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ORIGINAL ARTICLE

Reassessing bank monitoring models: an empirical analysis of the value of market signals in the period 2008–2020

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Abstract
One of the major goals of bank supervisors is to predict bank distress events. As the environment changes, it is crucial to reassess and improve the models used in monitoring banks. The financial soundness of banks is traditionally assessed based on accounting ratios. However, the incorporation of market information in these models may significantly improve its ability to predict bank distress. The present paper has two main objectives, the first is to assess if market information adds value to accounting-based monitoring models when the purpose is to detect bank distress situations. Further, it also seeks to understand if the predictive power of market signals increased with transparency requirements. To accomplish this purpose, a total of 81 distress events from a sample of 248 European banks between 2008 and 2020 were analyzed. First, a logit univariate analysis was used to evaluate the relevance of each accounting and market variable. Then, the optimal multivariate accounting-based model to predict distress events was constructed using a stepwise approach. Finally, the previous model was extended to include the relevant market variables. The results support the use of market variables in bank monitoring models. Further, the present study provides evidence that the predictive power of market variables increased after the strengthening of the information requirements set by the Basel agreements. It can be concluded that the results support the use of market information for banking supervisory purposes, especially, in transparent markets.

Keywords Bank failure · Early-warning model · Market assessment · Basel agreements

Introduction

One of the main goals of bank supervisors is to predict bank distress events in order to avoid the disrupting effects of bank failure. The financial system's main function is to channel funds. If the banking system does not work well, it can affect investments flows and, consequently, negatively impact economic growth. Additionally, the banking sector's fragility can exacerbate the effects of a crisis. Grossman [1] estimated that a small bank failure shock can cause a 2% decline in real gross national product and a large bank failure shock can cause up to a 20% decline. Hence, reassessing the performance of bank monitoring models is essential not only to strengthen the scientific literature but also to improve the bank monitoring models used. This last point is particularly relevant since external factors, such as regulatory changes, can cause a change in bank managers' behavior and other information might become more relevant.

Flannery and Bliss [2] argued that market information can provide a significant contribution to monitoring a bank's financial health. Further, the authors claimed that the use of market information in bank supervision can potentially help supervisors to establish priorities when scheduling in-site-examinations, and so, use supervisory resources more effectively. Previous studies found evidence of market discipline in financial institutions and suggested that it may be even stronger if greater disclosure

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and transparency of financial information were required [3–7]. Precisely, one of the most noteworthy bank regulations, the Basel agreements have been focused on enhancing banks' transparency by increasing both the quantity and the quality of the banks' information requirements.

The present paper aims to analyze if market information provides a valuable complement to accounting-based bank monitoring models. Additionally, this paper seeks to understand if the introduction of Pillar 3 affected the predictive content of market information over bank distress.

To accomplish the mentioned goals, a sample of 248 European banks was analyzed from 2008 to 2020 containing a total of 81 distress events. First, a univariate logistic analysis of accounting variables was performed to discover the most relevant variables. Then, a stepwise approach was used to find the optimal multivariate accounting-based model to predict bank distress events. Similarly, to analyze the individual importance of market indicators was performed a univariate logistic assessment. Finally, the accounting model was extended to include the most significant market variables. The results support the hypothesis that the information disclosure requirements of Pillar 3 positively affected the importance of market variables to predict bank distress events.

There was not found any other recent research that seeks to understand if the introduction of Pillar 3 changed the predictive power of market variables in bank monitoring models. An earlier example is Oliveira and Raposo [8], which examined the relationship between regulation, market discipline and banking distress, applying a multivariate logit model to an international sample of 586 banks from 21 European countries in the period between 2000 and 2012. The authors found that market discipline is a good indicator in signaling banking distress, that is, market discipline has penalized more banks with a higher likelihood of being in distress. Therefore, they concluded that Basel III was on the right path to mitigate the probability of occurring new banking crisis. Our empirical study updates and complements the current literature by adding an important contribution regarding the performance of bank monitoring models through time and the impact of information disclosure requirements on them. Additionally, in methodological terms, this research uses a multiple-criteria approach to detect distress events, namely, by including explicit failure or liquidation, rating downgrade, and state intervention. This study stands out by examining numerous ECB press releases and other official communications regarding state interventions in banks. In summary, the results suggest that market signals can help to predict bank distress events and that a higher level of transparency further improves their relevance. These findings are pertinent to guide regulators in future discussions regarding information disclosure requirements and the introduction of market signals in the banking supervisory process.

The structure of the paper is the following. "Literature review and hypotheses development" section discusses the most relevant literature including the concept of bank distress, the traditional models used to predict a bank's financial condition, the benefits of including market information, and an overview of the most recent regulatory changes. Then, to conclude, the main hypotheses will be presented. "Data and methodology" section describes the data and methodology used, and "Results" section presents and discusses the results. In "Robustness test" section, the robustness of the models will be assessed and the final section presents the conclusions.

Literature review and hypotheses development

Distress events

There are different approaches to identify bank distress events in the literature. In the studies that examined the US market, the authors used either explicit bank failures or supervisory ratings [3, 9–11]. However, in Europe, explicit bank bankruptcies are rare and supervisory ratings are not available. In the literature are found two options to solve this issue. It can be used an extended version of bank failure that includes not only bankruptcies but also liquidations, defaults, state interventions, and forced mergers [7, 12–14]. Alternatively, it can be used ratings from the rating agencies (Moody's, Standard&Poor's, and Fitch) as a proxy for a bank's financial health. Rating agencies have introduced bank ratings that only focus on the economic and financial soundness, which means, without taking into account possible external support—the Moody's Bank Financial Strength (MBFS) and the Fitch IBCA Individual (FII) rating. These ratings are claimed as more appropriate to identify distress events [15] and were used by Gropp, Vesala, and Vulpes [16], Distinguin, Rous, and Tarazi [17] and Miller, Olson, and Yeager [18], among others.

Traditional approach: accounting indicators

Given the importance of the banking system for the whole economy, assessing banks' risk is extremely relevant. One of the most used tools is the CAMELS rating system, an internal supervisory tool for evaluating the soundness of financial institutions. As described in the Commercial Bank Examination Manual [19], the CAMELS rating system uses financial ratios to assess the overall financial soundness of banks and it is focused on five components: (C) the bank's capital level; (A) the adequacy and quality of the bank's assets; (M) the management namely its ability to identify, measure, monitor, and control the risks of the bank's activities while ensuring the soundness and efficiency of the bank's operation and the compliance with applicable regulations; (E) the quantity, sustainability, and trend of the bank's earnings; (L) the adequacy of the bank's liquidity position; and, lastly, (S) sensitivity of the bank to market risk.

Several studies show the effectiveness of using accounting indicators to assess the risk class of banks or predicting bank failure [20, 21]. Cole and Gunther [22] studied bank survival and bank survival time. The authors found that basic indicators of a bank's condition, such as capital, troubled assets, and net income, are significantly related to the timing of bank failure. Yet, liquidity indicators are not found to be important determinants and asset size appears to not be related to the bank's survival time. Alternatively, Cole and White [9] revealed that CAMELS proxies, namely capital adequacy, asset quality, earnings, and liquidity, are powerful predictors of the failure of commercial banks during 2009, similar to the results on the 1985–1992 banking crisis. With a more recent sample, Cleary and Hebb [23], using discriminant analysis to examine the failure of 132 US banks over 2002–2009, stated that capital and loan quality and bank profitability appeared to be the most important variables.

Regarding European banks, Männasoo and Mayes [24] showed that CAMELS factors have an important role in distress detection and warning and Poghosyan and Cihak [7] revealed that asset quality and earning profiles of EU banks are important determinants of bank distress, next to leverage. Additionally, Filippopoulou et al. [25] suggested that specific banking variables are on average more important than macroeconomic variables for predicting systemic banking crisis in the Eurozone.

Market indicators

Market information has desirable characteristics that are not present in accounting-based indicators. Market information is (1) forward-looking, (2) frequent and widely available, and (3) can be used in a diversity of ways to extract information and calculate risk measures from market prices [26].

Market participants have a strong incentive to collect and evaluate information to accurately assess the potential risks and rewards [11]. Even though market participants have less access than supervisors to banks' information, the information obtained during the examinations performed by the supervisors becomes outdated. Market investors evaluate a bank continuously, hence providing more recent data to predict distress events. Accordingly, Berger et al. [27] concluded that supervisory assessments are generally less accurate than either stock or bond market indicators in predicting future changes in performance, except when those assessments derive from a recent on-site inspection visit. Thus, regulators may apply information embedded in market prices and trading patterns to improve off-site monitoring models.

