial ratios”, *The British Accounting Review,* 32(2), pp. 213-230.

Momparler, A., P. Carmona and F. Climent, (2016). “Banking failure prediction: a boosting classification tree approach”, *Spanish Journal of Finance and Accounting,* 45(1), pp. 63-91.

Pérez, C., and A. Ferrer (2018). “The impact of the interest rate level on bank profitability and balance sheet structure”, *Financial Stability Review,* 35, Banco de España, pp. 123-152.

Platt, H. D., and M. B. Platt (2002). “Predicting corporate financial distress: reflections on choice-based sample bias”, *Journal of Economics and Finance,* 26(2), pp. 184-199.

Platt, H., and M. Platt (2004). “Industry-relative ratios revisited: the case of financial distress”, *in FMA 2004 Meeting,* New Orleans (USA), pp. 6-9.

Podpiera, J., and M. I. Ötker (2010). *The fundamental determinants of credit default risk for European large complex financial institutions,* IMF Working Paper, No. 10-153.

Poghosyan, T., and M. Čihak (2011). “Determinants of bank distress in Europe: evidence from a new data set”, *Journal of Financial Services Research,* 40(3), pp. 163-184.

Sarmiento, M., and J. E. Galán (2017). “The influence of risk-taking on bank efficiency: evidence from Colombia”, *Emerging Markets Review,* 32, pp. 52-73.

Schularick, M., and A. Taylor (2012). “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008” *American Economic Review,* 102(2), pp. 1029-1061.

Shrivastava, S., P. M. Jeyanthi and S. Singh (2020). “Failure prediction of Indian Banks using SMOTE, Lasso regression, bagging and boosting”, *Cogent Economics & Finance,* 8(1), 1729569.

Sinkey Jr., J. F. (1975). “A multivariate statistical analysis of the characteristics of problem banks”, *The Journal of Finance,* 30(1), pp. 21-36.

Stiroh, K. J. (2010). “Diversification in banking”, *The Oxford handbook of banking,* pp. 90-111.

Switzer, L. N., Q. Tu and J. Wang (2018). “Corporate governance and default risk in financial firms over the post-financial crisis period: international evidence”, *Journal of International Financial Markets, Institutions and Money,* 52, pp. 196-210.

Thomson, J. B. (1991). “Predicting bank failures in the 1980s”, *Federal Reserve Bank of Cleveland Economic Review,* 27(1), pp. 9-20.

Tölo, E., H. Laakkonen and S. Kalatie (2018). "Evaluating indicators for use in setting the countercyclical capital buffer", *International Journal of Central Banking,* 14(2), pp. 51-111.

Wheelock, D. C., and P. W. Wilson (2000). "Why do banks disappear? The determinants of US bank failures and acquisitions", *Review of Economics and Statistics,* 82(1), pp. 127-138.

