Predicting European Banks Distress Events: Do Financial Information Producers Matter?

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Abstract

This article assesses the predictive power of sell-side stock analysts and credit rating agencies on the prevision of European banks distress events by introducing their respective disclosures into a logit early-warning system over the 2000Q3-2020Q1 period. As direct bank failures are rare in Europe, I construct a dataset accounting for direct failures and state and private sector interventions. The model is calibrated to minimize the loss of a decision-maker committed to prevent impending distress events and is estimated in a real-time fashion. I also control for bank- and macro-level data by integrating accounting ratios and variables related to the banking sector and the business cycle as a whole, following the existing literature on the topic. I find both financial information producers' disclosures to display forward-looking informative and predictive performance on bank distress risk up to two years in advance. My results highlight their added value in bank distress prevision with regard to accounting and macroeconomic data, that is beyond acting as a synthesis of such data.

JEL CLASSIFICATION

E44; F37; G21; G24

KEYWORDS

Bank Distress; Early Warning Systems; Financial Analysts; Credit Rating Agencies

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1. Introduction

While Lo Duca, Koban, Basten, Bengtsson, Klaus, Kusmierczyk, Lang, Detken, and Peltonen (2017) found the output losses of previous banking crisis to average 9% of GDP for European countries, more than EUR 5.02 trillion have been granted as stabilization aid by European Union member states over the 2008–2019 period[1] (30% of the E.U.-28 2019 GDP) to avoid a systemic collapse and ensure a proper financing of the economy. This has highlighted the usefulness of early-warning systems (EWS) for regulators, investors and bank creditors to limit the occurrences of distress events.

The aim of EWS is to prevent the failure of financial institutions (bank-level) or the incidence of systemic events such as banking or financial crises (macroeconomic level) to allow decision-makers[2] to identify vulnerabilities at the bank- or macroeconomic-level and to take preventive action. Most bank-level models focus on U.S. financial firms given the scarcity of direct bank failures in the E.U. These models aim to detect underlying vulnerabilities of banks to assess their probability of being distressed. They principally rely on accounting (e.g., DeYoung and Torna, 2013), market (e.g., Beltratti and Stulz, 2012, Avino, Conlon, and Cotter, 2019), and macroeconomic data (e.g., Demirgüç-Kunt and Detragiache, 1998, Betz, Opric, Peltonen, and Sarlin, 2014, Constantin, Peltonen, and Sarlin, 2018). Following Kaminsky and Reinhart (1999), a decision rule is extracted from the results to set the optimal moment for a decision-maker to act to prevent an impending distress event by warning financial market participants and regulators or by intervening directly (Davis and Karim, 2008). However, the early identification of bank-level vulnerabilities is constrained by the lack of reliable information given the opacity of these institutions (Morgan, 2002, Iannotta, 2006, Morgan, Peristiani, and Savino, 2014).

Financial information producers—in the remainder, sell-side stock analysts and credit rating agencies (CRAs; S&P, Moody's, and Fitch)—are acknowledged to improve

[1] https://webgate.ec.europa.eu/comp/redisstat/databrowser/view/AID_FI_USED/default/table

[2] That term refers principally to policy-makers, bank supervisors and regulators deemed to be concerned about the failure of financial institutions and able to take relevant action. We use both decision- and policy-maker terms indistinctly. However, that approach could also be relevant for investors and bank creditors, being part of the monitoring component of market discipline (Flannery and Bliss, 2019). That latter point is particularly relevant with regard to the implementation of the banking union in the E.U. whose aim is to favour bail-in procedures over bail-out ones to resolve distressed institutions.

information efficiency in capital markets (Bolton, Freixas, and Shapiro, 2012, Iannotta, Nocera, and Resti, 2013, Anolli, Beccalli, and Molyneux, 2014). The data they release on banks *via* their stock recommendations and credit ratings act as a synthesis of public and private data and is valuable for uncovering negative news on the financial health of firms that managers are less likely to disclose (Flannery, 2010), which is relevant to identify whether a bank enters a state of vulnerability. Such data is also easily interpretable *vis-à-vis* e.g., stress tests, which could be beneficial for market participants. Both financial information producers are deemed to be reactive to the disclosure of news on firms and flexible in their evaluation methods. That reactivity is relevant as distress events require a prompt intervention from authorities to prevent negative spillovers. The aim of this article is to assess the information content and predictive power of these two types of financial information producers' disclosures by integrating them in a logit EWS framework for European banks in 25 countries over the 2000–2020 period. The model is calibrated to minimize the loss a policy-maker would suffer in case of bank distress sufficiently in advance to allow him to act to prevent such outcomes. To overcome the data limitation problem linked to the scarcity of direct distress events in Europe, we construct a dataset of bank distress events accounting for direct failures as well as state and private support granted to banks.

Numerous studies focused on CRAs (e.g., Bannier and Hirsch, 2010, Bar-Isaac and Shapiro, 2013) and stock analysts (e.g., Clarke, Ferris, Jayaraman, and Lee, 2006, Cheng and Subramanyam, 2008, Brown, Call, Clement, and Sharp, 2015 or Ramnath, Rock, and Shane, 2008 for a literature review) to identify their information content. Given their specific characteristics, financial firms were almost always excluded from previous studies, notably on stock analysts. Among exceptions are Flannery (2010), Anolli *et al.* (2014) and Premti, Garcia-Feijoo, and Madura (2017). While focusing on the information content of financial information producers' disclosures, to our knowledge, none has intended to integrate them into an EWS framework to evaluate their usefulness in the monitoring of the health of financial institutions. None has also intended to take advantage of other types of disclosures, such as outlooks, watchlist additions and EPS forecasts on that matter. Therefore, this article contributes to two streams of the literature by evaluating the respective information content of financial information producers on the identification and prevision of bank vulnerabilities and assessing the usefulness a policy-maker would derive from their introduction into an EWS.

We find predicted distress probabilities of the EWS including financial information producer's disclosures to be in line with actual ones up to two years preceding the distress event, meaning that both CRA ratings and stock analyst recommendations are informative on the risks of European banks entering a state of distress. In particular, they contain additional information on such risks with regard to public accounting- and macro-level variables used in previous EWS studies. This also highlights the forward-looking nature of the data they disclose, which is generally implied in the literature. Consequently, we find that a decision-maker who fears missing crises would derive usefulness from the introduction of such variables into an EWS to identify impending distress events. More precisely, rating and recommendation levels perform better in distress prevision than their variations, as well as outlooks, watchlist additions, and EPS forecasts. We also find that performance of such disclosures in terms of distress prevision lowers along with the size of banks, meaning that the largest institutions are more difficult to monitor while being the most important to. Despite not being their main objective, performance of financial analysts in terms of distress event prevision tend to be equivalent to that of CRAs. It finally derives from this study that the monitoring of financial institutions by both financial information producers is valuable in identifying risks of distress for European banks.

Section 2 reviews the literature related to our topic, Section 3 presents our bank distress events dataset and our variables of interest, Section 4 displays the estimation framework and Section 5 the results for our baseline model, Section 6 and Section 7 our extensions and robustness checks while Section 8 concludes.

2. Literature Review

2.1. Bank Distress Events Prevision

Given the cost and complexity of examining banks, on-site examinations are complemented by off-site monitoring, that is, EWS. EWS intend to generate predictions of crises *via* an early-warning model (EWM) according to a definition of a distress event set *ex ante* to provide decision-makers a set of methods to identify vulnerabilities at the bank- or macroeconomic-level to take preventive action.

Most of the EWS literature relies on the binary-choice analysis developed by Martin (1977) at the bank level. Probabilities of distress are extracted from discrete choice models regarding a decision threshold. A structured framework was developed by Demirgüç-Kunt and Detragiache (2000) who introduced a loss function for the decision-maker that considers the costs for preventive actions, given his relative preferences between missing crises (Type I errors) and false alarms (Type II errors)—the relative costs of each type of error for him. That framework was extended by Alessi and Detken (2011) who computed a usefulness measure to consider the loss of disregarding the signals of the model and applied to a multivariate logit model by Lo Duca and Peltonen (2013). Sarlin (2013) refined it by reintroducing unconditional probabilities of the crisis events to account for differences in crisis and tranquil period frequencies (as in Demirgüç-Kunt and Detragiache, 2000). He also developed a measure of relative usefulness captured by the model as the proportion of the usefulness the decision-maker would have derived if the model performed perfectly to facilitate comparisons. Finally, his framework incorporates observation-specific weights to account for the relative relevance of banks for the decision-maker.

Despite the scarcity of direct bank failures in Europe, an increasing number of studies have dealt specifically with European banks in recent years (notably, Gropp, Vesala, and Vulpes, 2006, Ötker Robe and Podpiera, 2010, Betz *et al.*, 2014, Constantin *et al.*, 2018, Lang, Peltonen, and Sarlin, 2018, Avino *et al.*, 2019). The early identification of bank vulnerabilities is limited by the lack of reliable information on them given their opacity (Morgan, 2002, Iannotta, 2006, Morgan *et al.*, 2014) and increasing complexity, which highlighted the relevance of forward-looking information (Flannery, 2010). Most models rely on accounting ratios, particularly proxies for CAMELS[3] ratings. Their predictive performance is improved by the introduction of variables that account for evolutions in their activity, which increased their sensitivity to many types of risks, such as the structure of income from nontraditional activities (DeYoung and Torna, 2013). However, accounting data are produced periodically, are backward-looking and sensitive to choices in accounting procedures (Moses, 1990). Considering the increase in the share of market-price assets and liabilities in bank balance sheets, other studies introduced market indicators such as stock returns (Beltratti and Stulz, 2012), debt and equity pricing (Gropp *et al.*, 2006) and CDS (Ötker Robe and Podpiera, 2010, Avino *et al.*, 2019). These variables are deemed to be more reactive than financial ratios while being forward-looking and available at higher frequencies. Finally, several studies introduced macroeconomic factors to reflect country-level imbalances (Betz *et al.*, 2014, Lang *et al.*, 2018) or contagion mechanisms linked to bank interconnections among countries (Constantin *et al.*, 2018). These factors have been the main determinants of past banking crises (Demirgüç-Kunt and Detragiache, 1998). Still, no consensus has been reached over the best model and variables to predict whether a financial firm will become distressed.