Given the above, market information can be used to complement supervisory and accounting information in assessing banks' risk by adding a new source of information. It can improve the supervisors' responsiveness to emerging risks, especially in-between examinations. Additionally, market signals also provide quantitative rankings of risk that can help in the comparative evaluation of supervisory priorities [28]. But as Feldman and Levonian [29] explained there is a difficulty of detecting and measuring market signs given the multiple ways of interpreting the data and no clear orientation.

To understand the contribution of market signals is important to analyze the two main categories, equity and debt market signs. Furlong and Williams [5] extensively discussed the differences between debt and equity signals. In short, debt holders are more concerned about the downside risk while equity holders look at both downside and upside potential. Yet, the previous ones are still interested in identifying the bank's risk profile accurately to evaluate the risk-return trade-off.

Debt signals

Debt holders demand a larger risk premium as the risk increase. These signals from the bond market may help to predict distress events in banks. Several studies showed that the price in the debt market is sensitive to the risk profile of the issuing bank [5]. Flannery and Sorescu [4] revealed that subordinated debenture yields are correlated with the bank's risk indicators for a sample of banks between 1983 and 1991. Evanoff and Wall [30], analyzing data from 1990 to 1999, concluded that subordinated yields have as good or more predictive power over the supervisor's ratings than accounting information. Jagtiani and Lemieux [6] examined banks that failed during the period 1980–1995 and found that bond spreads start rising as early as six quarters before failure.

Similarly, the spread paid on a Credit Default Swap (CDS) should reflect the riskiness of the financial institution since it is based on the credit risk of the reference entity. Thus, if the CDS market is as liquid as the bond market, it should provide even better signals. Analyzing the ratings agencies' announcements from 2000 to 2002, Norden and Weber [31] found that CDS and stock prices predict rating downgrades. In addition, Flannery et al. [32] conclude that CDS spreads incorporate information more quickly than credit ratings and Ötker-Robe and Podpiera [33] suggested that CDS pricing can be used for bank assessment for

European large complex financial institutions. Yet, not all banks have underlying CDS limiting the use of this signal.

It should be emphasized that bond market signals are affected by implicit state guarantees. Balasubramnian and Cyree [34] examined the default risk sensitivity of yield spreads on bank-issued subordinated notes and debentures (SND) during the period 1994–1999 for a sample of US banks. The authors concluded that SND yield spreads are sensitive to conventional firm-specific default risk measures before the bailout period but not after. Cutura [35] studied European banks' bond yields around the introduction of the EU's Bank Recovery and Resolution Directive (BRRD) in 2014. The BRRD specified that bonds maturing after 2016 would be subject to "bail-in" in case of failure. Comparing bonds maturing after and before 2016, the results strongly suggested that the BRRD improved market discipline in the European banking sector.

These studies show that the use of bond market information in models to predict bank failure is less effective when there are implicit guarantees. Even though debt holders are sensitive to default risk they are not necessarily sensitive to a banks' risk profile when there are perceived government guarantees.

Equity signals

Assuming the market is reasonably efficient, the information about potential banks' problems will be translated into their stock prices. Pettway and Sinkey [36] analyzed US banks in the 1970s and concluded that equity price and returns provide signals about banks' condition. Similarly, Hall, King, Meyer, and Vaughn [37] tested the ability of market investors and supervisors to assess risk for a sample of US banks. The authors concluded that both equity investors and regulators scrutinize credit risk to a similar degree.

Curry et al. [10] analyzed 99 US banks during 1989–1995, 16 quarters before the failure. The authors examined the long-term pattern of market variables and extended traditional accounting-based models to include the most relevant market data. The results revealed a pattern in returns, market-to-book value of equity, dividends and return volatility. However, trading activity and skewness do not exhibit a consistent failure-related trend. Regarding the predictive content of equity market variables, the results showed an improvement of the failure-predictive content compared to traditional accounting-based models. Moreover, the relative accuracy of the extended model increased as the time to the date of failure also increased. The same authors showed in a subsequent article that equity data adds significant value in forecasting the BOPEC rating upgrades. The market variables include price variation, excess quarterly returns, standard deviation of quarterly returns, market-to-book of equity, and quarterly turnover of shares. The model demonstrated robustness up to 4 quarters of previous rating change [3].

Alternatively, Gunther et al. [11] used the expected default frequency (EDF), testing whether EDF added information regarding the bank's financial safety and soundness, measured by supervisory ratings. The results revealed that stock prices help to predict the financial condition of banks. Nonetheless, especially for the largest organizations, inspections produce relevant information not included in the model.

Moreover, Cannata and Quagliariello [38] established that accounting and equity indicators contain different information and indicators based on the option pricing framework seem to be better at identifying banks' specific riskiness. The results also demonstrated the informative content of equity-based variables and their complementarity with supervisory information. Further, the short-interest ratio was used by Balasubramnian and Palvia [39] as an equity signal, and the authors concluded that short interest in the bank's equity increases before downgrades in supervisory ratings but does not decrease before upgrades. However, the use of the options market and short interest variable for monitoring purposes is limited given the lack of data.

Debt and equity signals

Some researchers studied the value of using both debt and equity signals. Bliss and Flannery [40] found that equity and bond prices move in the same direction more than half the time. Moreover, Krainer and Lopez [41] tested the predictive content of returns and spread bonds yield. The authors concluded that equity and bond market investors possess different but complementary information that appears to be useful for explaining rating upgrades and downgrades. These findings are consistent with the ones of other authors [5, 16, 27].

Debt holders care about expected losses deriving from default and not about returns in non-default situations; therefore, it may seem logical to rely on debt market signs to assess banks' distress probability. However, the bond market tends to be relatively less liquid than the equity market, and thus the bond spreads may be noisy [16]. Further, debt signals are affected by government implicit guarantees.

To illustrate, Gropp et al. [16] used distance to default and subordinated bond spreads to predict bank fragility. The results suggested that the equity indicator has higher predictive content and it is the first to signal potential problems. Similarly, Kwan [42] studied the relationship between stock and bonds and concluded that stocks lead bonds in reflecting firm-specific information. Further, Gropp and Richards [43], using a sample of European banks from 1989 to 2000, concluded that monitoring banks' risk through debt holders appears to be relatively limited and suggested that this occurs due to the illiquidity of the bond market.

Despite this, Hancock and Kwast [44] supported the use of subordinated debt spreads in supervisory monitoring even though the authors noticed a need for careful judgment because some developments can affect the movement of the bond spreads such as the lack of liquidity. Persson and Blavarg [26] claimed their preference for equity signs due to the better quality of data and the absence of too big to fail problems. Similarly, Levonian [45] consented that equity information is preferable as a source of meaningful information about bank risk although the subordinated-debt market could contain complementary information.

Krainer and Lopez [46] stated that even if the equity market information does not improve the forecast accuracy of future changes in supervisory ratings it should still be useful for forecasting supervisory ratings. The authors argued that equity variables should be incorporated into supervisory monitoring models because of (1) the higher frequency of equity information that can potentially signal changes sooner, (2) the low cost of incorporating equity market variables, and, (3) the additional source of data that can be used as cross-checking. Similarly, Persson and Blavarg [26] also supported the idea that market indicators are important to complement and provide a reference point for conventional analysis.

Regulatory framework

The banking system is inherently fragile since a bank failure can cause the loss of public confidence and, consequently, adversely impact other financial institutions—contagion effect. The loss of confidence can cause bank runs which affect the stability of the banking system and can negatively impact the economy. For this reason, government tends to aid banks in trouble. In the euro area, from 2008 to 2014 the accumulated assistance amounted to 8% of GDP [47].

Given its systemic importance, banks are highly regulated. The Basel Committee on Banking Supervision (BCBS) is a global institution created to improve financial stability through a higher quality of bank supervision. From it emerged the Basel agreements being the EU one of its adopters. Currently, Basel regulation focus on three areas: minimum capital requirements (Pillar 1), supervisory review (Pillar 2), and market discipline (Pillar 3). However, Pillar 3 was only introduced in Basel II, published in 2004 [48]. In 2010, in response to the global financial crisis, a new Basel agreement emerged—Basel III. Basel III had different phases, the first was focused on improving capital requirements—adding macroprudential elements and introducing minimum leverage ratio—and tried to mitigate liquidity and maturity transformation issues [49, 50].

The purpose of Basel III is to make failure resolution less disruptive. To ensure that a distressed bank can be reorganized without neither disrupting the financial system nor require government rescues, Basel III redefined the capital requirements for each bank to maintain sufficient capacity to absorb losses without disrupting the markets. The goal is to allow banks to quickly sell or let the assets mature and use the earnings to redeem their short-term liabilities. Protecting short-term liabilities avoids the need for government rescues and prevents bank runs, one of the reasons behind the banks' liquidity shortfall. Chiaramonte and Casu [14] evaluated the impact of Basel III structural liquidity and capital ratios on bank stability from 2004 to 2013. Analyzing 123 banks investigated by the European Banking Authority (EBA) in the EU-wide stress testing of 2014, the authors found that capital ratios seem to only reduce bank fragility for large banks, whereas liquidity requirements are relevant for either large and small banks.