## Annex 1 Alternative CAMELS variables

Table A1.1
**SPECIFICATIONS USING ALTERNATIVE CAMELS VARIABLES**

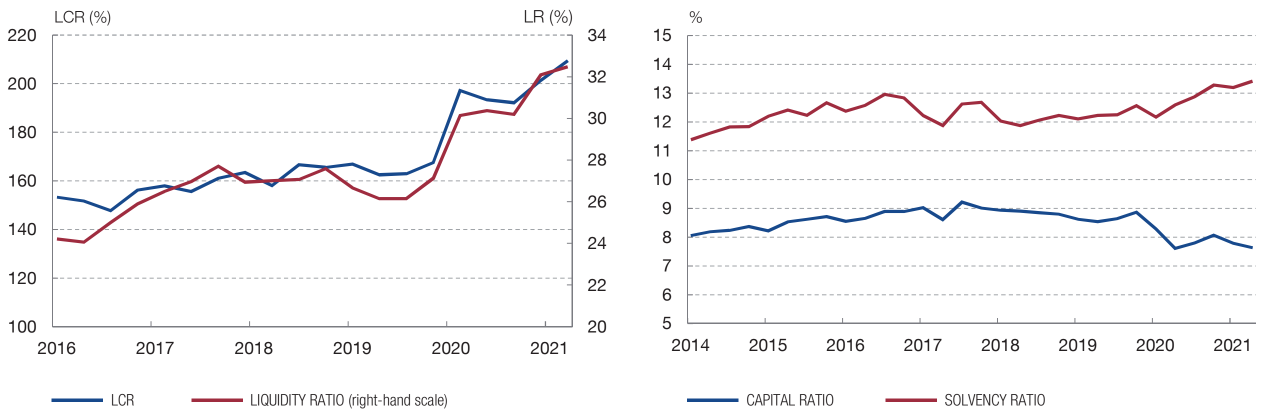
| Category | Variable | I | II | III | IV | V | VI | VII | VIII | IX | X |
|---|---|---|---|---|---|---|---|---|---|---|---|
| C | Capital ratio | – | – | – | – | – | – | – | – | – | – |
| A | Δ4 NPL ratio | x | | | | | | x | x | + | + |
| A | NPL ratio | | + | + | + | + | + | + | + | + | + |
| M | Losses / Interest Mg | x | x | | | | x | x | x | | |
| M | Labor exp. / Operating exp. | | | x | | | x | x | | | |
| M | Cost-to-income | | | | – | – | | | – | – | – |
| E | ROA | x | x | x | – | | x | x | x | – | |
| E | ROE | | | | | – | | | | | – |
| L | Liquidity ratio | – | – | – | – | – | – | – | – | – | – |
| S | Ln(assets) | – | – | – | – | – | – | – | – | – | – |
| Macro | Δ Real GDP | – | – | – | – | – | – | – | – | – | – |
| Macro | Δ Interest rates | + | + | + | + | + | + | + | + | + | + |
| **In-sample AUROC** | | 78.60% | 79.30% | 78.90% | 80.20% | 83.50% | 82.20% | 84.10% | 87.70% | 90.00% | **93.50%** |
| **Out-of-sample AUROC** | | 68.30% | 67.10% | 70.30% | 71.70% | 74.60% | 73.90% | 74.00% | 81.50% | 82.40% | **85.10%** |

**SOURCE:** Author's calculations.
NOTE: Estimations with data up to 2019Q2. The negative (-) and positive (+) signs represent the estimated sign of the coefficient, which corresponds with the expected sign. An 'x' represents that the estimated coefficient is either non-significant or presents the wrong sign. AUROC stands for Area under the ROC (Receiver Operating Characteristics Curve). It measures the probability that the model prediction is correct by comparing the false positive rate with the true positive rate. AUROC values ranges from 0.5 to 1, where a value equal to 1 indicates a perfect prediction model, and a value equal to 0.5 indicates predictions equivalent to those obtained randomly. The out-of-sample AUROC is obtained by estimating the model until 2009Q1 and predicting from 2009Q2 to 2019Q2.