2.2. Information Content of Financial Information Producers' Disclosures

Given their monitoring activity, stock analysts and CRAs contribute to limit information asymmetries on capital markets (Cheng and Subramanyam, 2008, Bannier and Hirsch, 2010, Barber, Lehavy, and Trueman, 2010, Bar-Isaac and Shapiro, 2013, Bolton *et al.*, 2012, Iannotta *et al.*, 2013, Anolli *et al.*, 2014), which is notably valuable for riskier and more opaque banks (Premti *et al.*, 2017). Their disclosures are widely considered by financial market participants that rely on them to follow their decisions (Becker and Milbourn, 2011). This prompts them to be reactive to the disclosure of news

[3] The capital adequacy, assets, management capability, earnings, liquidity, sensitivity to market risk (CAMELS) ratings system was developed in the 1970s by the U.S. supervisory authorities to assess bank soundness.

on the financial health of the firms they follow. That reactivity is relevant to identify potential distress events in advance and avoid the negative spillovers such occurrences could lead to. Stock analysts have been found more reactive to the disclosure of news than CRAs (Ederington and Goh, 1998, De Franco, Vasvari, and Wittenberg-Moerman, 2009) given the commitment of the latter to rating stability. However, their extensive use of instruments other than ratings, such as watchlist additions, allow them to improve their reactivity (Bannier and Hirsch, 2010) without altering ratings. Both analysts and CRAs take public macro- (financial, regulatory and operating environment) and bank-specific factors (financial ratios) into account to derive their reports, as well as private data and qualitative nonfinancial factors (Jorion, Liu, and Shi, 2005, Ramnath *et al.*, 2008). CRAs still benefit from insider information (e.g., financial projections, minutes of boards) whose access has been reduced to analysts owing to regulation[4]. However, Cheng and Subramanyam (2008) documented that collectively, stock analysts acquire more information than that available to credit raters, reflected in the information content of both levels and changes in their recommendations (Barber *et al.*, 2010).

By monitoring financial institutions and disseminating expectedly forward-looking information on the markets, financial information producers contribute to facilitate the identification of vulnerable entities. While ratings are explicitly probabilities of distress, stock analyst recommendations are fundamentally assessments of the investment value of a stock provided to investors. However, they draw on issues linked to valuation and profitability of firms that are related to their probability of being distressed. Analysts and CRAs interact with each other and benefit from reciprocal disciplinary effects that improve the quality of the data they disclose. Thus, Ederington and Goh (1998) found Granger-causality between Moody's ratings and stock analysts EPS estimates to flow both ways over the 1984–1990 period. Fong, Hong, Kacperczyk, and Kubik (2014) indicated that a drop in analysts' coverage reduces the quality of ratings owing to the reduction of information efficiency linked to analysts' coverage and competition. Indeed, the latter tends to improve the accuracy of their previsions (Hong and Kacperczyk, 2010).

[4] Since 2000, regulation in the U.S. such as the Regulation Fair Disclosure have efficiently curbed biases and conflicts of interests of analysts but reduced their access to information (Gintschel and Markov, 2004). Similar pieces of regulation have been implemented in Europe since 2003 (MAD and MiFID I and II and the Regulation (EC) No 1060/2009 on CRAs), with mixed effects (e.g., Dubois, Fresard, and Dumontier, 2013).

Yet, both financial information producers are subject to self-selection concerns (Lang and Lundholm, 1996), the influence of the economic environment and biases[5] that could hinder their performance. By introducing their disclosures into an EWS, we therefore assess whether they display an informative value on distress likelihood for banks.

3. Data

The construction of variables is detailed in Table A1 (page 34) in Appendix A.

3.1. Distress Events Dataset

Ideally, the evaluation of an EWS performance would rely on the comparison of distress probabilities predicted by the model to actual distress probabilities (Bussière and Fratzscher, 2006). As the latter are not directly observable, we replace them by actual occurrences of distress events to derive an *ex post* predistress variable. Given that direct bank failures are rare in Europe, we follow the methodology developed by Betz *et al.* (2014) to construct a dataset of bank distress events. We cover the 2000Q1–2020Q4 period and 29 European countries[6]. We take into account direct bank failures (bankruptcies, liquidations and defaults[7]), state support (capital injection by the state or participation to asset protection, asset guarantees and liquidity support programs) and private sector support (mergers in distress—a parent receives state aid within 12 months after the merger or the coverage ratio[8] of one of the merged banks is negative within 12 months before the merger—and takeovers and liquidity providing from private entities). Data for distress events are extracted from the European Commission, the ECB, European countries central banks, the BIS, Eikon Refinitiv and academical papers (Betz *et al.*, 2014, Kerlin, Malinowska-Misig, Smaga, Witkowski, Nowak, Kozowska, Winiewski, and Iwanicz-Drozdowska (Ed.), 2016, Lo Duca *et al.*,

[5] In particular, both CRAs and stock analysts tend to overreact to positive news (e.g., Becker and Milbourn, 2011, Bolton *et al.*, 2012 for CRAs, Galanti and Vaubourg, 2017 for stock analysts).

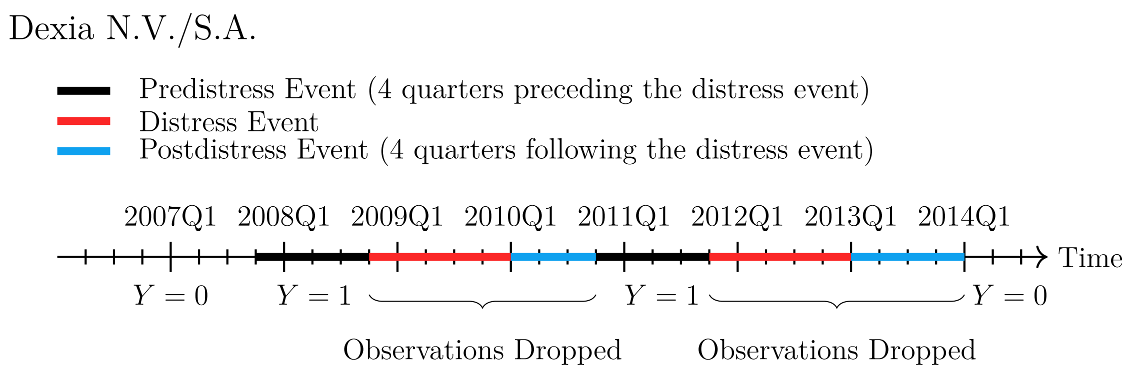
[6] Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Faroe Islands, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Liechtenstein, Lithuania, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom.

[7] Default ratings by CRAs are not accounted for to prevent endogeneity issues.

[8] Capital equity and loan reserves minus nonperforming loans to total assets (González-Hermosillo, 1999).

2017, Constantin *et al.*, 2018). Events begin when the program, failure or merger is announced (or the coverage ratio of the bank falls below 0 within 12 months) and end when it occurs. Our approach to distress events leads to 134 bank occurrences with a 452-quarter duration (Table B2, page 35 in Appendix B). As the categories are not mutually exclusive, the sum of distress events in each category outstrips the total number of distress events. Predistress events are defined as the four quarters preceding distress events to keep a sufficiently long period of time to allow the policy-maker to take preventive action once a distress signal has been issued while restraining the incidence of a likely reverse causality bias. That bias could be owed to a panic caused by a downgrade in the rating or recommendation of a bank, the negative impact of such an event on its financing terms or a correction owed to market discipline mechanisms. Thus, we aim to ensure that the evolution of the rating or recommendation is not the main cause of the distress event, which is supported by the fact that most distress events in our sample occurred during crisis periods. We create a binomial variable Y that takes the value of 1 if it occurs four quarters before the distress event, otherwise 0. We also exclude distress and postdistress periods (set to four quarters following the distress period) to account for crisis and postcrisis biases (Bussière and Fratzscher, 2006). For instance, the construction of our dependent variable for Dexia N.V./S.A. is presented in Figure 1 (page 9).

Figure 1. Binomial Predistress Variable Construction



3.2. Financial Information Producers

3.2.1. Credit Rating Agencies

For all three CRAs, we consider long-term issuer ratings that are opinions of the ability of a bank to honor current and future senior unsecured debt and debt like obligations and incorporate explicit and implicit external support, extracted from Eikon Refinitiv and FitchConnect. For each agency, we convert the last rating of the quarter to a numerical value going from 1 (S&P, Fitch AAA/Moody's Aaa) to 21 (Default) to get an intuitive measure of default risk[9]. For each quarter t and bank i, we compute the average of all available ratings over the number of agencies that maintain an active rating at that date.

All three agencies supplement their rating services by providing additional information with outlooks and watchlists that are informative on future rating variations. Outlooks reflect the agency's opinion on the development of the likely rating direction over the medium term, while watchlists focus on a shorter time horizon (on average three months). Both are used by CRAs to be more reactive to news without altering rating stability (Bannier and Hirsch, 2010). To each positive outlook and agency we associate the value of 1 to construct an ordered variable ranking from 0 to 3. We do the same for stable and negative outlooks, positive and negative watchlist additions, upgrades and downgrades.

3.2.2. Financial Analysts

We focus on sell-side equity analyst recommendations. We consider the consensus estimates extracted from Thomson Financial's Institutional Brokers Estimate (I/B/E/S), which is computed as the mean of a standard set of analyst recommendations. To obtain quarterly data, we use the last value available for each quarter. Each numerical value is rounded to the nearest integer and labelled by I/B/E/S as 1 = *Strong buy*, 2 = *Buy*, 3 = *Hold*, 4 = *Sell*, 5 = *Strong sell*, which means that *in fine* values from 1 to 1.49 correspond to *Strong buy*, 1.5 to 2.49 to *Buy* and so on. We integrate consensus

[9] Quarters with more than one rating for the same agency were extremely rare. Thus, by construction, the number of agencies is equivalent to the number of ratings each quarter.

downgrade and upgrade dummies to account for the change in recommendations each quarter. We introduce the former as both recommendation levels and variations can send opposite signals. We also introduce the quarterly number of recommendations[10]. In further analysis, we replace the recommendation consensus by current and next fiscal year (FY1 and FY2) EPS forecasts, found to convey information on default risk by Moses (1990), though on nonfinancial firms.

3.3. Additional Variables

To test whether our variables of interest retain an information content *vis-à-vis* other data sources and to capture a wide range of potential risk factors, we add additional controls to our baseline equation. Data are extracted from Datastream, FitchConnect and Eurostat.

3.3.1. Macroeconomic Controls

To control for macro imbalances we add country-specific macroeconomic variables to our model and a global market factor. The idea is also to account for the economic cycle, given that it has an impact on the performance of financial analysts and CRAs as uncertainty and bank opacity rise in downturn periods (Bar-Isaac and Shapiro, 2013, Anolli *et al.*, 2014, Premti *et al.*, 2017).

Regarding the economic cycle, we consider the annual real GDP growth rate which has a direct impact on the vulnerability of banks (Demirgüç-Kunt and Detragiache, 1998). In depression periods, the interest income and average asset quality of banks tend to decrease along with investment and household income and corporate profitability, which also weighs on credit risk given the increase in nonperforming loans (Mody and Sandri, 2012, Altavilla, Boucinha, and Peydró, 2018). The inflation rate proxies for macroeconomic mismanagement (Demirgüç-Kunt and Detragiache, 1998), which adversely affects the economy and the banking system. Rises in inflation impact the vulnerability of banks by favoring an increase in their leverage.