Further, government safety net, deposit insurance, or the market's perception that some large banks may be "too big to fail" (TBTF) can affect the market signals. With a safety net, banks benefit from taking more risk without paying for the full cost in case of default, since they expect a government bailout [5]. However, equity holders continue to have incentives to monitor banks' risk since they are not fully protected by the TBTF policy.

Additionally, Basel III sets a more normative Pillar 3, giving banks less flexibility about the information to report and its frequency. The standardization of reports is expected to decrease the cost of collecting information and, consequently, make market participants better equipped to assess banks' financial health. As a result, the quality of market signals is anticipated to improve.

Overall, the increase in capital and the liquidity requirements aim to reduce individual banks' probabilities of default by protecting short-term debt holders, but it can also undermine the bond market discipline [14]. On the other side, the cost decrease of obtaining information and the increase of equity holders exposure may positively affect the equity market discipline.

As is shown by Charalambakis and Garrett [51], we cannot use a common model to predict corporate financial distress regardless of the stage of development of the economy. It is important to consider how structural changes may affect predictive models. This study focuses on distress events of European banks from 2008 to 2020; hence, it is relevant to take into account not only the changes caused by the regulatory framework but also their time of implementation.

In 2017, the Basel Committee presented Basel III reforms to complement the initial phase of Basel III [50]. Further, in a press release in December 2018, it was announced a revision of Pillar 3; nonetheless, its implementation is not yet completed, and, due to the impact of Covid-19 on the global banking system, the Committee deferred its implementation to 1 January 2023 [52]. Additionally, EBA analyses Pillar 3 reports for a sample of European banks in terms of compliance with the Basel requirements since 2008. The last report available assesses the year 2019, and it shows that despite important developments there are still some aspects in transparency and consistency of information needing further improvement [53]. So, given the reasons mentioned above, it is important to see if the increase in bank transparency positively impacted the predictive power of market variables over banks' distress.

Hypotheses development

The goal of the present paper is to examine the value of extending accounting-based monitoring models to include market variables. Particularly, this study is focused on the predictive content of equity market indicators over bank stress events. The choice of analyzing equity signals is motivated by both theoretical and practical reasons. As mentioned above, the changes in the regulatory framework and the greater liquidity and data availability make equity signals preferable when compared to bond market signals.

Hypothesis I: Equity market variables add significant value to accounting monitoring models for predicting the bank's distress events.

Further, this study also seeks to complement the current literature by analyzing if the changes in Pillar 3 achieve their goal of making information more accessible to market participants and, consequently, improving the quality of equity signals. Therefore, it will be tested if the increase in market transparency translated into an increase in the equity signals predictive content.

Hypothesis II: The predictive power of equity market signals over bank distress increased with the development and strengthening of information disclosure requirements.

Data and methodology

Data

This study will use a sample that includes both active and non-active banks, similarly to Chiaramonte and Casu [14]. Including banks that failed or were liquidated during the considered period avoids the survivorship bias. The sample for the European Economic Area was collected in the BankFocus database.

First, concerning location, the EU 27, UK, Norway, Liechtenstein, and Iceland were selected. The UK was included because during the analyzed period it was still an EU country. In the literature, EU countries do not show much heterogeneity across countries [7]. These findings support the use of common benchmark criteria for banking sectors across the EU countries. Finally, the other three countries were added since they also belong to the group of countries assessed by the EBA. Second, given the goal of exploring market information, only publicly listed parent companies were chosen. Lastly, following the approach of Distinguin et al. [17], regarding the specialization criterion were included Commercial banks, Savings banks, Cooperative banks, Real estate & mortgage banks, Investment banks, Specialized governmental credit institutions, Bank holdings & holding company and other non-banking credit institutions.

Consequently, the study comprises a dataset of 248 financial institutions, and Table 1 shows the distribution of the entities by country and specialization. The sample exhibits a higher dimension in terms of bank per country and per specialization compared to Distinguin et al. [17].

The sample of banks used to assess equity market signals in the European market tends to be smaller when compared to the US market. Gropp et al. [16] analyzed from January 1991 to March 2001 a sample of 86 EU banks to assess equity signals, and Distinguin et al. [17] for the 1995–2002 period studied 64 European banks. The existence of missing values limits the use of banks' observations to calibrate the model and, as a result, affects the models' quality. This paper considers that the data available before 2007 are insufficient to obtain reliable results and, consequently, the accounting and market variables were collected from 2007 to 2019. The distress events are analyzed from 2008 to 2020 since are considered one-year prediction windows.

Table 2 presents descriptive statistics on the sample of banks used in this paper where it is possible to observe the sample's heterogeneity. Heterogeneity is valuable to investigate the robustness of the indicators since it allows to research the probability of distress events for banks with different capital structure, size, and earnings profile. Compared to Distinguin et al. [17], the sample of this study presents a higher standard deviation in terms of the variable total assets, the ratio of total loans to total assets, and the indicator ROA.

Distress events

In the present paper, distress events are defined using a three-criteria approach, similar to Miller et al. [18]. The first criterion is banks that undergo explicit bankruptcy or liquidation, being inactive. However, instead of immediately classify it as a distress event, the bank will be flagged. Then, analogous to Poghosyan and Cihak [7], an individual research was performed using news, articles,

Table 1 Distribution of banks by country and specialization

Country	Number	Country	Number	Specialization	Number
Austria	10	Italy	26	Bank holding and holding company	43
Belgium	3	Liechtenstein	1	Commercial bank	119
Bulgaria	4	Lithuania	1	Cooperative bank	20
Croatia	8	Luxembourg	1	Investment bank	16
Cyprus	2	Malta	3	Other non-banking credit institution	2
Czech Rep	3	Netherlands	4	Real estate and mortgage bank	7
Denmark	26	Norway	40	Savings bank	40
Estonia	1	Poland	13	Specialized governmental credit institution	1
Finland	5	Portugal	3		
France	21	Romania	3		
Germany	13	Slovakia	4		
Greece	6	Slovenia	1		
Hungary	3	Spain	9		
Iceland	2	Sweden	7		
Ireland	4	UK	21	Total number	**248**

Table 2 Summary of accounting statistics from 2007 to 2019

	Average	Standard deviation	Minimum	Maximum
Total assets (000 €)	107,583.64	320,365.93	1.59	2,416,906.14
Net loans to total assets (%)	59.34	20.23	0.02	96.40
Liquid assets to total assets (%)	27.00	16.28	0.00	97.09
Total capital ratio (%)	17.89	13.07	− 5.00	339.48
ROA (%)	0.52	4.65	− 128.80	18.77
Loan loss reserves to gross loans (%)	4.92	6.93	0.01	94.51
Non-performing loans to gross loans (%)	8.65	11.66	0.00	192.53
Impaired loans (000 €)	3390.21	8999.18	0.00	82,859.44

Units are indicated in front of the indicators between parentheses. This table presents the average values of each indicator in the total sample from 2007 to 2019

and other sources of information to assess if there are indeed reasons to declare it as a distress event. This investigation was conducted to ensure that liquidations were caused by the deterioration of the bank's financial condition. Arena [12] and Chiaramonte and Casu [14] argued that mergers and acquisitions might have strategic reasons and these should not be considered distress events.

In this research, a bank is also flagged if it suffers a rating decrease to a level below the BBB category, in other words, if it becomes a speculative-grade investment. Instead of using rating downgrades to C or below as Gropp et al. [16], this paper considers any category downgrading in the speculative grade, following an approach more similar to the one used by Distinguin et al. [17]. In case of subsequent decreases, it was normally considered a new distress event if the rating decrease to another category except if the investigation suggested otherwise. To illustrate, if the rating decreases from BB to CCC, it was considered another event, but from BBB to BB it was not.

The last criterion is banks that benefit from state interventions. As Chiaramonte and Casu [14] stated, state aid can take different forms including nationalization, recapitalization, guarantee lines, and loans. Information regarding state intervention is difficult to collect since it is not available in any accessible databases. As a starting point, the Mediobanca [54] and European Commission [55] reports were analyzed. Then, a further investigation was performed for each state intervention to obtain a deeper understanding, namely through ECB press releases. It is frequent to observe multiple state interventions in the same bank; thus, it is crucial to determine if two or more state interventions in the same bank correspond to the same distress event or if each state intervention represents different events. To distinguish distress events within the same bank the unexpected criteria was applied, meaning that if the initial plan did not have considered the following intervention it was considered a separate distress event. Note that this classification is to some extent subjective and state interventions are long processes in which the announcement, approval, and execution dates are often separated by long periods of time. Further, these dates are hard to obtain, consequently, defining the time of the distress is not as accurate as desirable.