Chart A1.1
**COMPARISON OF ALTERNATIVE REGULATORY VARIABLES OF LIQUIDITY AND CAPITAL**

1 LIQUIDTY RATIO INCLUDED IN THE MODEL VS THE LCR

2 CAPITAL RATIO INCLUDED IN THE MODEL VS THE SOLVENCY RATIO

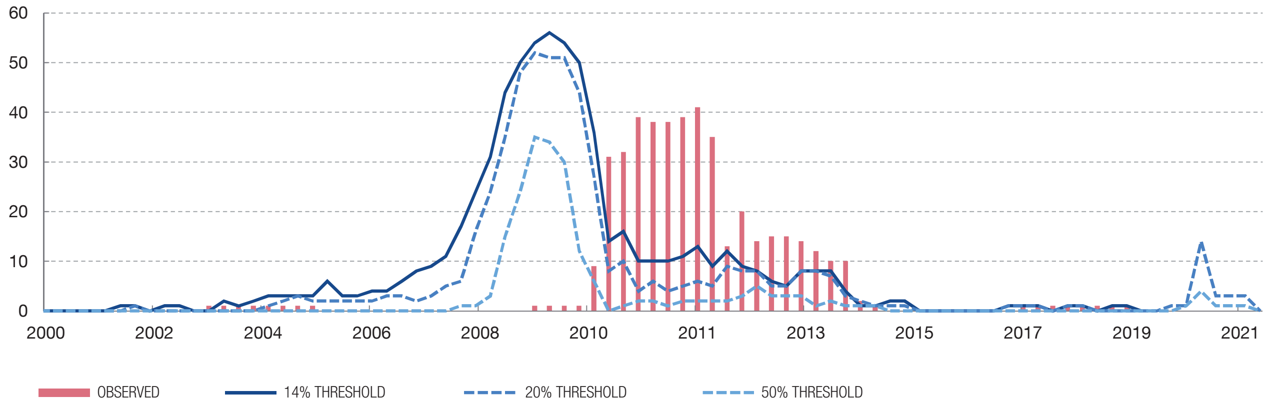



**SOURCE:** Author's calculations.
NOTE: The LCR and their components are reported by Spanish banks from 2016Q3. The LCR is the ratio between the stock of high-quality liquid assets (HQLA) and the total net cash outflow over the next 30 calendar days. Basel III standards introduced a minimum requirement based on this ratio on 1 January 2015, with a minimum value set at 60%. From 1 January 2019 this ratio should be above 100%. The solvency ratio is defined as common equity tier 1 capital (CET1) divided by risk-weighted assets (RWA), and is available from 2014Q1.

## Annex 2 Sensitivity of model predictions to different thresholds

Chart A2.1

**PREDICTION OF THE NUMBER OF BANKS IN DISTRESS USING DIFFERENT THRESHOLDS VS THE NUMBER OF OBSERVED BANKS EXPERIENCING DISTRESS SITUATIONS**



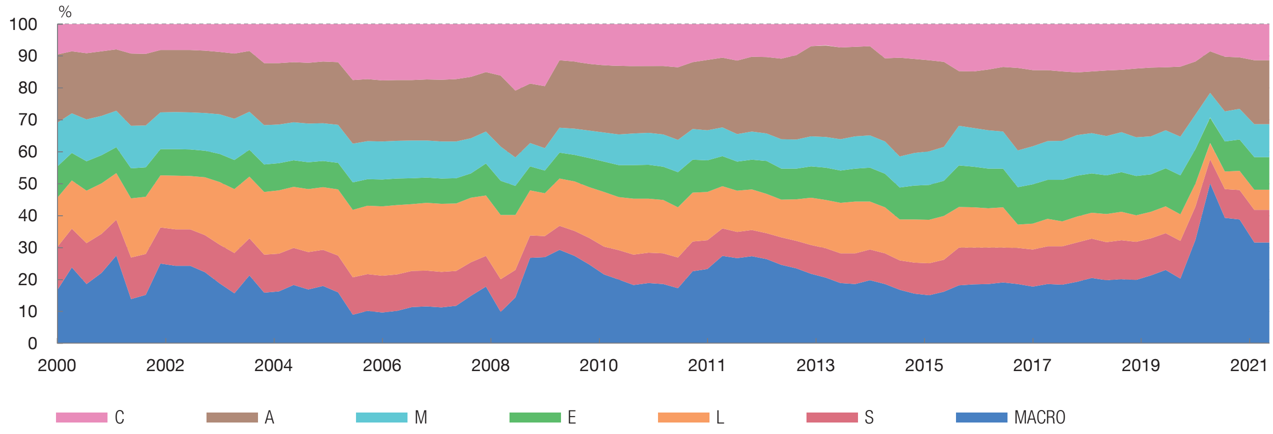

**SOURCE:** Author's calculations.

NOTE: The solid blue, dotted blue and dotted black lines represent predictions of the number of banks in distress at the optimal (14%), 20%, and 50% thresholds, respectively. The optimal threshold is the one optimizing the relationship between false positives and true positives. In-sample predictions are showed from 2000Q1 to 2019Q2 and out-of-sample predictions are presented from 2019Q3 to 2021Q2. The bars represent the observed number of banks in distress during the previous two years.