[10] The number of recommendations is not equivalent to the number of analysts as the same analyst sometimes issues more than one recommendation in a given quarter, but both are very close. Using the latter in robustness led to similar results.

The annual 10-year sovereign bond yield proxies for macroeconomic imbalances. An increase in that yield reflects a depreciated opinion of investors over the riskiness of the country. Such events also lead to a drop in the price of sovereign bonds that weighs on the profitability of domestic banks if they hold quantities of them with short maturity in their balance sheets. Higher yields may also prompt fiscal consolidation that weighs on GDP and bank profitability (Mody and Sandri, 2012)[11]. To account for the orientation of monetary policy and interest rate risk, we add a composite variable constructed as the Wu-Xia shadow rate for the Euro Area and the U.K. and the actual policy rate when values are missing. Beyond its effects on credit and investment growth, a restrictive monetary stance impedes bank profitability by compressing their interest margin (Davis and Karim, 2008) and weighing on credit risk.

The private sector credit flow to GDP ratio measures the exposition of the banking sector to the nonfinancial private sector. Demirgüç-Kunt and Detragiache (1998) displayed evidence that the more exposed to the private sector, the more vulnerable the banking sector given the rise in credit risk in downturn periods.

Finally, to account for market risk we add the Vix index that measures the implied volatility of the S&P 500 stock market options as a global factor. We only consider one market control as these variables tend to have a short horizon of prediction. Given the interconnection of the U.S. and European markets, it appears a good predictor of volatility changes in Europe (Sarwar, 2020) and allows us to include securities market instability that matter for banks given the increase in the share of market-price assets and liabilities in their balance sheets[12].

3.3.2. Banking Sector Controls

To control for country-level imbalances in banking systems, we introduce the following three variables. First, the ratio of total assets to GDP controls for the relative size of

[11] Similarly, in further analysis we replace that variable by 5-year sovereign CDS spreads that reflect fundamentals of the underlying sovereign as well. Results are similar but as data was not available before 2008, the out-of-sample windows then begins in 2010Q1, leading to a loss in observations.

[12] We also tested the Vstoxx in another specification as that index is more relevant in the European case. However, we achieved lower performance while the variable was insignificant and negatively associated to distress risk. Thus, we consider the Vix instead. Still, both indexes are strongly correlated, particularly during crises (Shu and Chang, 2019).

the banking sector and the evolution of bank balance sheets to identify lending boom episodes. Moreover, as noted by Kaminsky and Reinhart (1999), banking problems often arise from the asset side rather than the liability side of balance sheets, owing to a deterioration in asset quality e.g., following a collapse in real-estate prices. The next two ratios reflect the building up of banking sector vulnerabilities. The ratio of debt securities to liabilities accounts for securitization, which exposes banks to interest and macroeconomic risks owing to changes in the valuation of the securities they hold. This was particularly relevant for European countries during the Sovereign Debt Crisis as sovereign debt accounts for two-thirds of securities held by banks in the E.U., the latter representing 15 to 20% of their balance sheets (Altavilla *et al.*, 2018). Finally, we proxy banking sector leverage by the ratio of loans to deposits. The more leveraged the banking sector, the less room it has to maneuver in downturn periods.

3.3.3. Accounting Ratios

With regard to the extensive literature on the topic, we consider widely used proxies for CAEL ratings. We proxy the capital adequacy (C) of the bank by the leverage—equity to assets—ratio. A higher level of capital acts as a buffer to financial losses and reduces a bank's probability of distress. Return on assets (ROA)—an indicator of profitability—proxies for asset quality (A)[13] As an indicator of financial performance, return on equity (ROE) proxies for earnings risks (E). Finally, we proxy the liquidity risk (L) by the loans to deposits ratio following Anolli *et al.* (2014), which displays the ability of a bank to cover loan losses or face sudden massive withdrawals[14].

We control by the size of the bank as the natural logarithm of its total assets. Theoretically, larger banks are less prone to be distressed as they are more likely to receive external support when identified as vulnerable, are most cost-efficient and take advantage of more investment opportunities. Yet, Boyd and Runkle (1993) found that

[13] Widely used proxies for asset quality also include the share of nonperforming loans to total loans, nonperforming assets to total assets and provisions for loan-losses to total loans. We tested all three specifications but achieved similar to lower performance, with substantial restrictions in estimation samples. Consequently, we did not keep them.

[14] Following Betz *et al.* (2014), we also consider the cost to income ratio as a proxy for management risk (M) and the share of trading income to total revenue for the sensitivity to market risk (S). Both ratios turned out to be insignificant while prompting a substantial loss in observations, so we disregarded them.

larger banks are not less likely to be distressed as they are systematically more highly leveraged and less profitable in terms of assets returns. The size of the bank also allows us to control for bank opaqueness following Premti *et al.* (2017) as Iannotta (2006) indicated that opacity increases with bank size. Still, the effect of size on that matter remains ambiguous. While a large bank may receive more coverage from analysts and CRAs and benefit from a greater dissemination of information, that is, an increased probability of being rescued in a timely manner, it has more opportunities to expand into nontraditional or complex activities and to become more difficult to monitor.

4. Methodology

4.1. Modeling Framework

Our modeling framework is similar to that of Sarlin (2013) and reproduces the decision problem faced by a decision-maker that can be summarized as classifying the banks into vulnerable and nonvulnerable categories. We assume that the decision-maker has the ability and concern to act to prevent bank distress events. The evaluation criterion must account for the fact that distress events occur rarely and are often costly. We consider a decision-maker with relative preferences ($\mu \in [0,1]$)—related to his degree of risk aversion—between Type I (missing crises) and Type II (false alarms) errors and the usefulness he gets by considering the model for making his decisions over disregarding it. Both types of errors are costly for him owing to the cost of crises, and the damaging effects on his credibility and the cost of taking preventive actions, which is internalized into his preferences. Let $Y_i^h \in \{0,1\}, i \in [\![1,N]\!]$ be a binary state variable that represents the occurrence of a predistress event for a bank i, with h a forecast horizon to define predistress events. $Y_i^h = 1$ during predistress periods and 0 otherwise. Let p_i be the probability of being in a predistress state ($Y_i^h = 1$) estimated using a discrete-choice model. To classify observations into vulnerable and nonvulnerable states, p_i is turned into a binary (warning) signal $P_i \in \{0,1\}$ that equals 1 if p_i exceeds a threshold $\lambda \in [0,1]$, otherwise 0. The correspondence between P_i and Y_i^h is derived from the contingency matrix displayed in Table 1 (page 15).

Table 1. Contingency Matrix

		Actual Class (Y_i^h)	
		Predistress period (1)	Tranquil period (0)
Predicted Class (P_i)	Signal (1)	Correct call *True positive (TP)*	False alarm *False positive (FP)*
	No signal (0)	Missed crisis *False negative (FN)*	Correct silence *True negative (TN)*

For a time horizon h, the decision-maker chooses a threshold λ given probabilities p_i to minimize his loss with regard to his relative preferences μ between missing crises and false alarms. Type I errors ($T_1(\lambda)$) are the probabilities of not receiving a warning signal conditional on a crisis occurring, estimated with in-sample (IS) frequencies as the proportion of missed crises over the number of crises. Similarly, Type II errors ($T_2(\lambda)$) are the probabilities of receiving a warning signal conditional on no crisis occurring, estimated with in-sample frequencies as the proportion of false alarms over the number of calm periods. Formally, $T_1(\lambda) \in [0,1] = P(p_i \leq \lambda | Y_i^h = 1) = FN/(FN + TP)$ and $T_2(\lambda) \in [0,1] = P(p_i > \lambda | Y_i^h = 0) = FP/(FP + TN)$. To enhance the framework we introduce observation-specific differences in costs that are linked to the systemic relevance of banks for the decision-maker, which impacts misclassification costs (e.g., spillovers following the failure of a systemic bank are more important than those of a small bank). We define w_i as bank-specific weights that approximate the importance of correctly classifying observation i for the policy-maker, and TP_i, FP_i, TN_i, FN_i binary vectors of combinations of predicted and actual classes. Weighted Type I and Type II errors are $T_{w1}(\lambda) \in [0,1] = \sum_{i=1}^{N} w_i FN_i / (\sum_{i=1}^{N} w_i FN_i + \sum_{i=1}^{N} w_i TP_i)$ and $T_{w2}(\lambda) \in [0,1] = \sum_{i=1}^{N} w_i FP_i / (\sum_{i=1}^{N} w_i FP_i + \sum_{i=1}^{N} w_i TN_i)$. We compute weights as the share of total assets of a bank relative to the sum of total assets of all banks in the sample for each quarter. To gauge the loss of the decision-maker, T_1 (T_{w1} in the weighted case) and T_2 (T_{w2}) are weighted by his preferences parameter between missing crises (μ) and issuing false alarms ($1 - \mu$). Finally, to account for class-imbalance issues we consider the unconditional probabilities of predistress and tranquil periods: $P_1 = P_i(Y_i^h = 1)$ and $P_2 = P_i(Y_i^h = 0) = 1 - P_1$. The loss function is given in equation (1).

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

When weights are introduced, the function becomes: $L(\mu, \lambda, w_j) = \mu T_{w1}(\lambda)P_1 + (1 - \mu)T_{w2}(\lambda)P_2,\ j \in \{1, 2\}$. If the decision-maker chooses to ignore the model by always signaling a crisis when $P_1 \geq 0.5$ or equivalently, never signaling it when $P_2 > 0.5$ (a coin toss), given his preferences he can achieve a loss of $\min(\mu P_1, (1 - \mu)P_2)$. Thus, his absolute usefulness (U_a) is defined as the loss suffered when ignoring the model minus the loss suffered when considering it (equation (2)):

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

Finally, the relative usefulness (U_r) is the percentage of absolute usefulness to the maximum possible usefulness the policy-maker could derive from the model (i.e., $L(\mu, \lambda) = 0$ as the model is performing perfectly, $T_1 = T_2 = 0$) to obtain a more interpretable measure that allows the comparison of models for decision-makers with different sets of preferences μ (equation (3)).

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

In the weighted case, we get $U_a(\mu, \lambda, w_j)$ and $U_r(\mu, \lambda, w_j)$. The decision-maker's preferences μ are exogenous as they depend on his degree of risk-aversion and the relative cost of a crisis *vis-à-vis* the cost of taking preventive actions. Once given, Bussière and Fratzscher (2008) showed that both the time horizon h and the threshold λ are uniquely determined. We set the former to 4 quarters. Then, there exists a unique optimal threshold λ^*, which we obtain post estimation by minimizing equation (1).