The final sample of distress events is composed of 81 events from which two events are due to explicit bankruptcy, 29 events originated from the rating criterion, 12 events detected due to both state intervention and rating approach, and, finally, 38 events derived from state interventions alone. As expected, the distress events are much less frequent compared to non-distress, in the specific sample used in this study, for a sample of 248 banks during 13 years there are only 81 distress events.

Italy and Greece are the most affected countries during 2008–2020, presenting the highest number of distress events, respectively, 17 and 14. They are followed by Poland and Belgium, and other peripheral countries, such as Spain and Portugal, were also relatively harshly affected. There is a concentration of distress events from 2008 to 2012, being 2012 the year with more distress events (17). This is not surprising since the financial crisis of 2008 hit Europe severely and was further amplified by the sovereign debt crisis that peaked between 2010 and 2012.

Further, Table 3 indicates a descriptive analysis summarizing some accounting ratios. The average of total assets, loan loss reserves to gross loans, non-performing loans to gross loans, and impaired loans of distress banks from 2007 to 2019 present higher values compared to non-distress banks. Compared with the sample used by Poghosyan and Cihak [7], the liquid assets to total assets ratio shows less discrepancy between distressed and non-distressed banks.

Explanatory variables

Most of the accounting variables found in the literature are based on CAMELS proxies. Distinguin et al. [17] argued that using the absolute values of the variables can introduce some bias because banks have different sizes and, consequently, are expected to have different ratio dimensions. This study will address this problem by introducing the control variable total assets, similar to other previous studies [3, 11, 20, 27]. Another important issue related to accounting variables is multicollinearity since many variables used in the literature use similar information. Moreover, even though BankFocus have some of the regulatory ratios, these ratios will be avoided because their way of computation had changed through time and even between banks; in other words, it is not available on a consistent basis. Additionally, regulatory ratios present significant gaps in the sample.

From the 58 variables found in the literature, only 37 are analyzed in this study since the remaining have not enough data available or are not considered consistent throughout the whole period, namely the variables associated with sensitivity to market risk (S), not considered below. Table 4 describes the accounting variables analyzed and the authors that use them. Note that, in the literature, sometimes the same ratio is attributed to a different CAMELS element. Hence, the present classification is to some extent subjective. The accounting data were collected from BankFocus on a yearly basis.

From BankFocus were additionally collected the market monthly data. Monthly stock returns (computed using price logs) are expected to have a negative relation with the probability of distress event [17, 39, 60]. Monthly turnover, that is computed as the number of shares traded during a month divided by the total number of shares in that month, is a proxy of the flow of information. Therefore, the trading volume should rise as the information about financial distress is released, so distress event is expected to be anticipated by an increase in the turnover variable [3, 5]. Moreover, variables composed of both market and accounting information were analyzed, including market-to-book of equity [3, 15], market-to-book of assets [3], and stock price-to-earnings [5]. These variables allow the detection of divergences between market and accounting assessments.

Table 3 Summary of accounting statistics of distressed and non-distressed banks from 2007 to 2019

	Distressed banks	Non-distressed banks
Total assets (000 €)	192,328.6	82,250.59
Net loans to total assets (%)	58.37	59.15
Liquid assets to total assets (%)	25.47	27.60
Total capital ratio (%)	15.99	19.60
ROA (%)	– 0.29	0.55
Loan loss reserves to gross loans (%)	7.72	4.49
Non-performing loans to gross loans (%)	13.15	7.65
Impaired loans (000 €)	7268.23	2119.22

Units are indicated in front of the indicators between parentheses. First, was computed the average of each variable per bank during the period 2007–2019. Then, banks were distributed into the distressed and non-distressed category and the average of each group was computed

Table 4 Accounting early warning indicators

Name	Description	Literature reference
Panel A: Capital variables		
Total capital ratio	Total equity/risk-weighted assets	Chiaramonte and Casu [14], Cleary and Hebb [23], Climenta et al. [56], Distinguin et al. [17], Jing and Fang [57], Otker and Podpiera [58] and Poghosyan and Cihak [7]
Equity-to-assets	Equity/total assets	Arena [12], Curry et al. [3], Distinguin et al. [17], Ötker-Robe and Podpiera [33], Parrado-Martinez et al. [59] and Sironi [15]
Equity-to-net loans*	Equity/net loans	Arena [12] and Jing and Fang [57]
Equity-to-gross loans*	Equity/gross loans	Distinguin et al. [17]
Equity-to- dep. and st term funding	Equity/deposits and short-term funding	Climenta et al. [56] and Distinguin et al. [17]
Equity-to-liabilities	Equity/liabilities	Climenta et al. [56] and Distinguin et al. [17]
Capital funds-to-assets	(Equity + debt)/total assets	Climenta et al. [56] and Distinguin et al. [17]
Capital funds-to-gross loans*	(Equity + debt)/gross loans	Distinguin et al. [17]
Panel B: Asset quality variables		
Impaired loans-to-equity	Impaired loans/equity	Betz et al. [13]
Non perf. loans-to-gross loans	Non-performing loans/total gross loans	Chiaramonte and Casu [14], Parrado-Martinez et al. [59] and Poghosyan and Cihak [7]
Loan loss res.-to- non perf. loans	Loans loss reserves/non-performing loans	Ötker-Robe and Podpiera [33]
Coverage ratio*	Loans loss reserves/impaired loans	Betz et al. [13] and Parrado-Martinez et al. [59]
Loan loss res.-to-gross loans	Loans loss reserves/gross loans	Climenta et al. [56], Cole and White [9] and Distinguin et al. [17]
Loan loss res.-to- total loans*	Loans loss reserves/total loans	Arena [12], Ötker-Robe and Podpiera [33] and Sironi [15]
Loan loss res.-to-assets*	Loan-loss-reserves/assets	Avino et al. [60], Betz et al. [13], Cole and White [9], Curry et al. [3] and Milne [61]
Loan loss res.-to-interest revenue	Loan loss reserves/net interest revenue	Climenta et al. [56] and Distinguin et al. [17]
ROA	Net income/total assets	Betz et al. [13], Cleary and Hebb [23], Cole and White [9], Curry et al. [3], Distinguin et al. [17], Jing and Fang [57], Ötker-Robe and Podpiera [33], Parrado-Martinez et al. [59] and Sironi [15]
ROAA	Net income/average assets	Chiaramonte and Casu [14], Climenta et al. [56] and Krainer and Lopez [45]
Past due loans*	Past due loans(> 90 days)/total assets	Curry et al. [3] and Jing and Fang [57]
Loans-to-assets*	Total loans/total assets	Arena [12] and Climenta et al. [56]
Panel C: Management variables		
ROE	Net income/equity	Betz et al. [13], Distinguin et al. [17], Ötker-Robe and Podpiera [33], Parrado-Martinez et al. [59] and Poghosyan and Cihak [7]
ROAE	Net income/average equity	Avino et al. [60], Climenta et al. [56] and Milne [61]
Cost to income ratio	Loans/deposit ratio	Betz et al. [13], Chiaramonte and Casu [14], Climenta et al. [56], Filippopoulou et al. [25], Milne [61], Ötker-Robe and Podpiera [33] and Poghosyan and Cihak [7]
Operating expenses-to- revenues*	Operating expenses/operating revenues	Ötker-Robe and Podpiera [33]
Noninterest expenses-to-total assets	Noninterest expenses/total aveg. assets	Climenta et al. [56] and Jing and Fang [57]
Net interest income ratio*	Net interest income/operational revenue	Betz et al. [13], Jing and Fang [57] and Ötker-Robe and Podpiera [33]
Panel D: Earning variables		
Net interest margin		Climenta et al. [56]
Net interest-to-assets*	Net interest revenue/total assets	Climenta et al. [56], Distinguin et al. [17] and Jing and Fang [57]
Panel E: Liquidity variables		
Liquidity ratio	Liquid assets/total assets	Arena [12], Avino et al. [60], Curry et al. [3], Jing and Fang [57], Ötker-Robe and Podpiera [33] and Parrado-Martinez et al. [59]

Table 4 (continued)

Name	Description	Literature reference
Liquid assets-to- dep. and st funding	Liquid assets /customer(deposits) and short term funding	Climenta et al. [56], Distinguin et al. [17], Filippopoulou et al. [25] and Sironi [15]
Liquid assets-to-dep. and borrowings	Liquid assets/total deposits and borrowings	Climenta et al. [56] and Distinguin et al. [17]
NCO-to-gross Loans	Net charge offs/gross loans	Cleary and Hebb [23]
St funding-to-total liabilities*	Short term funding/total liabilities	Betz et al. [13], Filippopoulou et al. [25] and Ötker-Robe and Podpiera [33]
Interbank ratio	Interbank assets/interbank liabilities	Climenta et al. [56] and Distinguin et al. [17]
Net loans-to-total assets	Net loans/total assets	Cleary and Hebb [23] and Climenta et al. [56]
Net loans-to-dep. and st funding	Net loans/deposits and short term funding	Cleary and Hebb [23] and Climenta et al. [56]
Net loans-to-dep. and borrowings	Net loans/deposits and borrowings	Climenta et al. [56]