## Annex 3 Determinants of bank distress

Chart A3.1

**PERCENTAGE CONTRIBUTION OF THE DETERMINANTS OF THE PREDICTED PROBABILITY OF DISTRESS IN A TWO-YEAR HORIZON OVER TIME**




**SOURCE:** Author's calculations.
NOTE: The colored areas represent the contribution of each of the CAMELS categories and macroeconomic conditions to the predicted probability of bank distress at a two-year horizon for a bank with average values of all the included variables at each period, where C stands for capital adequacy, A for assets quality, M for management efficiency, E for earnings ability, L for liquidity, and S for sensitivity to market. Macro includes GDP growth and interest rate change. Values from 2019Q3 to 2021Q2 correspond to out-of-sample predictions.

## BANCO DE ESPAÑA PUBLICATIONS

### OCCASIONAL PAPERS

2020 ROBERTO BLANCO, SERGIO MAYORDOMO, ÁLVARO MENÉNDEZ and MARISTELA MULINO: Spanish non-financial corporations' liquidity needs and solvency after the COVID-19 shock. (There is a Spanish version of this edition with the same number).

2021 MAR DELGADO-TÉLLEZ, IVÁN KATARYNIUK, FERNANDO LÓPEZ-VICENTE and JAVIER J. PÉREZ: Supranational debt and financing needs in the European Union. (There is a Spanish version of this edition with the same number).

2022 EDUARDO GUTIÉRREZ and ENRIQUE MORAL-BENITO: Containment measures, employment and the spread of COVID-19 in Spanish municipalities. (There is a Spanish version of this edition with the same number).

2023 PABLO HERNÁNDEZ DE COS: The Spanish economy and the COVID-19 crisis. Appearance before the Parliamentary Economic Affairs and Digital Transformation Committee – 18 May 2020. (There is a Spanish version of this edition with the same number).

2024 PABLO HERNÁNDEZ DE COS: The main post-pandemic challenges for the Spanish economy. Appearance before the Parliamentary Committee for the Economic and Social Reconstruction of Spain after COVID-19/Congress of Deputies – 23 June 2020. (There is a Spanish version of this edition with the same number).

2025 ENRIQUE ESTEBAN GARCÍA-ESCUDERO and ELISA J. SÁNCHEZ PÉREZ: Central bank currency swap lines (There is a Spanish version of this edition with the same number).

2026 PABLO AGUILAR, ÓSCAR ARCE, SAMUEL HURTADO, JAIME MARTÍNEZ-MARTÍN, GALO NUÑO and CARLOS THOMAS: The ECB monetary policy response to the COVID-19 crisis. (There is a Spanish version of this edition with the same number).

2027 EDUARDO GUTIÉRREZ, ENRIQUE MORAL-BENITO and ROBERTO RAMOS: Tendencias recientes de la población en las áreas rurales y urbanas.

2028 ÁNGEL LUIS GÓMEZ: The effects of changes in the composition of employment on euro area wage growth: panel data analysis. (There is a Spanish version of this edition with the same number).

2029 MIGUEL GARCÍA-POSADA GÓMEZ: Analysis of insolvency proceedings in Spain against the backdrop of the COVID-19 crisis: insolvency proceedings, pre-insolvency arrangements and the insolvency moratorium. (There is a Spanish version of this edition with the same number).

2030 ÁNGEL GÓMEZ-CARREÑO GARCÍA-MORENO: Juan Sebastián Elcano – 500 años de la Primera vuelta al mundo en los billetes del Banco de España. Historia y tecnología del billete.