For each estimated model, we compute the receiver operating characteristics (ROC) curve and the area under the ROC curve (AUC). Both measure the performance for all combinations of preferences $\mu \in [0, 1]$ and thresholds λ while the usefulness is only computed for a given threshold λ—a unique point on the ROC curve. For each λ, the ROC curve displays the trade-off between the benefits (True Positive Rate) and costs (False Positive Rate) of a given classifier model. The AUC measures the probability that a randomly chosen predistress event ($Y = 1$) is ranked higher than a randomly chosen tranquil period ($Y = 0$) by the model. A perfectly performing model would display an AUC of 1. However, both measures are limited in that the AUC includes situations that are not policy relevant while ROC curves do not account for misclassification costs and class imbalance issues.

4.2. Estimation Procedure

We consider a discrete-choice logit model. As predistress events are less frequent than calm periods, they are better modelled by a logit model than by a probit one owing to the former's assumption of more fat-tailed error distribution (van den Berg, Candelon, and Urbain, 2008). Pooled logits are preferred to panel ones by the literature (e.g., Lo Duca and Peltonen, 2013, Betz *et al.*, 2014, Constantin *et al.*, 2018) for increasing the number of observations so as to capture a wide variety of distress events whose occurrences are rare in individual countries. Fuertes and Kalotychou (2006) also documented that using time- and country-fixed effects models weighs on the predictive out-of-sample (OOS) performance while improving in-sample fit. Still, in our model, country-fixed effects are to a certain extent taken into account by the country- and banking sector-specific independent variables while time effects are considered by global factors. Our logit EWM is displayed in equation (4).

$$P(Y_{i,t}^{h} = 1|X_{i,t}) = p_{i,t} = \frac{e^{X'_{i,t}\beta}}{1 + e^{X'_{i,t}\beta}},\ i \in [\![1, N]\!], t \in [\![1, T]\!]. \tag{4}$$

With $p_{i,t}$ the probability of bank i to be in a vulnerable state within forecast horizon h at quarter t (thus, ($Y_{i,t} = 1$) h quarters before the distress event), β a vector of coefficients and $X_{i,t}$ a vector of an intercept and independent variables. To replicate a real-time information structure, independent variables are lagged by two quarters for financial statements, and one quarter for macroeconomic and banking sector variables. We assume that financial information producers' disclosures, the Vix, the shadow and policy rates and the 10-year sovereign bond yield are known at least within the quarter of their implementation. Therefore, we do not apply lags to them.

We follow the strategy of Betz *et al.* (2014) by estimating our model on recursive increasing windows for the in-sample period and one-quarter rolling windows for the out-of-sample period to test the model performance in real-time use. We estimate our model each quarter $t \in [\![1, T]\!]$ on all information available up to that quarter, we evaluate the signals to set an optimal threshold λ and estimate the current vulnerability state of each bank with it. Formally, we estimate the model with in-sample data that would have been available from the beginning of the sample to quarter t (excluded), we collect the probabilities of the model for the in-sample period and compute the usefulness for all thresholds $\lambda \in [0, 1]$. Then, we choose the threshold λ^* that maximizes in-sample usefulness, estimate distress probabilities for the out-of-sample data (quarter t) and apply the threshold to obtain the signals given by: $P_{i,t} = 1$ if $\hat{p}_{i,t} > \lambda^*, 0$ otherwise. Finally, we set $t = t + 1$ and reestimate the model from the first step at each quarter t until $t = T$.

5. Results

5.1. Summary Statistics

We perform our estimations over the 2000Q3-2020Q1 period owing to lags in control variables. Our predictions draw on an increasing window for the in-sample part (2000Q3–2019Q4) and one-quarter rolling windows for the out-of-sample part, starting in 2008Q3 until 2020Q1 to get half of the precrisis observations in the initial in-sample part. Data are winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles to limit the incidence of outliers. Our initial dataset covers 204 European banks covered by financial information producers in 29 countries. Summary statistics are displayed in Table 2 (page 30). The size variable reveals that our sample is mostly composed of systemic institutions. On average, banks benefit from 14.1 recommendations per quarter and 1.4 ratings. Pearson's correlation coefficients[15] remain globally moderate. Of particular interest are the size and number of recommendations and ratings that are positively correlated.

[Insert Table 2 (page 30) here]

[15] All untabulated results in the remainder are available from the author upon request.

5.2. Estimation

Our baseline model introduces both our variables of interest and macro-financial controls to capture a wide variety of risks while keeping a sufficient number of observations. Given the proportion of missing values for ratings and recommendations the baseline sample accounts for 148 of 204 banks (73% of the sample or roughly 50% of quarter-distress events)[16], in 25 countries. Country distribution remains stable over time and countries (Figure B1, page 36 and Table B1, page 35 in Appendix B), except for Denmark and the Netherlands. Total sample refers to the observations remaining following the removal of distress and postdistress periods (204 banks in 29 countries).

Table 3 (page 31) presents the in-sample estimated coefficients of the baseline regression and out-of-sample performance measures for a decision-maker with preferences $\mu \in [0.6, 0.95]$ obtained for each quarter over the out-of-sample time period (2008Q3–2020Q1). Considering that early-warning signals at the bank-level would primarily lead to an in-depth review of fundamentals and peers of the bank predicted to be distressed rather than to a direct corrective action, that is, more costly, the loss in credibility for the decision-maker would remain limited whether the signal turned out to be false (Betz *et al.*, 2014). Thus, it is plausible for him to be strongly more concerned about missing bank distress events than issuing false alarms. However, despite performance of our model being generally maximized for $\mu = 0.95$ we disregard that value considering policy-maker preferences would be too skewed toward missing crises—in-depth reviews are still expensive—while $\mu = 0.9$ remains more plausible. Model (1) (column 1 in Table 3) is our baseline case. Accounting ratios are removed in Model (2), and ratings and recommendations are in Model (3) to assess their respective added value. In Models (4) and (5), ratings and recommendations are introduced independently from each other.

[Insert Table 3 (page 31) here]

In the baseline case (Model (1)), both coefficients for rating and recommendation averages are strongly significant with a positive influence on the likelihood of a

[16] Banks in that subsample are covered on average by 1.4 CRAs and benefit from around 13 recommendations. Statistics for other variables are similar.

bank entering a predistress state. Hence, as expected, an increase in the rating or recommendation for a bank is linked to an increase in its distress risk. This result means CRA disclosures effectively reflect distress risk as they are expected to by financial markets participants. Despite not being their primary concern, analyst recommendations are useful alike on that matter. Then, both appear to disclose forward-looking information on the financial health of banks. The number of ratings is negatively significant, while the number of recommendations is significant in Models (2) only. These negative sings can be explained by improvements in the information environment of widely covered firms owed to competition among analysts and mutual interactions between analysts and agencies (Cheng and Subramanyam, 2008).

Regarding macroeconomic controls, an increase in real GDP growth tends to reduce the risk of entering a predistress state, while rises in inflation, the 10-year sovereign bond yield, the policy rate and private sector credit flow to GDP all tend to increase distress risk. Among banking sector controls, the total assets to GDP ratio is significantly positive whereas other variables are not significant. Thus, the larger the banking sector, the higher the probability of banks entering a predistress state. This is relevant given that the size of banks has a positive influence on their distress risk. Finally, all accounting variables are significant with signs in line with related literature (Betz *et al.*, 2014, Constantin *et al.*, 2018). Banks benefiting from higher capital ratios and return on equity (ROE) are less likely to be distressed. The size of the banks finally turns out to have a positive influence on distress risk, which means that bigger banks are more likely to be distressed as in Boyd and Runkle (1993) or Jin, Kanagaretnam, and Lobo (2011). The loans to deposits ratio is positively related to bank distress given that the more elevated this ratio, the less the ability of the bank to cover loan losses and withdrawals. As both ROA and loans to deposits were found negatively correlated with the size variable, the positive effect of the size of the bank on distress risk is likely to be owed to lukewarm asset returns for European banks. Variations present marginal changes only, except that the consensus recommendations is insignificant in Model (5), while securitization tends to limit the risk of a bank entering a state of predistress in Models (3) and (4). In short, in-sample results reveal that both ratings and recommendations convey information on distress risk, particularly when considered simultaneously. When introduced alone, ratings remain more informative than recommendations.

Turning to out-of-sample performance, in terms of classification accuracy, reflected by the AUC, the best performing model is Model (1), followed by Models (4) and (2) with AUCs over 0.87. Models including ratings tend to perform better in classification accuracy. Regarding the relative usefulness[17] a decision-maker could get *vis-à-vis* disregarding the model with preferences $\mu = 0.9$, in the nonweighted case, the best performing model is the (1) with a relative usefulness of 36%—36% of the usefulness that would be derived from a perfectly performing model—while the worst performing is Model (3). Again, ratings tend to perform better than recommendations, as usefulness is lower for model (5) *vis-à-vis* model (4). The picture is less clear-cut in the weighted case, as all models tend to display similar performance for $\mu = 0.95$, except the second one. Model (3)—including accounting variables—performs best for lower values of μ. Hence, a decision-maker more concerned by systemic institutions would derive relatively more usefulness from models that include ratings only than those that include both ratings and recommendations, except if his preferences are strongly skewed toward missing crises. On the contrary, for more balanced sets of preferences, a policy-maker would sometimes optimally disregard the EWM. The general decrease in usefulness when weights are included highlights that predicting distress risk is more difficult for larger—and more complex and opaque (Iannotta, 2006)—banks. Thus, from a policy-maker's point of view, financial information producers' disclosures appear not to be more informative when opacity rises as evidenced by Iannotta *et al.* (2013) and Anolli *et al.* (2014), which offsets the positive effect of an increase in their coverage on the information environment of banks, reflected in the negative influence of the number of CRAs and analysts on distress risk. This is particularly true when both types of disclosures are introduced simultaneously, as CRA ratings tend to perform slightly better than analyst recommendations overall. Finally, keeping only macro- and banking-sector wide variables yielded performance close to that of Model (3).

Variations in the number of observations are important among the samples owing

[17] Negative usefulness is normalized to 0.

to missing values going from 4,914 (Model (1)) to 10,116 (Model (3)), which hinders comparability. Reproducing all regressions on the baseline sample (4,914 observations) did not change the results. Our results highlight that financial information producers complement accounting and macro-level variables in- and out-of-sample and are useful to detect distress risk in advance, which means they are forward-looking. Thus, their monitoring on financial institutions does have an influence on distress risk, and could favor effective indirect market discipline mechanisms (Flannery and Bliss, 2019, given that direct influence has proven to be weak along time (Flannery, 2010). The coefficient associated to analyst recommendations is significant only when ratings are taken into account, which is reflected in a lower classification accuracy but do not translate into lower out-of-sample performance from a policy-maker's point of view. In terms of usefulness, by considering the model instead of disregarding it, both ratings and recommendations tend to be complementary in distress prevision. That relation weakens when the systemic relevance of banks is taken into account. In that case, they tend to become substitutes with a slightly equivalent performance. Therefore, both CRA ratings and analyst recommendations could usefully be introduced into an EWM in complement or substitute accounting variables to obtain more parsimonious models if necessary. Yet, 26% of banks are lost in the baseline sample, which means that such models could only be applied to a limited number of systemic institutions[18], that are also more difficult to monitor. Finally, performance achieved tends to highlight a redundancy between accounting data and financial information producers' disclosure, though at the expense of a significant loss of observations when opting for the latter case.