*Variable is calculated using data extracted from BankFocus

Methodology

Model specification

This paper will use a binary-dependent variable DIS, which assumes the value one if there is a distress event and zero otherwise. Similar to previous studies, logit regression will be used to estimate the probability of distress as a function of lagged explanatory variables, as Eq. 1 shows [7, 9, 17].

$$\mathrm{Log}\left(\frac{\mathrm{DIS}=1|X_i}{\mathrm{DIS}=0|X_i}\right)_{\mathrm{B,T}} = f(x_i) = \mathrm{Intercept} + \beta_i \mathrm{Early\ warning\ indicators}_{\mathrm{B,T-1}} + \varepsilon_{\mathrm{B,T-1}} \quad (1)$$

A simple logit model assumes independence of errors across individual banks and through time. Nevertheless, in the present study, this assumption is likely to be violated. Failing to acknowledge this dependence of errors leads to downward-biased estimations of the standard errors of the coefficients. To account for the dependence of errors within banks, the heteroskedasticity robust variance–covariance matrix will be used, similar to Poghosyan and Cihak [7] and Distinguin et al. [17].

Further, as argued by Curry et al. [10], there is a synchronization issue that must be addressed, since the market and accounting information are not available at the same time. The present research will follow the approach of Distinguin et al. [17]. Starting from the disclosure date of accounting information, 31 December for European banks, this study will use the market information respective to before or at the same time as the accounting information. This approach focus is to analyze if, even when the market information is not closer than the accounting information, it adds values to the accounting one. The market variables mentioned above will be analyzed as one month (December), quarterly (average of the monthly variable from October to December), half-year (average of the monthly variable from July to December), yearly, and two years previous the prediction date. Hence, market signals will be tested over different horizons.

Finance theory indicates many accounting and market variables that may contain relevant information to assess a bank's financial health. As mentioned, the control variable that will be used is the total amount of assets. Total asset is a measure of bank size which is a proxy of systemic importance. Moreover, in this paper, several explanatory variables will be analyzed to construct the most powerful model. Similar to Curry et al. [10] and Distinguin et al. [17], a logistic univariate analysis will be conducted to assess the relevance of both accounting and market variables, as Eq. 2 shows.

$$\mathrm{DIS}_{\mathrm{T}} = \mathrm{intercept} + \beta\ \mathrm{Accounting}_{\mathrm{T-1}} \quad (2)$$

First, accounting variables are individually evaluated using the univariate analysis, and the most relevant variable among the ones with similar information is kept. Afterward, an optimal accounting-based model will be constructed using a stepwise approach. Next, market variables will be individually examined using the same process. Finally, the most relevant market variables will be used to extend the accounting model. The goal is to obtain a model similar to Eq. 3 in which distress and non-distress banks are analyzed simultaneously. Curry et al. [10] argue that this approach reduces the potential spurious result caused by different macroeconomic environments. Additionally, it helps to deal with the reduced number of distress events. The dependent variable, $\mathrm{DIS}_{\mathrm{B,T}}$, is considered for each bank (B) and year (T). It is taken into consideration accounting and market information at the previous year (T-1).

$$\mathrm{DIS}_{B,T} = \mathrm{Intercept} + \beta\mathrm{Control\ variable}_{B,T-1} + \beta\mathrm{Accounting}_{B,T-1} + \beta\mathrm{Market}_{B,T-1} + \varepsilon_{B,T-1} \tag{3}$$

Several criteria will be used to compare and assess the most superior model in the stepwise approach, namely, McFadden's R-squared, also known as pseudo-R-squared, the Akaike information criterion (AIC) and the likelihood ratio (LR). These indicators are used by several authors in the literature including Curry et al. [10], Poghosyan and Cihak [7], and Cleary and Hebb [23].

Results

Accounting model

Each of the 37 accounting variables will be individually analyzed, starting with a simple univariate analysis as Eq. 2 shows.

Table 5 shows the output from the univariate analysis to the accounting indicators. From the analysis of the capital measures, the results show that total capital ratio, equity-to-assets, and both ratios using capital funds ratio as numerator present p-values equal to zero. Moving to the capital adequacy proxies, just loan loss reserves-to-total loans, loan loss reserves-to-interest revenue and loans-to-assets are irrelevant. Concerning the management variables only cost to income ratio suggests some importance, but it is low. Further, for the earnings profile component, non-interest expenses-to-total assets and net interest income ratio present a p-value lower than 5%, and there is no other relevant variable. Finally, in the liquidity indicators, liquid assets to deposits and short-term fundings present the lowest p-value followed by liquid assets to deposits and borrowings. It should be emphasized that Chiaramonte and Casu [14] concluded that liquidity is relevant, contrasting to other results using older data that did not found liquidity proxies significant [7, 21–23].

As can be seen in Table 5, the results indicate that the p-value of 14 accounting variables is less than 1%, six have it between 1 and 5%, and three variables have it between 5 and 10%. Hence, in total, there are 23 significant accounting variables for the sample used. To help to guide the following stepwise approach, each relevant indicator is classified as one of the CAMEL elements.

In the literature, the capital, asset quality, and earnings proxies are critical to predictive distress and failure events [7, 21–23]. Similarly, in this paper most of the relevant variables (65%) are capital and asset quality proxies. The liquidity component is the third more represented CAMEL component.

To construct the optimal accounting model, it will be used a stepwise approach, analyzing in each model the McFadden's R-squared, the AIC, and the LR. Similar to Männasoo and Mayes [24], this study will not consider management variables due to the low relevance observed in the univariate analysis. However, for theoretical reasons, it aims to keep at least one variable from each of the remaining CAMEL components. Before constructing models, variables are analyzed to exclude ratios that contains the same information.

For the capital component total capital ratio, equity-to-assets, and both ratios using capital funds ratio as numerator seem the best variables in the univariate analysis. Further, equity-to-deposits and short-term funding and equity-to-liabilities also present a very low p-value; therefore, these six variables will be inspected.

Considering the capital adequacy ratios, loan loss reserves-to-gross loans is the ratio with the loan loss reserves numerator that presents more significance. Moreover, impaired-to-assets and ROA are significant at 99% confidence level, leading to disregard coverage ratio and ROAA since they are similar to the firsts mentioned. Past due loans is excluded since the number of observations is lower (minus almost 1000 observations than the average of the other observations). Lastly, to incorporate a ratio with non-performing loans, the univariate analysis shows that the non-performing loans to gross loans are preferable compared to loan loss reserves to non-performing loans.

Regarding the earning component, the noninterest expenses-to-total assets and net interest income ratio will be analyzed since they are the only relevant variables of this component. Concerning the liquidity variables, this paper will consider liquid assets to deposits and short-term fundings and liquid assets to deposits and borrowings since they are the two variables with the best performance in the univariate analysis with similar information.

Among the selected fourteen variables, some are expected to be correlated, and consequently, their combined use is expected to create multicollinearity problems in the multivariate model.

As Table 6 shows, a model with all the 14 variables does not perform well since many variables appear insignificant. Since the variables in the capital component are strongly correlated, models with only one capital variable included are estimated. Analyzing McFadden's R-squared and AIC measure, it is observed that when the capital funds-to-assets variable is used, the model is superior compared to the alternatives (Model 2). Through a series of regressions, it is observed that maintaining only non-performing loans-to-gross loans is better in terms of McFadden's R-squared and AIC measure than have all the capital adequacy variables