2031 OLYMPIA BOVER, NATALIA FABRA, SANDRA GARCÍA-URIBE, AITOR LACUESTA and ROBERTO RAMOS: Firms and households during the pandemic: what do we learn from their electricity consumption?

2032 JÚLIA BRUNET, LUCÍA CUADRO-SÁEZ and JAVIER J. PÉREZ: Contingency public funds for emergencies: the lessons from the international experience. (There is a Spanish version of this edition with the same number).

2033 CRISTINA BARCELÓ, LAURA CRESPO, SANDRA GARCÍA-URIBE, CARLOS GENTO, MARINA GÓMEZ and ALICIA DE QUINTO: The Spanish Survey of Household Finances (EFF): description and methods of the 2017 wave.

2101 LUNA AZAHARA ROMO GONZÁLEZ: Una taxonomía de actividades sostenibles para Europa.

2102 FRUCTUOSO BORRALLO, SUSANA PÁRRAGA-RODRÍGUEZ and JAVIER J. PÉREZ: Taxation challenges of population ageing: comparative evidence from the European Union, the United States and Japan. (There is a Spanish version of this edition with the same number).

2103 LUIS J. ÁLVAREZ, M.ª DOLORES GADEA and ANA GÓMEZ LOSCOS: Cyclical patterns of the Spanish economy in Europe. (There is a Spanish version of this edition with the same number).

2104 PABLO HERNÁNDEZ DE COS: Draft State Budget for 2021. Testimony before the Parliamentary Budget Committee, 4 November 2020. (There is a Spanish version of this edition with the same number).

2105 PABLO HERNÁNDEZ DE COS: The independence of economic authorities and supervisors. The case of the Banco de España. Testimony by the Governor of the Banco de España before the Audit Committee on Democratic Quality / Congress of Deputies, 22 December 2020. (There is a Spanish version of this edition with the same number).

2106 PABLO HERNÁNDEZ DE COS: The Spanish pension system: an update in the wake of the pandemic. Banco de España contribution to the Committee on the Monitoring and Assessment of the Toledo Pact Agreements. 2 September 2020. (There is a Spanish version of this edition with the same number).

2107 EDUARDO BANDRÉS, MARÍA-DOLORES GADEA and ANA GÓMEZ-LOSCOS: Dating and synchronisation of regional business cycles in Spain. (There is a Spanish version of this edition with the same number).

2108 PABLO BURRIEL, VÍCTOR GONZÁLEZ-DÍEZ, JORGE MARTÍNEZ-PAGÉS and ENRIQUE MORAL-BENITO: Real-time analysis of the revisions to the structural position of public finances.

2109 CORINNA GHIRELLI, MARÍA GIL, SAMUEL HURTADO and ALBERTO URTASUN: The relationship between pandemic containment measures, mobility and economic activity. (There is a Spanish version of this edition with the same number).

2110 DMITRY KHAMETSHIN: High-yield bond markets during the COVID-19 crisis: the role of monetary policy.

2111 IRMA ALONSO and LUIS MOLINA: A GPS navigator to monitor risks in emerging economies: the vulnerability dashboard.

2112 JOSÉ MANUEL CARBÓ and ESTHER DIEZ GARCÍA: El interés por la innovación financiera en España. Un análisis con Google Trends.

2113 CRISTINA BARCELÓ, MARIO IZQUIERDO, AITOR LACUESTA, SERGIO PUENTE, ANA REGIL and ERNESTO VILLANUEVA: Los efectos del salario mínimo interprofesional en el empleo: nueva evidencia para España.

2114 ERIK ANDRES-ESCAYOLA, JUAN CARLOS BERGANZA, RODOLFO CAMPOS and LUIS MOLINA: A BVAR toolkit to assess macrofinancial risks in Brazil and Mexico.

2115 ÁNGEL LUIS GÓMEZ and ANA DEL RÍO: The uneven impact of the health crisis on the euro area economies in 2020. (There is a Spanish version of this edition with the same number).