6. Further Analysis

6.1. Ratings, Outlooks, Watchlists

Table 4 (page 32) introduces other types of CRA disclosures. To assess their respective performance, analyst recommendations are excluded from the regressions[19]. Variations

[18] Mean and median size of banks are significantly different among samples with 17.05 and 16.85 for the whole sample, 18.06 and 17.88 for the reduced one, respectively.

[19] Results including the latter are broadly unchanged, with relative usefulness only slightly higher.

in ratings are introduced in Model (1) and complemented by outlooks and watchlist levels and variations in Models (2), (3) and (5). Among all specifications, coefficients for downgrades in ratings and stable and negative outlooks are positively significant. That is, they convey additional information on distress risk *vis-à-vis* rating levels. That result may highlight both the incidence of an optimism bias and the fact that CRAs are effectively deemed by market participants as discovering negative news. On the contrary, as they are likely to reflect a piece of information already disclosed to the markets or an overreaction to that piece of information, upgrades appear not to be informative on distress risk. Regarding out-of-sample performance, results are equivalent to those of Model (4) in Table 3 (page 31), meaning that introducing these other types of disclosures in the model is not crucial from a decision-maker's point of view. In model (4), we introduce a disagreement index, computed as the quarterly standard deviation of ratings among all agencies. When the index increases, CRAs do not agree with each other, which likely reflect an increase in the opacity of the bank. In both models (5) and (6), the coefficient associated to the index is positive, meaning opaque banks are more likely to experience a state of predistress, but insignificant[20].

6.2. Recommendations and EPS Forecasts

We replicate the same exercise for analyst recommendations in Model (5) of Table 4 (page 32), following Barber *et al.* (2010) and Premti *et al.* (2017) who found both recommendation levels and variations to convey information for investors. The number of recommendations only turns out to be weakly significant. The recommendation consensus is still insignificant[21]. Relative usefulness keeps pace with those of Model (5) in Table 3 (page 31). Therefore, the introduction of recommendation variations is not crucial for a policy-maker. Replacing the number of analysts by the number of recommendations and the recommendation consensus (mean) by the median in untabulated analyses yielded similar results. Finally, as EPS forecasts convey relevant information on the distress risk of (nonfinancial) firms (Moses, 1990), we

[20] Again, it becomes significant when recommendations are accounted for.

[21] It becomes significant when ratings are introduced while the coefficient for downgrades in recommendations loses its significance in additional estimations.

alternatively substitute the average and number of FY1 and FY2 EPS forecasts to the recommendation consensus and number of analysts in the baseline model of Table 3 (page 31) and introduce upgrades and downgrades in EPS[22]. As an indicator of opacity, we also introduce the standard deviation of EPS forecasts, higher values of which indicating more disagreement between analysts. Only the coefficient associated to that latter variable turned out to be significant and positive. Hence, EPS forecasts do not appear as a straightforward indicator of distress while displaying lower out-of-sample performance. All in all, rating and recommendation levels appear to be more informative than any other specification. A policy-maker would only marginally benefit—and sometimes suffer—from the introduction of the latter.

[**Insert Table 4 (page 32) here**]

6.3. Prudential Regulation

To account for the incidence of prudential regulation—that directly impacts bank's profitability, risk behaviour and more broadly, probabilites of entering a state of distress—on the ability of financial information producers to predict bank default risk, I introduce the tier 1 capital adequacy ratio and a macroprudential index into the baseline model. To derive the macroprudential index I rely on the IMFs integrated Macroprudential Policy (iMaPP) Database, originally constructed by Alam, Alter, Eiseman, Gelos, Kang, Narita, Nier, and Wang (2019) that covers the 2000Q1–2019Q4 period. For each macroprudential tool, an indicator is constructed to record tightening actions (+1), loosening actions (−1) and *statu quo* (0), based on 1990M1 situation and reported monthly. I construct an aggregated index by taking the quarterly sum of all instrument indicators focusing on financial institutions[23]. Results are broadly unchanged, both ratings and recommendations remain significantly positive with similar out-of-sample performance. While the coefficient associated to the macroprudential index is insignificant, the one associated to the tier 1 capital ratio displays a significant

[22] In that, we followed evidence of Agarwal and Hess (2012) that macroeconomic news tends to be reflected in medium-term (FY2) EPS while firm-specific variables tend to have more impact on short-term ones (FY1).

[23] E.g., capital buffers, loan loss provisions and reserves requirements, and limits on the growth of credit.

negative sign, meaning banks achieving higher capital requirements are less likely to enter a state of predistress.

Finally, to account for the fact that my sample encompasses countries from different monetary zones, as well as the potential effect of the homogenisation in rules and policy practices arising for the membership of banks to both the Euro Area and the banking union (e.g., Koetter, Krause, and Tonzer, 2019), I restrict my sample to banks whose headquarters are located in Euro Area member countries. Again, while the sample is restricted to 86 banks in 14 countries, results are similar to those of the baseline case (Table 3, page 31). Going further, I introduce instead a dummy taking the value of 1 if the headquarters of the bank are located in the Euro Area, 0 otherwise in the baseline sample, that I interact with ratings and recommendations variables. While the coefficient associated to the rating variable is not significant anymore, the one associated to its interaction with the Euro Area dummy is with a greater magnitude than in other models. This highlights an amplification effect of the performance of CRAs for Euro Area banks, which then benefit from their membership to the Euro Area. It is thus likely that results in previous regressions are mainly driven by these very banks. Recommendations display the reverse case, with a large positive significant for the noninteracted term, and an insignificant negative coefficient for the interacted one. Consequently being a Euro Area bank do not translate into better analyst performance on distress prevision. The coefficient associated to the dummy variable is no longer significant. Out-of-sample performance also tends to increase, indicating a better accuracy—and usefulness to a decision-maker's viewpoint—of financial information producers when accounting for the membership to the monetary union[24].

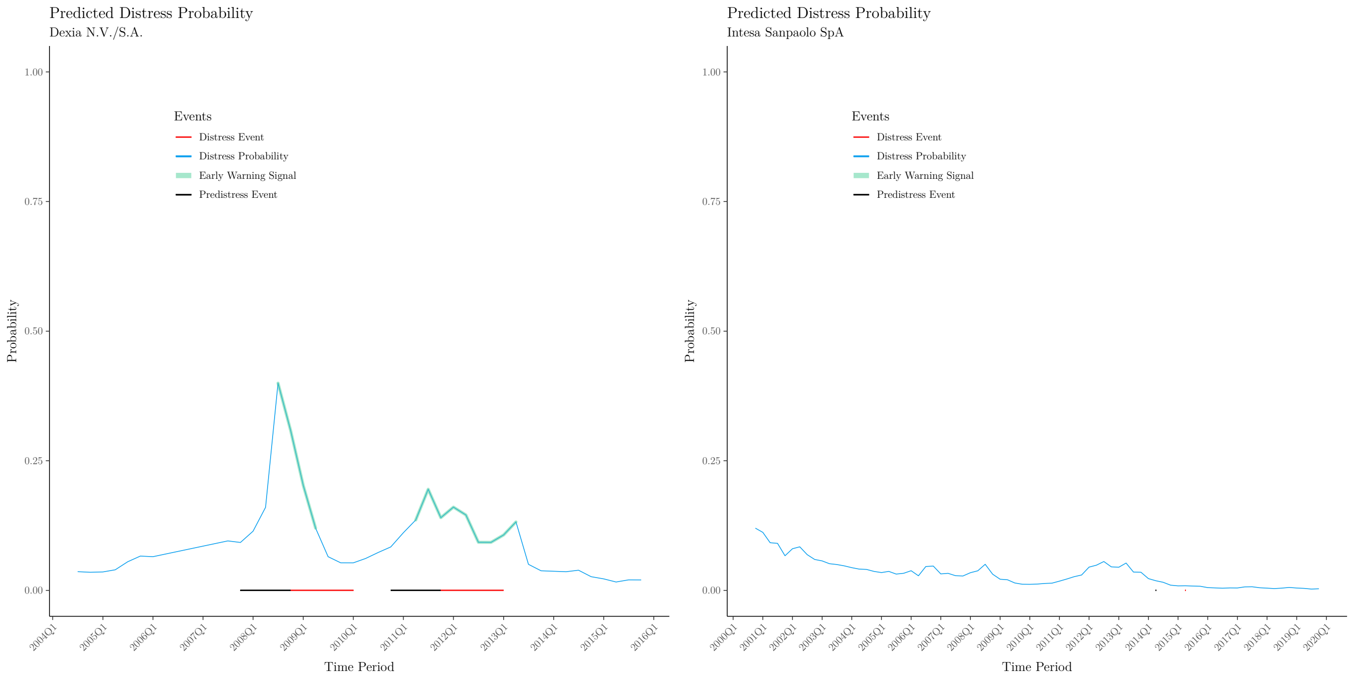
[24] An interesting extension would have been to account for progress towards the banking union in Europe, whose aim is precisely to curb banks' risk-taking behaviour by limiting moral hazard generated by the uncertainty on the likelihood of state support to distressed banks and the too-big-to-fail status of some institutions. However, given the lack of distress events since the beginning of the implementation of the scheme (from June 2013 for the publication of related E.U. directives), results when introducing theses pieces of regulation into the regressions were inconclusive.

7. Robustness Checks

7.1. Case Studies

Figure 2 (page 26) presents in- and out-of-sample predicted distress probability for Dexia N.V./S.A and Intesa Sanpaolo SpA. with regard to predistress and distress events for a policy-maker with preferences $\mu = 0.9$. The model performs reasonably well in both cases by issuing an early-warning signal before and during most distress events, or no early-warning signal at all in the Intesa Sanpaolo case, which did not experience any, as expected.

Figure 2. Case Studies ($\mu = 0.9$)



7.2. Fixed Dataset

Baseline regressions of Table 3 (page 31) display significant variations in the number of observations among the samples owing to missing values, which hinders comparability[25]. We get broadly similar results when performing all estimations on the baseline sample (4,914 observations). Notably, the coefficient for recommendation consensus becomes

[25] T tests and F tests revealed significant differences in means and variances.

significantly positive in Model (5). For preferences $\mu = 0.9$, Model (1) displays a 36% gain in usefulness *vis-à-vis* disregarding the model, while Models (4) and (5) also both achieve 36%. The worst performing model is Model (2) (31%). Models (4) and (5) perform particularly well when the systemic relevance of banks is accounted for. In that case, both CRA ratings and stock analyst recommendations turn out to be almost perfect substitutes in both the unweighted and weighted cases rather than complementary.