Table 5 Univariate analysis of accounting early indicators from 2007 to 2019

Panel A	C—Capital variables								A—Asset quality variables				
	Total capital ratio	Equity-to-assets	Equity-to-net loans	Equity-to-gross loans	Equity-to-dep. and st funding	Equity-to-liabilities	Capital funds-to-assets	Capital funds-to-gross loans	Impaired loans-to-equity	Non perf. loans-to-gross loans	Loan loss res.-to-non perf. loans	Coverage ratio	Loan loss res.-to-gross loans
Coefficient	− 0.233	− 0.055	− 0.014	− 0.018	− 0.006	− 0.072	− 0.239	− 0.201	0.002	0.025	− 0.013	− 1.300	0.034
p-value	0.000***	0.000***	0.283	0.315	0.002***	0.002***	0.000***	0.000***	0.005***	0.003***	0.008***	0.008***	0.000***
McFadden R-squared	0.099	0.028	0.012	0.014	0.013	0.036	0.075	0.111	0.029	0.022	0.015	0.015	0.013
S.D. dependent var	0.157	0.152	0.155	0.155	0.153	0.152	0.142	0.142	0.157	0.157	0.158	0.158	0.157
Akaike info criterion	0.215	0.219	0.230	0.229	0.226	0.217	0.189	0.182	0.231	0.234	0.236	0.236	0.236
Schwarz criterion	0.221	0.224	0.235	0.235	0.231	0.222	0.197	0.190	0.237	0.240	0.242	0.242	0.241
Hannan-Quinn criterion	0.217	0.221	0.232	0.231	0.227	0.219	0.192	0.185	0.233	0.236	0.238	0.238	0.238
Prob(LR statistic)	0.000	0.000	0.016	0.010	0.014	0.000	0.000	0.000	0.000	0.002	0.009	0.009	0.012
Dep = 1	48	51	51	51	51	51	27	27	48	48	48	48	51
Dep = 0	1844	2113	2026	2026	2073	2113	1281	1281	1850	1841	1837	1837	1956

Panel B	A—Asset quality variables (cont.)							M—Management variables					
	Loan loss res.-to-total loans	Loan loss res.-to-assets	Loan loss res.-to-interest revenue	ROA	ROAA	Past due loans	Loans-to-assets	ROE	ROAE	Cost to income ratio	Operating expenses-to-revenues	Noninterest expenses-to-total assets	Net interest income ratio
Coefficient	0.072	1.244	0.001	− 0.025	− 0.031	0.000	0.897	− 0.002	− 0.002	0.001	0.002	− 0.024	0.322
p-value	0.248	0.027**	0.196	0.007***	0.026**	0.016**	0.144	0.239	0.226	0.075*	0.728	0.045**	0.039**
McFadden R-squared	0.000	0.004	0.000	0.005	0.006	0.007	0.003	0.001	0.002	0.003	0.000	0.002	0.002
S.D. dependent var	0.157	0.157	0.157	0.152	0.152	0.159	0.155	0.152	0.152	0.152	0.152	0.152	0.152
Akaike info criterion	0.239	0.238	0.239	0.225	0.224	0.243	0.232	0.225	0.225	0.226	0.226	0.225	0.226
Schwarz criterion	0.244	0.243	0.244	0.230	0.230	0.251	0.237	0.231	0.231	0.231	0.231	0.230	0.231
Hannan-Quinn criterion	0.241	0.240	0.241	0.226	0.226	0.246	0.234	0.227	0.227	0.228	0.227	0.227	0.228

Table 5 (continued)

Panel B	A—Asset quality variables (cont.)							M—Management variables					
	Loan loss res.-to-total loans	Loan loss res.-to-assets	Loan loss res.-to-interest revenue	ROA	ROAA	Past due loans	Loans-to-assets	ROE	ROAE	Cost to income ratio	Operating expenses-to-revenues	Noninterest expenses-to-total assets	Net interest income ratio
Prob(LR statistic)	0.758	0.144	0.737	0.126	0.081	0.142	0.229	0.395	0.389	0.269	0.936	0.276	0.309
Dep = 1	51	51	51	51	51	35	51	51	51	51	51	51	51
Dep = 0	1956	1956	1956	2106	2106	1309	2026	2106	2106	2096	2107	2107	2099
Panel C	E—Earning variables		L—Liquidity variables										
	Net interest margin	Net interest-to-assets	Liquidity ratio	Liquid assets-to-dep. and st funding	Liquid assets-to-dep. and borrowings	NCO-to-gross loans	St funding-to-total liabilities	Interbank ratio	Net loans-to-total assets	Net loans-to-dep. and St term funding	Net loans-to-dep. and borrowings		
Coefficient	− 0.017	− 7.056	− 0.017	− 0.048	− 0.058	− 0.027	1.860	0.000	0.009	− 0.004	− 0.001		
p-value	0.223	0.216	0.065*	0.000***	0.000***	0.625	0.017**	0.457	0.144	0.074*	0.606		
McFadden R-squared	0.001	0.001	0.006	0.063	0.058	0.000	0.012	0.001	0.003	0.004	0.001		
S.D. dependent var	0.152	0.152	0.152	0.153	0.154	0.161	0.153	0.155	0.155	0.155	0.156		
Akaike info criterion	0.226	0.226	0.224	0.214	0.218	0.247	0.226	0.233	0.232	0.232	0.236		
Schwarz criterion	0.231	0.231	0.229	0.219	0.223	0.254	0.231	0.239	0.237	0.238	0.242		
Hannan-Quinn criterion	0.228	0.228	0.226	0.216	0.220	0.250	0.228	0.236	0.234	0.234	0.238		
Prob(LR statistic)	0.616	0.411	0.081	0.000	0.000	0.672	0.015	0.477	0.229	0.162	0.574		
Dep = 1	51	51	51	51	50	44	51	48	51	51	50		
Dep = 0	2098	2099	2113	2073	2000	1614	2073	1895	2026	2016	1942		

*, **, ***Means the value is significant at 10%, 5%, and 1%, respectively. Huber White estimation was used

Table 6 Multivariate logistic models—accounting model

	Model 1	Model2	Model 3	Model 4	Model 5
Intercept	− 4.956	− 5.750	− 5.438	− 4.592	− 4.801
	(0.068)*	(0.019)**	(0.022)**	(0.054)*	(0.048)**
log(assets)	0.228	0.278	0.249	0.222	0.236
	(0.106)	(0.039)**	(0.060)*	(0.101)	(0.083)*
Total capital ratio	− 0.067				
	(0.490)				
Equity-to-assets	1.634				
	(0.451)				
Equity-to-dep. and st funding	− 0.036				
	(0.860)				
Equity-to-liabilities	− 1.497				
	(0.454)				
Capital funds-to-assets	0.068	− 0.202	− 0.191	− 0.202	− 0.207
	(0.824)	(0.040)**	(0.001)***	(0.001)***	(0.001)***
Capital funds-to-gross loans	− 0.060				
	(0.583)				
Loan loss res.-to-gross loans	− 0.0251	− 0.041			
	(0.639)	(0.474)			
Impaired loans-to-equity	0.000	0.001			
	(0.724)	(0.076)*			
ROA	− 0.156	− 0.098			
	(0.457)	(0.573)			
Non perf. loans-to-gross loans	0.063	0.069	0.066	0.075	0.073
	(0.014)**	(0.005)***	(0.000)***	(0.000)***	(0.000)***
Noninterest expenses-to-total assets	0.099	0.147	0.145		
	(0.713)	(0.329)	(0.117)		
Net interest income ratio	− 0.966	− 0.961	− 0.996	− 0.913	− 0.975
	(0.183)	(0.045)**	(0.0290)**	(0.047)**	(0.035)**
Liquid assets-to-dep. and st funding	− 0.013	− 0.038	− 0.029	− 0.037	− 0.058
	(0.881)	(0.421)	(0.508)	(0.419)	(0.001)***
Liquid assets-to-dep. and borrowings	− 0.050	− 0.032	− 0.041	− 0.031	
	(0.650)	(0.654)	(0.541)	(0.656)	
McFadden R-squared	0.2748	0.2704	0.2500	0.2449	0.2440
Akaike info criterion	0.1711	0.1655	0.1644	0.1638	0.1624
Prob(LR statistic)	0.0000	0.0000	0.0000	0.0000	0.0000
Obs with Dep = 0	1157	1221	1225	1225	1225
Obs with Dep = 1	24	26	26	26	26

Each column presents the estimated coefficient for the respective explanatory variable, followed by the correspondent *p* value under brackets below it. *, **, ***means the value is significant at 10%, 5%, and 1%, respectively. Huber White estimation was used

(Model 3). Further, the AIC measure improves if noninterest expenses-to-total assets is dropped (Model 4). Finally, in terms of liquidity variables, using only liquid assets-to-deposits and short-term funding improves the model (Model 5).