2116 FRUCTUOSO BORRALLO EGEA and PEDRO DEL RÍO LÓPEZ: Monetary policy strategy and inflation in Japan. (There is a Spanish version of this edition with the same number).

2117 MARÍA J. NIETO and DALVINDER SINGH: Incentive compatible relationship between the ERM II and close cooperation in the Banking Union: the cases of Bulgaria and Croatia.

2118 DANIEL ALONSO, ALEJANDRO BUESA, CARLOS MORENO, SUSANA PÁRRAGA and FRANCESCA VIANI: Fiscal policy measures adopted since the second wave of the health crisis: the euro area, the United States and the United Kingdom. (There is a Spanish version of this edition with the same number).

2119 ROBERTO BLANCO, SERGIO MAYORDOMO, ÁLVARO MENÉNDEZ and MARISTELA MULINO: Impact of the COVID-19 crisis on Spanish firms' financial vulnerability. (There is a Spanish version of this edition with the same number).

2120 MATÍAS PACCE, ISABEL SÁNCHEZ and MARTA SUÁREZ-VARELA: Recent developments in Spanish retail electricity prices: the role played by the cost of $CO_2$ emission allowances and higher gas prices. (There is a Spanish version of this edition with the same number).

2121 MARIO ALLOZA, JAVIER ANDRÉS, PABLO BURRIEL, IVÁN KATARYNIUK, JAVIER J. PÉREZ and JUAN LUIS VEGA: The reform of the European Union's fiscal governance framework in a new macroeconomic environment. (There is a Spanish version of this edition with the same number).

2122 MARIO ALLOZA, VÍCTOR GONZÁLEZ-DÍEZ, ENRIQUE MORAL-BENITO and PATROCINIO TELLO-CASAS: Access to services in rural Spain. (There is a Spanish version of this edition with the same number).

2123 CARLOS GONZÁLEZ PEDRAZ and ADRIAN VAN RIXTEL: The role of derivatives in market strains during the COVID-19 crisis. (There is a Spanish version of this edition with the same number).

2124 IVÁN KATARYNIUK, JAVIER PÉREZ and FRANCESCA VIANI: (De-)Globalisation of trade and regionalisation: a survey of the facts and arguments.

2125 BANCO DE ESPAÑA STRATEGIC PLAN 2024: RISK IDENTIFICATION FOR THE FINANCIAL AND MACROECONOMIC STABILITY: How do central banks identify risks? A survey of indicators.

2126 CLARA I. GONZÁLEZ and SOLEDAD NÚÑEZ: Markets, financial institutions and central banks in the face of climate change: challenges and opportunities.

2127 ISABEL GARRIDO: The International Monetary Fund's view of social equity throughout its 75 years of existence. (There is a Spanish version of this edition with the same number).

2128 JORGE ESCOLAR and JOSÉ RAMÓN YRIBARREN: European Central Bank and Banco de España measures against the effects of COVID-19 on the monetary policy collateral framework, and their impact on Spanish counterparties. (There is a Spanish version of this edition with the same number).

2129 BRINDUSA ANGHEL, AITOR LACUESTA and FEDERICO TAGLIATI: Encuesta de Competencias Financieras en las Pequeñas Empresas 2021: principales resultados.

2130 PABLO HERNÁNDEZ DE COS: Draft State Budget for 2022. Testimony before the Parliamentary Budget Committee, 25 October 2021.

2131 LAURA AURIA, MARKUS BINGMER, CARLOS MATEO CAICEDO GRACIANO, CLÉMENCE CHARAVEL, SERGIO GAVILÁ, ALESSANDRA IANNAMORELLI, AVIRAM LEVY, ALFREDO MALDONADO, FLORIAN RESCH, ANNA MARIA ROSSI and STEPHAN SAUER: Overview of central banks' in-house credit assessment systems in the euro area.

2132 JORGE E. GALÁN: CREWS: a CAMELS-based early warning system of systemic risk in the banking sector.