7.3. 8-Quarter Predistress Events Variable

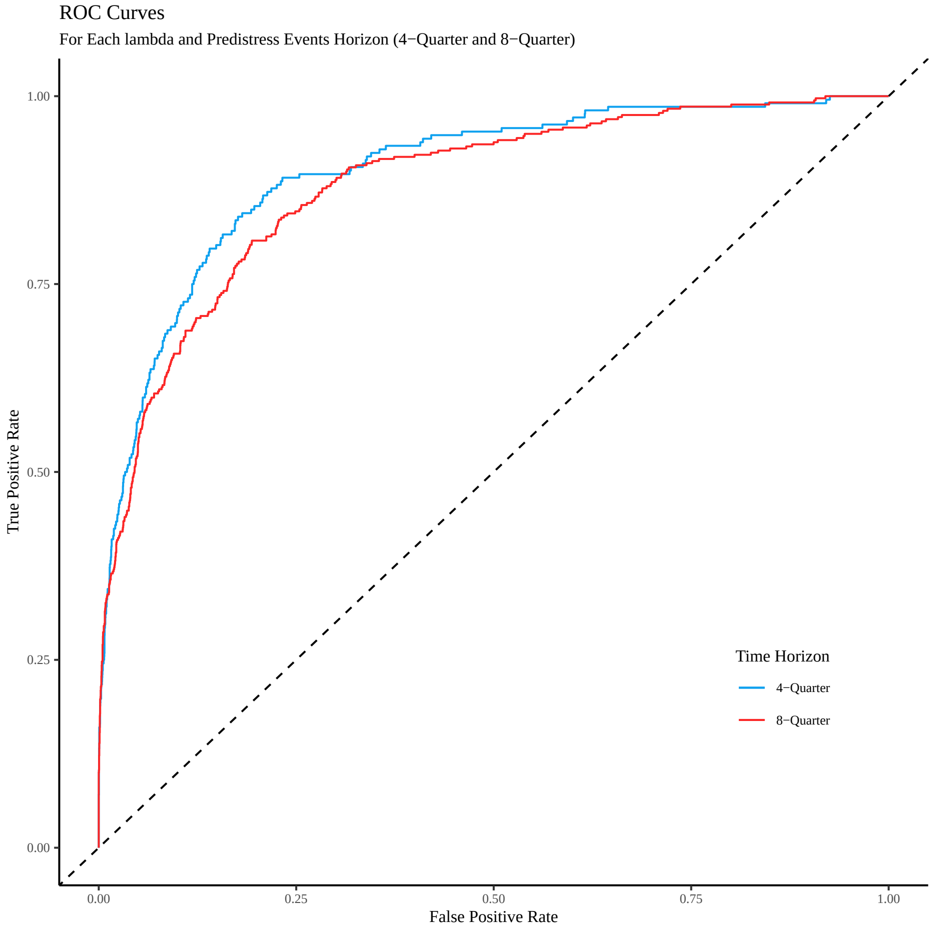
Following Betz *et al.* (2014) and Constantin *et al.* (2018), we set the predistress event time horizon to 8 quarters to assess to what extent our EWS performance holds when estimated on a longer period preceding distress events and reproduce estimations of Table 3 (page 31). The results are fairly similar, except for the Vix, which displays a unexpected negative and significant coefficient. Similarly, the overall out-of-sample performance is slightly lower. Model (3) performs worse than the others, except when bank-specific weights are introduced. Notably, the best model for preferences $\mu = 0.9$ is now Model (2), which is also the worst performing one in the weighted case[26]. All in all, financial information producers' disclosure are informative on distress risk up to two years in advance. Figure 3 (page 28) displays that performance of both baseline Models (1) are close and better than a coin toss (the bisector) for each λ, even though the model of Table 3 (page 31) is slightly better than the other estimated over 8 quarters.

7.4. Variations in the Sets of Preferences

Setting the threshold *ex post* as displayed in Section 4 can lead to sub-optimal results in terms of policy guidance and weigh on out-of-sample performance (Fuertes and Kalotychou, 2006). When the model is estimated recursively, the threshold is reoptimised each time and may vary accordingly, which impacts policy guidance that should be driven by changes in the vulnerability of banks only. Sarlin and von Schweinitz

[26] Results are similar when reproduced on the fixed baseline dataset.

Figure 3. ROC Curves (Model (1))



(2021) provided an alternative *ex ante* method by using the long-term optimal threshold which equalizes total costs from false negatives and false positives for the decision-maker, that is, $\lambda^{\infty} = 1 - \mu$. Table 5 (page 33) presents performance for the baseline model of Table 3 (page 31) for both methods and all sets of preferences μ. Outcomes using one or the other method are very close. In both cases, the policy-maker gets additional relative usefulness (U_r) by considering the model but it is optimal for him to disregard the model when the systemic relevance of banks is accounted for ($U_r(w)$) until $\mu = 0.85$. Alternative measures are presented, such as the True Positive Rate (TPR, or recall positives, banks correctly classified as having failed) and the False Negative Rate (FNR, banks classified as not having failed whereas they have a missed crisis) which a perfectly performing model would minimize. Again, the results are similar for both methods.

[Insert Table 5 (page 33) here]

8. Summary and Conclusions

In this article we estimate an EWS in a real-time fashion from a policy-maker viewpoint in 25 to 29 European countries over the 2000Q3–2020Q1 period. We find both CRA ratings and stock analyst recommendations to display an informative value on distress risk in- and out-of-sample up to two years in advance, hence to be forward-looking. Both disclosures profitably complement accounting, market and macroeconomic data used into EWS, particularly when introduced simultaneously but at the expense of a significance loss in observations. While subsequent improvements in performance are valuable to prevent banks entering a state of distress more accurately and in a more timely manner, such models would still be skewed towards systemic banks owing to the uneven coverage of financial information producers. These institutions are both the most important to monitor and the most difficult to as shown by the overall lowering in performance when accounting for the relevance of banks. Both rating and recommendation levels are more informative on distress risk than other specifications, including variations, outlooks, watchlist additions, and EPS forecasts, except for downgrades. That latter result may be owed either to the incidence of an optimism bias or to the reluctance of management to disclose negative news on bank soundness. Finally, our results show that a policy-maker would benefit from the introduction of such disclosures in an EWS, provided his preferences are hedged towards missing crises. It derives from this study that, while direct influence has proven to be weak along time (Flannery, 2010), the monitoring of financial institutions by financial information producers—the indirect component of market discipline (Flannery and Bliss, 2019)—appears to be useful to prevent bank distress events, along with the one of regulators, while being more synthetic and interpretable than e.g., stress tests. Given the scarcity of papers on the topic, analysing further the influence of financial information producers—notably stock analysts—on the financial health of banks would be insightful for further research.

Table 2. Summary Statistics

	Mean	StDev	Median	25^{th} Pct	75^{th} Pct	Min	Max	Skew	Kurtosis	N
Average Ratings	7.16	3.06	6.5	5	8	1	21	1.52	3.63	9,169
Number Ratings	1.4	0.63	1	1	2	1	3	1.33	0.61	9,169
Positive Outlooks	0.1	0.34	0	0	0	0	3	3.58	13.68	16,261
Stable Outlooks	0.7	0.78	1	0	1	0	3	0.81	−0.23	16,261
Negative Outlooks	0.28	0.56	0	0	0	0	3	2.1	4.11	16,261
Positive Watchlist	0.11	0.38	0	0	0	0	3	4.3	22.64	16,261
Negative Watchlist	0.33	0.57	0	0	1	0	3	1.57	1.57	16,261
Upgrade Ratings	0.02	0.16	0	0	0	0	3	7.58	64.58	16,261
Upgrade Outlooks	0.03	0.18	0	0	0	0	2	5.84	35.58	16,261
Upgrade Watchlists	0	0.06	0	0	0	0	2	18.98	391.71	16,261
Downgrade Ratings	0.03	0.18	0	0	0	0	2	6.3	42.85	16,261
Downgrade Outlooks	0.04	0.21	0	0	0	0	3	5.4	32.31	16,261
Downgrade Watchlists	0	0.06	0	0	0	0	2	19.4	398.54	16,261
Disagreement Index	0.17	0.37	0	0	0	0	2.5	2.44	6.32	9,169
Average Recommendations	2.64	0.61	2.57	2.22	3	1	5	0.51	0.96	8,558
Number Recommendations	14.1	10.28	12	5	22	1	47	0.63	−0.53	8,558
Upgrade Recommendations	0.42	0.49	0	0	1	0	1	0.32	−1.9	8,377
Downgrade Recommendations	0.42	0.49	0	0	1	0	1	0.34	−1.88	8,377
Real GDP Growth	1.7	2.86	1.89	0.71	3.24	−10.8	8.33	−1.4	4.48	16,057
Inflation	1.91	1.67	1.7	0.9	2.7	−1.35	9.5	1.45	4.56	16,057
Composite Rate	0.9	3.98	1.5	−0.75	3.5	−7.68	13.3	−0.15	0.43	16,247
10-Year Bond Yield	3.33	2.04	3.63	1.67	4.66	−0.46	10.79	0.32	0.49	16,066
Private Credit Flow to GDP	5.75	7.43	4.6	1.2	9.4	−12	35.5	1.01	2.64	15,146
Vix	19.84	8.45	17.47	13.78	23.65	9.45	57.06	1.79	4.15	16,261
Total Assets to GDP	934.47	450.58	842.8	626.5	1,201.9	258.3	2634.4	1.04	1.46	15,541
Loans to Deposits^{m}	124.11	63.23	100.48	82.82	124.69	63.43	342.32	1.67	1.95	15,003
Debt Securities to Liabilities	15.88	12.77	13.09	6.43	21.83	0.2	70.4	1.34	2.28	14,611
Total Assets	1.48E+08	3.25E+08	21,201,349	7,143,706	91,130,844	179,191	1.84E+09	3.29	11.29	13,815
Size	17.05	1.96	16.85	15.77	18.31	12.1	21.33	0.13	−0.28	13,483
Equity to Assets	7.63	4.27	6.66	4.75	9.62	0.37	25.29	1.4	2.86	13,430
ROA	0.98	1.02	0.89	0.5	1.4	−3.91	5.17	0.08	6.3	12,825
ROE	8.59	13.73	9.36	5.18	14.36	−106.31	34.78	−4.09	28.67	13,166
Loans to Deposits	147.6	98.68	124.59	93.86	166.82	18.2	752.04	3.19	14.52	12,809
Tier 1	12.81	4.9	12.3	8.88	15.9	4	29.58	0.81	0.71	10,394
Macroprudential Index	0.21	0.74	0	0	0	−3	8	3.2	16.71	15,448

Note: 1% Winsorization applied. ^{m} for banking sector-wide variable.