From Models 1 to 5, AIC decreases, indicating that Model 5 is superior. Even though McFadden's R-squared decreases, given that this indicator does not take into account the number of parameters used, AIC is considered a better criterion to select the optimal accounting model. Similar to studies mentioned in the literature review, the results suggest that few accounting ratios can fit the data relatively well. In this case, capital funds-to-assets, non-performing loans-to-gross loans, net interest income ratio, and liquid assets-to-deposits and short-term borrowings. Note that a more recent paper, Chiaramonte and Casu [14] concluded that liquidity is relevant, in contrast to many

Table 7 Univariate analysis of market early indicators

	Return last month	Return last quarter	Return last half-year	Return last year	Return last two years	Turnover last month	Turnover last quarter	Turnover last half-year	Turnover last year	Turnover last two years	Book to market Equity	Earnings per share
Coefficient	− 2.670	− 5.332	− 12.535	− 15.670	− 22.648	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p value	0.001***	0.000***	0.000***	0.000***	0.000***	0.487	0.320	0.319	0.382	0.225	0.031**	0.004***
McFadden R-squared	0.016	0.056	0.111	0.114	0.141	0.000	0.001	0.001	0.001	0.001	0.011	0.021
S.D. dependent var	0.158	0.159	0.160	0.158	0.146	0.159	0.162	0.164	0.166	0.166	0.147	0.147
Akaike info criterion	0.236	0.230	0.217	0.214	0.183	0.244	0.249	0.254	0.259	0.260	0.212	0.211
Schwarz criterion	0.241	0.235	0.223	0.219	0.190	0.249	0.254	0.259	0.265	0.266	0.219	0.217
Hannan–Quinn criterion	0.238	0.232	0.219	0.216	0.186	0.245	0.251	0.256	0.261	0.262	0.215	0.213
Prob(LR statistic)	0.003	0.000	0.000	0.000	0.000	0.660	0.570	0.540	0.566	0.428	0.040	0.005
Dep = 1	58	58	57	51	38	58	58	58	57	50	39	39
Dep = 0	2206	2166	2120	1933	1697	2164	2105	2049	1961	1714	1722	1715

*, **, ***Mean the value is significant at 10%, 5%, and 1%, respectively. Huber White estimation was used. Turnover = Trading shares/Number of shares

articles using older data that did not found liquidity proxies significant [7, 21–23].

Extended model

Each of the market variables is individually analyzed through a univariate analysis, as illustrated by Eq. 2 previously presented, and Table 7 presents the results obtained. Observing the p-value, it is possible to conclude that all return variables tested are significant. Additionally, it is noted that the returns of half-year and longer periods present higher coefficients, higher McFadden R-squared, and lower AIC. Further, measures containing both accounting and market information—book-to-market of equity, and earnings per share—seem to be important to explain bank distress. In contrast, the results suggest that turnover indicators for several periods are irrelevant to predict distress events. The results obtained are similar to the ones of Curry et al. [10].

Table 8 reveals the results of the extended models. Compared to the optimal accounting model (Model 5), it is possible to observe that all the extended models represented have higher McFadden R-squared and lower AIC, indicating that extended models are superior. Model I includes all the market variables mentioned above. It is possible to see that few variables are relevant in Model I, meaning that the coefficients have high standard deviations. Further, the variable last year's return presents an unexpected positive signal, and turnover of last month, turnover of last quarter, and turnover of last year present an unexpected negative signal. Additionally, book-to-market equity also presents a negative signal. These unanticipated results may be due to the high standard deviation of coefficients.

A predictive model containing variables with high standard deviations tends to be very sample dependent, which means it is not robust and not useful for the purpose under study. Hence, market variables with a high p-value are dropped. Finally, Model III, which only includes the market variable last half-year return, is superior compared to the optimal accounting model found in the previous section.

Moreover, Table 8 shows that the intercept decreases; in other words, the remaining probability of bank distress after controlling for the impact of the mention variables is not significant considering a 90% confidence level. The control variable, the logarithm of total assets, becomes irrelevant as it does capital funds to assets.

To conclude, for the purposes of this study more than compare the predictive power with previous studies, the relevance is to analyze the differences between the accounting (Model 5) and the extended model (Model III). Given the higher McFadden R-squared and lower AIC in Model III, the results suggest that including market information can significantly add value to accounting-based monitoring models, thus supporting Hypothesis I of this research. These results are coherent with previous literature (e.g., [10, 28, 36]).

Robustness test

To test if the extended model has more predictive power after the strengthening of Pillar 3 information requirements is necessary to evaluate the model's performance before and after. Based on Progress Reports of Basel Committee on Banking Supervision [62] and the EBA Pilar 3 reports [53], it is possible to consider 2013 as the first year with the implementation of the disclosure information requirements.

To assess if a higher information disclosure conducts to a higher ability of market signals to foreseen bank distress events, we will compare the result from the univariate and multivariate logit analysis in two periods (2007–2012 and 2013–2020). Table 9 contains a summary of the univariate analysis of the accounting variables.

Overall, more variables are significant in 2013–19 than in 2007–12 (81% compared to 30%, respectively). The capital indicators are all significant with a 90% confidence level in the most recent period; nevertheless, in 2007–2012 only total capital ratio, capital funds to assets and capital funds to gross loans are relevant. Regarding the capital adequacy component, only ROA and ROAA are significant for the two periods considered. Further, loan loss reserves to interest revenue, ROA and ROAA are more relevant in 2007–2012. Cost to income is the only important management variable in both periods, and interestingly, all the management variables are relevant in the most recent period. Finally, regarding the liquidity measures, liquid assets to deposits and short-term funding and liquid assets to total deposits and borrowings have a p-value lower than 1% in both periods. Additionally, the liquidity ratio, short-term funding to total funding, and net loans to deposits and borrowings have a lower p-value in 2013–2020, compared to the previous period.

Note that in the more recent period, Europe has experienced a low-interest rates environment. Consequently, the interest margin in banks has decreased pressuring banks to change their business model. Therefore, an earning variable based on fees and commissions might become more relevant in the future. The results show that no earning variable is considered important in both periods. In 2007–2012 only operating expenses to total revenues are significant, and in 2013–2020 only noninterest expenses to total assets and net interest ratio are relevant.

In Table 10, it is possible to observe the univariate analysis of the market variables. For both periods, all the return measures are significant, but in 2013–2020 all have p-value equal to zero. For the period 2008–2012, there is no relevant turnover indicator; nonetheless, in the most recent period,

Table 8 Multivariate logistic models—Extended model

	Model 5	Model I	Model II	Model III
Intercept	− 4.801	− 4.410	0.603	− 1.008
	(0.048)**	(0.613)	(0.877)	(0.787)
log(assets)	0.236	0.267	0.032	0.090
	(0.08)*	(0.557)	(0.866)	(0.622)
Capital funds-to-assets	− 0.207	− 0.023	− 0.187	− 0.145
	(0.001)***	(0.920)	(0.199)	(0.104)
Non perf. Loans-to-gross loans	0.073*	0.077	0.067	0.081
	(0.000)***	(0.005)***	(0.014)**	(0.001)***
Net interest income ratio	− 0.975	− 7.610	− 5.524	− 5.747
	(0.035)**	(0.096)*	(0.059)*	(0.032)**
Liquid assets-to-dep. and st funding	− 0.058	− 0.075**	− 0.070	− 0.059
	(0.001)***	(0.026)	(0.002)***	(0.001)***
Return last month		− 1.309		
		(0.774)		
Return last quarter		− 0.331		
		(0.963)		
Return last half-year		− 28.376	− 22.160	− 17.691
		(0.029)**	(0.000)***	(0.000)***
Return last year		15.703		
		(0.355)		
Return last two years		− 12.225		
		(0.120)		
Turnover last month		− 0.000		
		(0.999)		
Turnover last quarter		− 0.009		
		(0.566)		
Turnover last half-year		0.012		
		(0.288)		
Turnover last year		− 0.007		
		(0.002)***		
Turnover last two years		0.001	− 0.000	
		(0.003)***	(0.910)	
Book to market equity		− 0.000	0.000	
		(0.860)	(0.816)	
Earnings per share		− 0.000	− 0.000	
		(0.406)	(0.967)	
McFadden R-squared	0.2440	0.5066	0.4065	0.3767
Akaike info criterion	0.1624	0.1162	0.1268	0.1146
Prob(LR statistic)	0.0000	0.0000	0.0000	0.0000
Obs with Dep = 0	1225	792	807	948
Obs with Dep = 1	26	11	14	15

Model 5 represents the best accounting model found in the previous step. Model I, II, and III include market variables. Each column presents the estimated coefficient for the respective explanatory variable, followed by the correspondent *p* value under brackets below it. *, **, ***Means the value is significant at 10%, 5%, and 1%, respectively. Huber White estimation was used

turnover of last month and turnover of the last year present a p-value lower than 10%. Lastly, book-to-market of equity ratio and earnings per share are relevant in 2008–2012 but not in 2013–2020.