Table 3. Baseline Models (2000Q3–2019Q4 — OOS 2008Q3–2020Q1)

	Dependent Variable: Predistress (4Q)				
	(1)	(2)	(3)	(4)	(5)
Average Ratings	0.340***	0.261***		0.273***	
	(0.048)	(0.041)		(0.036)	
Number Ratings	−0.448***	−0.378**		−0.405***	
	(0.165)	(0.155)		(0.149)	
Average Recommendations	0.446***	0.617***			−0.073
	(0.153)	(0.142)			(0.127)
Number Recommendations	−0.002	−0.025**			−0.015
	(0.013)	(0.012)			(0.011)
Growth Real GDP	−0.066*	−0.131***	−0.081***	−0.083***	−0.072**
	(0.037)	(0.034)	(0.026)	(0.031)	(0.032)
Inflation	0.204***	0.165***	0.175***	0.224***	0.224***
	(0.064)	(0.058)	(0.042)	(0.051)	(0.053)
Composite Rate	0.289***	0.283***	0.255***	0.300***	0.228***
	(0.047)	(0.043)	(0.031)	(0.040)	(0.036)
10-Year Bond Yield	0.278***	0.270***	0.212***	0.197***	0.350***
	(0.076)	(0.070)	(0.052)	(0.065)	(0.062)
Private Credit Flow to GDP	0.030***	0.037***	0.009	0.031***	0.008
	(0.012)	(0.011)	(0.008)	(0.010)	(0.010)
Vix	0.009	0.011	0.007	0.014	0.001
	(0.011)	(0.010)	(0.008)	(0.010)	(0.009)
Total Assets to GDP	0.002***	0.001***	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
Loans to Deposits^m	−0.004*	−0.001	0.001	−0.001	−0.002
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Debt Securities to Liabilities	0.0002	0.012	−0.037***	−0.018*	−0.017
	(0.013)	(0.012)	(0.009)	(0.011)	(0.011)
Size	0.595***	0.811***	0.225***	0.521***	0.279***
	(0.106)	(0.094)	(0.040)	(0.067)	(0.077)
Equity to Assets	−0.273***		−0.101***	−0.171***	−0.153***
	(0.050)		(0.023)	(0.035)	(0.034)
ROA	0.410***		−0.004	0.098	0.105
	(0.139)		(0.087)	(0.117)	(0.119)
ROE	−0.027***		−0.025***	−0.023***	−0.037***
	(0.007)		(0.004)	(0.005)	(0.006)
Loans to Deposits	0.006***		0.001***	0.004***	0.002***
	(0.001)		(0.001)	(0.001)	(0.001)
Constant	−20.077***	−24.065***	−9.298***	−16.623***	−10.230***
	(2.283)	(1.902)	(0.920)	(1.528)	(1.536)
Observations	4,914	5,089	10,116	7,082	6,441
Log Likelihood	−569.919	−662.454	−1,200.692	−781.165	−815.986
Akaike Inf. Crit.	1,177.837	1,354.908	2,431.383	1,596.330	1,665.972
AUC	0.900	0.877	0.838	0.884	0.856
McFadden's R^2	0.348	0.286	0.239	0.313	0.272
Number of Banks	148	153	195	172	179
Number of Countries	25	25	29	28	27
$U_r(\mu = 0.6)$	9%(0%)	0%(0%)	7%(0%)	3%(0%)	6%(0%)
$U_r(\mu = 0.7)$	17%(0%)	13%(0%)	17%(9%)	21%(0%)	14%(0%)
$U_r(\mu = 0.8)$	28%(0%)	20%(0%)	23%(19%)	26%(12%)	24%(7%)
$U_r(\mu = 0.85)$	31%(19%)	27%(7%)	26%(27%)	31%(22%)	27%(18%)
$\boldsymbol{U_r(\mu = 0.9)}$	**36%(31%)**	**34%(23%)**	**30%(32%)**	**35%(33%)**	**31%(29%)**
$U_r(\mu = 0.95)$	52%(48%)	47%(39%)	38%(44%)	43%(46%)	42%(44%)

Note: *p<0.1; **p<0.05; ***p<0.01, ^{m} for banking sector-wide variable, standard errors and weighted relative usefulness in brackets.

Table 4. Ratings and Analysts Extensions (2000Q3–2019Q4 — OOS 2008Q3–2020Q1)

	Dependent Variable: Predistress (4Q)					
	(1)	(2)	(3)	(4)	(5)	(6)
Average Ratings	0.260***	0.277***	0.270***	0.265***	0.258***	
	(0.036)	(0.037)	(0.036)	(0.036)	(0.037)	
Number Ratings	−0.489***	−0.640***	−0.455***	−0.578***	−0.872***	
	(0.154)	(0.156)	(0.166)	(0.197)	(0.216)	
Upgrade Ratings	−0.967				−0.989	
	(0.621)				(0.619)	
Downgrade Ratings	0.775***				0.716***	
	(0.187)				(0.203)	
Positive Outlooks		0.226			0.331	
		(0.255)			(0.256)	
Stable Outlooks		0.614***			0.658***	
		(0.135)			(0.136)	
Negative Outlooks		0.835***			0.789***	
		(0.173)			(0.176)	
Upgrade Outlooks		−0.190			−0.451	
		(0.344)			(0.356)	
Downgrade Outlooks		0.125			0.120	
		(0.226)			(0.236)	
Positive Watchlists			−0.169		−0.220	
			(0.225)		(0.232)	
Negative Watchlists			0.188		0.138	
			(0.132)		(0.137)	
Upgrade Watchlists			−12.135		−11.924	
			(318.203)		(310.391)	
Downgrade Watchlists			0.697		0.587	
			(0.717)		(0.732)	
Disagreement Index				0.371	0.280	
				(0.253)	(0.253)	
Average Recommendations						−0.011
						(0.134)
Number Recommendations						−0.021*
						(0.012)
Upgrade Recommendations						0.258
						(0.259)
Downgrade Recommendations						0.104
						(0.261)
Growth Real GDP	−0.087***	−0.070**	−0.085***	−0.082***	−0.080**	−0.083**
	(0.032)	(0.032)	(0.031)	(0.031)	(0.033)	(0.033)
Inflation	0.208***	0.187***	0.216***	0.224***	0.173***	0.220***
	(0.052)	(0.054)	(0.052)	(0.052)	(0.054)	(0.054)
Composite Rate	0.304***	0.309***	0.311***	0.297***	0.321***	0.210***
	(0.039)	(0.040)	(0.040)	(0.040)	(0.040)	(0.038)
10-Year Bond Yield	0.167***	0.209***	0.184***	0.204***	0.175***	0.372***
	(0.065)	(0.065)	(0.066)	(0.065)	(0.066)	(0.063)
Private Credit Flow to GDP	0.033***	0.027***	0.033***	0.032***	0.029***	0.010
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Vix	0.009	0.019**	0.014	0.014	0.013	0.001
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Total Assets to GDP	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Loans to Deposits^{m}	0.0001	−0.002	−0.001	−0.001	−0.002	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Debt Securities to Liabilities	−0.025**	−0.015	−0.020*	−0.018*	−0.022*	−0.011
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Size	0.504***	0.468***	0.502***	0.515***	0.435***	0.308***
	(0.067)	(0.068)	(0.068)	(0.067)	(0.070)	(0.079)
Equity to Assets	−0.175***	−0.190***	−0.173***	−0.172***	−0.193***	−0.164***
	(0.035)	(0.036)	(0.035)	(0.035)	(0.036)	(0.035)
ROA	0.107	0.029	0.107	0.097	0.056	0.191
	(0.117)	(0.117)	(0.118)	(0.117)	(0.118)	(0.122)
ROE	−0.022***	−0.016***	−0.023***	−0.022***	−0.016***	−0.036***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Loans to Deposits	0.004***	0.005***	0.004***	0.004***	0.005***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	−15.860***	−16.236***	−16.146***	−16.297***	−14.983***	−11.060***
	(1.542)	(1.545)	(1.554)	(1.544)	(1.591)	(1.603)
Observations	7,082	7,082	7,082	7,082	7,082	6,284
Log Likelihood	−771.776	−764.349	−777.966	−780.125	−752.339	−786.920
Akaike Inf. Crit.	1,581.552	1,572.698	1,597.933	1,596.250	1,562.679	1,611.841
AUC	0.887	0.892	0.885	0.885	0.897	0.858
McFadden's R^2	0.321	0.328	0.316	0.314	0.338	0.273
Number of Banks	172	172	172	172	172	179
Number of Countries	28	28	28	28	28	27
$U_r(\mu = 0.6)$	8%(0%)	0%(0%)	10%(0%)	5%(0%)	0%(0%)	7%(0%)
$U_r(\mu = 0.7)$	17%(0%)	10%(0%)	15%(0%)	15%(0%)	9%(0%)	17%(0%)
$U_r(\mu = 0.8)$	27%(0%)	18%(0%)	20%(8%)	25%(10%)	22%(0%)	23%(6%)
$U_r(\mu = 0.85)$	32%(17%)	22%(3%)	25%(17%)	33%(21%)	31%(8%)	28%(15%)
$\boldsymbol{U_r(\mu = 0.9)}$	**37%(28%)**	**32%(17%)**	**35%(21%)**	**37%(33%)**	**34%(26%)**	**34%(22%)**
$U_r(\mu = 0.95)$	42%(47%)	45%(41%)	44%(42%)	45%(47%)	47%(44%)	44%(44%)

Note: *p<0.1; **p<0.05; ***p<0.01, ^{m} for banking sector-wide variable, standard errors and weighted relative usefulness in brackets. Standard errors omitted for controls for parsimony.

Table 5. Baseline Model Detailed Performance Measures

					Positives		Negatives									
μ	TP	FP	FN	TN	Precision	Recall	Precision	Recall	Accuracy	FPR	FNR	L	U_a	$U_a(w)$	U_r	$U_r(w)$
							Logit optimised threshold									
0	17	0	109	3232	1.00	0.13	0.97	1.00	0.97	0.00	0.87	0.00	0.00	0.00	NaN	NaN
0.1	18	1	108	3231	0.95	0.14	0.97	1.00	0.97	0.00	0.86	0.00	0.00	0.00	0.07	0.00
0.2	23	5	103	3227	0.82	0.18	0.97	1.00	0.97	0.00	0.82	0.01	0.00	0.00	0.02	0.00
0.3	26	10	100	3222	0.72	0.21	0.97	1.00	0.97	0.00	0.79	0.01	0.00	0.00	0.02	0.00
0.4	31	19	95	3213	0.62	0.25	0.97	0.99	0.97	0.01	0.75	0.01	0.00	0.00	0.02	0.00
0.5	39	32	87	3200	0.55	0.31	0.97	0.99	0.96	0.01	0.69	0.02	0.00	0.00	0.06	0.00
0.6	43	47	83	3185	0.48	0.34	0.97	0.99	0.96	0.01	0.66	0.02	0.00	0.00	0.09	0.00
0.7	48	62	78	3170	0.44	0.38	0.98	0.98	0.96	0.02	0.62	0.02	0.00	0.00	0.17	0.00
0.8	61	101	65	3131	0.38	0.48	0.98	0.97	0.95	0.03	0.52	0.02	0.01	0.00	0.28	0.00
0.85	62	130	64	3102	0.32	0.49	0.98	0.96	0.94	0.04	0.51	0.02	0.01	0.01	0.31	0.19
0.9	64	166	62	3066	0.28	0.51	0.98	0.95	0.93	0.05	0.49	0.02	0.01	0.01	0.36	0.31
0.95	79	251	47	2981	0.24	0.63	0.98	0.92	0.91	0.08	0.37	0.02	0.02	0.02	0.52	0.48
1	126	3221	0	11	0.04	1.00	1.00	0.00	0.04	1.00	0.00	0.00	0.00	0.00	NaN	NaN
							Logit set threshold ($\lambda^{\infty} = 1 - \mu$)									
0	0	0	126	3232	NaN	0.00	0.96	1.00	0.96	0.00	1.00	0.00	0.00	0.00	NaN	NaN
0.1	17	0	109	3232	1.00	0.13	0.97	1.00	0.97	0.00	0.87	0.00	0.00	0.00	0.13	0.06
0.2	19	4	107	3228	0.83	0.15	0.97	1.00	0.97	0.00	0.85	0.01	0.00	0.00	0.02	0.00
0.3	22	8	104	3224	0.73	0.17	0.97	1.00	0.97	0.00	0.83	0.01	0.00	0.00	0.03	0.00
0.4	32	17	94	3215	0.65	0.25	0.97	0.99	0.97	0.01	0.75	0.01	0.00	0.00	0.05	0.00
0.5	34	23	92	3209	0.60	0.27	0.97	0.99	0.97	0.01	0.73	0.02	0.00	0.00	0.09	0.00
0.6	39	34	87	3198	0.53	0.31	0.97	0.99	0.96	0.01	0.69	0.02	0.00	0.00	0.13	0.00
0.7	43	52	83	3180	0.45	0.34	0.97	0.98	0.96	0.02	0.66	0.02	0.00	0.00	0.16	0.00
0.8	57	99	69	3133	0.37	0.45	0.98	0.97	0.95	0.03	0.55	0.02	0.01	0.00	0.26	0.02
0.85	63	134	63	3098	0.32	0.50	0.98	0.96	0.94	0.04	0.50	0.02	0.01	0.01	0.31	0.18
0.9	71	183	55	3049	0.28	0.56	0.98	0.94	0.93	0.06	0.44	0.02	0.01	0.01	0.40	0.28
0.95	79	291	47	2941	0.21	0.63	0.98	0.91	0.90	0.09	0.37	0.02	0.02	0.02	0.51	0.43
1	126	3232	0	0	0.04	1.00	NaN	0.00	0.04	1.00	0.00	0.00	0.00	0.00	NaN	NaN

Note: Performance measures: 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), FPR (False Positive Rate) = FP/(TN+FP), FNR (False Negative Rate) = FN/(TP+FN). $P_1 = 0.04, P_2 = 0.96$.

Appendix A. Construction of Variables

Table A1. Construction of Variables

Variable	Construction	Source
Average Ratings	Average of ratings (sum ratings/number of agencies for each quarter), 1 = AAA/Aaa, 21 = default, assumed to hold until modified or withdrawn	Eikon, FitchConnect
Number Agencies	Number of agencies that issued a rating over the quarter (1-3)	Eikon, FitchConnect
Outlooks, Watchlists dummies	1 for each positive, stable, negative outlook or watchlist addition by agency over the quarter (1-3), else 0, assumed to hold until modified or withdrawn	Eikon, FitchConnect
Upgrade/Downgrade dummy	1 if quarterly upgrade (downgrade) for each agency over the quarter (1-3), else 0	Eikon, FitchConnect
Disagreement index	Standard deviation of ratings	
Average Recommendations	Recommendation consensus (average), 1 = *Strong buy*, 5 = *Strong sell*, assumed to hold until modified	I/B/E/S
Number Recommendations	Number of recommendations issued over the quarter	I/B/E/S
Upgrade/Downgrade dummy	1 if quarterly upgrade (downgrade) in recommendation consensus, else 0	I/B/E/S
Real Growth GDP	Annual real GDP growth	Datastream
Inflation	Annual HIPC rate	Datastream
Composite Rate	Wu-Xia Shadow rate (U.K. for the U.K., Euro Area for the Euro Area), domestic central bank or ECB policy rate when not available (for nonEuro Area countries and prior to 2004 for Euro Area countries)	Wu and Xia (2016), Central Banks' websites
10-Year Bond Yield	10-year sovereign bond yield	Datastream
Private Credit Flow to GDP	Private sector credit flow to GDP	Datastream
Vix	Chicago Board Options Exchange Market Volatility Index (USD)	Datastream
Total Assets to GDP	Total assets/GDP, country aggregates	Eurostat
Loans to Deposits^m	Total loans/total deposits, country aggregates	Datastream
Debt Securities to Liabilities	Debt securities/total liabilities	Datastream
Size	Natural logarithm of total assets (EUR thousands)	Datastream
Equity to Assets	Total common equity/total assets	Datastream
ROA	Return on Assets	Datastream
ROE	Return on Equity	Datastream
Loans to Deposits	Total loans/total deposits (bank level)	Datastream
Tier 1 Capital Adequacy Ratio	Tier 1 capital/risk-weighted assets	Datastream
Prudential Policy Index	Quarterly sum of following monthly indexes targeting financial institutions and extracted from the iMaPP database (+1 for tightening actions, −1 for loosening, 0 for hold): countercyclical capital buffers, capital conservation buffer and other capital requirements (e.g., risk weights, systemic risk buffers), leverage ratio limits, loan loss provisions requirements, limits on growth or the volume of aggregated credit, loan restrictions, limits on foreign currency lending and rules on foreign currency loans, taxes, measures taken to mitigate systemic liquidity and funding risks (e.g., minimum requirements for liquidity coverage ratios, liquid asset ratios), limits to the loan to deposits ratio, limits on net or gross open foreign exchange positions, reserve requirements (in domestic or foreign currency), measures taken to mitigate risks from global and domestic systemically important financial institutions and other measures (e.g., stress testing, restrictions on profit distribution, limits on exposures between financial institutions) (−3 to 8)	Alam *et al.* (2019)
Euro Area Dummy	1 if the headquarters of the bank are located in a Euro Area Member Country at date t, 0 otherwise	Own Calculation
Weights	Total assets of the bank/total assets in the sample for each quarter (EUR thousands)	Datastream

Note: ^{m} for banking sector variable.

Appendix B. Banks and Country Distribution

Table B1. Predistress Event-Country Distribution

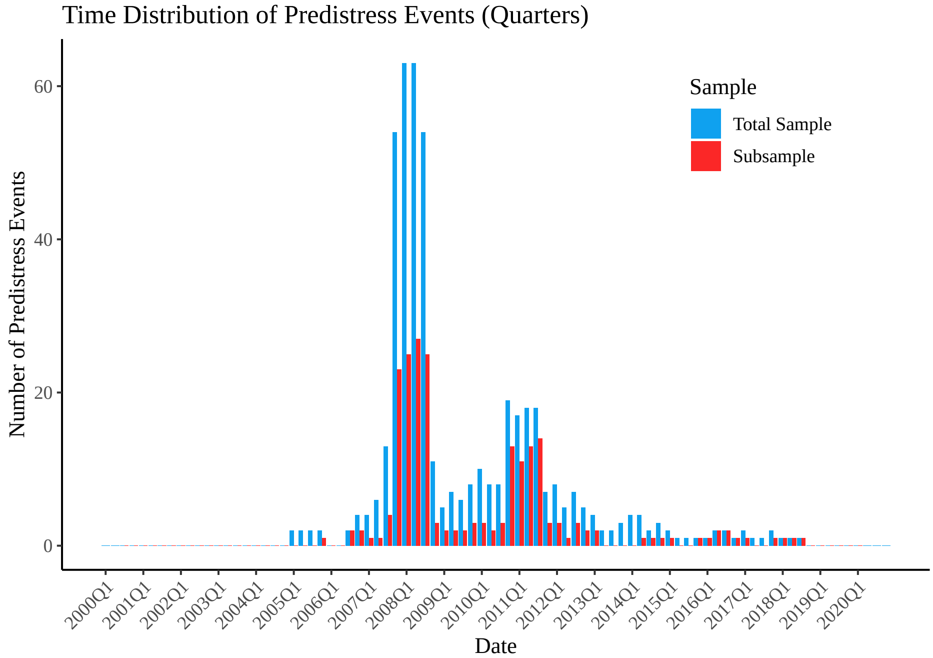
Country	Number Banks	Number Banks^s	Number Predistress	Number Predistress^s
Austria	7	4	20	4
Belgium	3	2	16	12
Bulgaria	3	1	4	0
Croatia	1	0	0	0
Cyprus	3	3	19	12
Czech Republic	3	2	0	0
Denmark	10	3	34	0
Faroe Islands	1	0	0	0
Finland	3	3	4	4
France	14	8	16	15
Germany	14	11	22	9
Greece	10	6	78	40
Hungary	2	1	8	0
Iceland	5	4	16	9
Ireland; Republic of	4	4	29	20
Italy	26	23	34	27
Liechtenstein	2	2	0	0
Lithuania	2	0	4	0
Netherlands	6	4	24	0
Norway	14	12	0	0
Poland	13	10	0	0
Portugal	5	4	28	8
Romania	2	2	0	0
Slovak Republic	1	0	0	0
Slovenia	2	1	16	3
Spain	12	11	38	15
Sweden	4	3	12	8
Switzerland	13	8	8	0
United Kingdom	19	16	52	26
Total	204	148	482	212

Note: ^{s} for baseline subsample (4,996 observations), else total sample (16,261 observations)

Table B2. Distress Event Distribution

Distress Event	Frequency
Direct Failure	*23*
Bankruptcy	1
Liquidation	16
Default	8
State Support	*106*
Capital Injection	85
Nationalization	19
Relief/Guarantee Program	30
Private Sector Support	*34*
Private Liquidity Support	6
Distressed Merger	28
Other	1
Total	*134*

Figure B1. Predistress Event-Time Distribution (2000Q1-2020Q4)



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