Analyzing the model performance output in Table 11, it is possible to conclude that both the extended and the accounting model perform better in the most recent period (Model 5.2 and Model III.2), with an AIC of 0.085 compared to 0.111, respectively. However, notice that in the

Table 9 Univariate analysis of accounting variables: 2007–12 and 2013–20

		2007–2020		2007–2012		2013–2020	
		Coefficient	*p* value	Coefficient	*p* value	Coefficient	*p* value
C	Total capital ratio	− 0.233	0.000***	− 0.213	0.004***	− 0.212	0.000***
	Equity-to-assets	− 0.055	0.000***	− 0.086	0.390	− 0.051	0.000***
	Equity-to-net loans	− 0.014	0.283	− 0.003	0.558	− 0.025	0.000***
	Equity-to-gross loans	− 0.018	0.315	− 0.003	0.593	− 0.035	0.072*
	Equity-to-dep. and st funding	− 0.006	0.002***	− 0.049	0.558	− 0.006	0.001***
	Equity-to-liabilities	− 0.072	0.002***	− 0.047	0.579	− 0.073	0.000***
	Capital funds-to-assets	− 0.239	0.000***	− 0.266	0.001***	− 0.164	0.002***
	Capital funds-to-gross loans	− 0.201	0.000***	− 0.191	0.000***	− 0.176	0.000***
A	Impaired loans-to-equity	0.002	0.005***	0.002	0.259	0.002	0.006***
	Non perf. loans-to-gross loans	0.025	0.003***	0.026	0.139	0.028	0.006***
	Loan loss res.-to-non perf. loans	− 0.013	0.008***	− 0.004	0.196	− 0.022	0.002***
	Coverage ratio	− 1.300	0.008***	− 0.307	0.426	− 2.160	0.002***
	Loan loss res.-to-gross loans	0.034	0.000***	0.038	0.138	0.040	0.000***
	Loan loss res.-to-total loans	0.072	0.248	1.733	0.246	0.097	0.120
	Loan loss res.-to-assets	1.244	0.027**	3.850	0.209	1.403	0.016**
	Loan loss res.-to-interest revenue	0.001	0.196	0.186	0.024**	0.002	0.109
	ROA	− 0.025	0.007***	− 0.261	0.001***	− 0.021	0.005***
	ROAA	− 0.031	0.026**	− 0.260	0.001***	− 0.026	0.009***
	Past due loans	0.000	0.016**	0.000	0.264	0.000	0.015**
	Loans-to-assets	0.897	0.144	− 0.626	0.507	2.365	0.000***
M	ROE	− 0.002	0.239	0.000	0.635	− 0.002	0.006***
	ROAE	− 0.002	0.226	0.000	0.769	− 0.002	0.019**
	Cost to income ratio	0.001	0.075*	0.006	0.000***	0.001	0.080*
	Operating expenses-to-revenues	0.002	0.728	0.619	0.000***	0.000	0.970
	Noninterest expenses-to-total assets	− 0.024	0.045**	0.004	0.892	− 0.029	0.014**
	Net interest income ratio	0.322	0.039**	− 0.181	0.800	0.387	0.014**
E	Net interest margin	− 0.017	0.223	− 0.097	0.162	− 0.010	0.418
	Net interest-to-assets	− 7.056	0.216	− 26.414	0.154	− 4.175	0.452
L	Liquidity ratio	− 0.017	0.065*	0.003	0.820	− 0.033	0.003***
	Liquid assets-to-dep. and st funding	− 0.048	0.000***	− 0.051	0.006***	− 0.047	0.001***
	Liquid assets-to-dep. and borrowings	− 0.058	0.000***	− 0.080	0.005***	− 0.050	0.005***
	NCO-to-gross loans	− 0.027	0.625	0.134	0.730	− 0.053	0.373
	St funding-to-total liabilities	1.860	0.017**	0.326	0.735	3.783	0.004***
	Interbank ratio	0.000	0.457	− 0.009	0.020**	0.000	0.417
	Net loans-to-total assets	0.009	0.144	− 0.006	0.507	0.024	0.000***
	Net loans-to-dep. and St term funding	− 0.004	0.074*	− 0.005	0.390	− 0.004	0.050*
	Net loans-to-dep. and borrowings	− 0.001	0.606	− 0.007	0.433	0.000	0.020**

*, **, ***Means the value is significant at 10%, 5%, and 1%, respectively

period 2007–2012 the differences between the extended and accounting model are less noticeable, with an AIC of 0.336 compared to 0.344, respectively.

The results presented in this section support Hypothesis II of this research, the market variable has more predictive power after the implementation of Pillar 3 information requirements. This is observed not only by the univariate analysis but also through the higher superiority of the extended model compared to the accounting model in the most recent period considering the AIC and the McFadden R-squared.

Conclusion

A stable banking system is crucial to the stability of the overall economy; thus, having adequate bank monitoring models is important. The results of this study are essential

Table 10 Univariate analysis of market variables: 2007–2012 and 2013–2019

	Return last month	Return last quarter	Return last half-year	Return last year	Return last two years	Turnover last month	Turnover last quarter	Turnover last half-year	Turnover last year	Turnover last two years	Book to market Equity	Earnings per share
Panel A: Period 2007–2012												
Coefficient	− 2.610	− 7.118	− 10.323	− 10.050	− 15.252	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p value	0.054*	0.000***	0.000***	0.025**	0.048**	0.314	0.162	0.167	0.206	0.140	0.001***	0.000***
McFadden R-squared	0.012	0.060	0.073	0.067	0.051	0.002	0.004	0.004	0.004	0.008	0.048	0.050
S.D. dependent var	0.213	0.216	0.216	0.221	0.197	0.217	0.221	0.224	0.226	0.233	0.231	0.232
Akaike info criterion	0.384	0.373	0.369	0.386	0.331	0.399	0.409	0.419	0.425	0.445	0.428	0.429
Schwarz criterion	0.397	0.386	0.382	0.402	0.352	0.412	0.422	0.433	0.440	0.463	0.455	0.456
Hannan-Quinn criterion	0.389	0.378	0.374	0.392	0.339	0.404	0.414	0.424	0.431	0.452	0.439	0.439
Prob(LR statistic)	0.062	0.000	0.000	0.000	0.009	0.455	0.314	0.308	0.334	0.190	0.019	0.017
Dep = 1	35	35	34	28	16	35	35	35	34	28	15	15
Dep = 0	699	679	659	515	380	671	648	625	595	458	251	250
Panel B: Period 2013–2019												
Coefficient	− 2.865	− 4.109	− 13.298	− 19.018	− 25.123	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p value	0.002***	0.000***	0.000***	0.000***	0.000***	0.087*	0.390	0.152	0.067*	0.625	0.538	0.165
McFadden R-squared	0.023	0.049	0.119	0.134	0.197	0.001	0.000	0.001	0.001	0.000	0.000	0.001
S.D. dependent var	0.122	0.123	0.124	0.125	0.127	0.122	0.124	0.125	0.128	0.130	0.126	0.126
Akaike info criterion	0.155	0.153	0.144	0.145	0.138	0.160	0.163	0.166	0.171	0.177	0.167	0.168
Schwarz criterion	0.162	0.160	0.151	0.152	0.145	0.167	0.170	0.173	0.179	0.185	0.174	0.175
Hannan-Quinn criterion	0.158	0.155	0.146	0.147	0.140	0.162	0.166	0.169	0.174	0.180	0.170	0.170
Prob(LR statistic)	0.012	0.001	0.000	0.000	0.000	0.627	0.791	0.684	0.621	0.870	0.862	0.680
Dep = 1	23	23	23	23	22	23	23	23	23	22	24	24
Dep = 0	1507	1487	1461	1418	1317	1493	1457	1424	1366	1256	1471	1465

*, **, ***Means the value is significant at 10%, 5%, and 1%, respectively. Huber White estimation was used. Turnover = Trading shares/Number of shares

Table 11 Accounting and extended model: 2007–12 and 2013–20

	Model 5.1	Model 5.2	Model III.1	Model III.2
Intercept	− 11.695	− 0.327	− 0.629	0.914
	(0.004)***	(0.922)	(0.884)	(0.879)
log(assets)	0.689	− 0.082	0.113	− 0.014
	(0.004)***	(0.643)	(0.516)	(0.958)
Capital funds-to-assets	− 0.157	− 0.173	− 0.220	− 0.113
	(0.070)*	(0.020)**	(0.278)	(0.323)
Non perf. Loans-to-gross loans	0.051	0.107	0.034	0.104
	(0.101)	(0.000)***	(0.696)	(0.000)***
Net interest income ratio	− 0.668	− 1.582	− 4.064	− 6.732
	(0.553)	(0.016)**	(0.231)	(0.113)
Liquid assets-to-dep. and st funding	− 0.091	− 0.059	− 0.044	− 0.091
	(0.001)***	(0.0865)*	(0.002)***	(0.060)*
Return half-year			− 10.335	− 17.395
			(0.021)**	(0.005)***
McFadden R-squared	0.3103	0.2779	0.2509	0.4460
Akaike info criterion	0.3438	0.1109	0.3358	0.0851
Prob(LR statistic)	0.0000	0.0000	0.0473	0.0000
Obs with Dep = 0	224	1001	149	799
Obs with Dep = 1	13	13	6	9

Model x.1 indicates that is the model x in the first period, from 2007 to 12, and the Model x.2 indicates that is the model x estimation for the period 2013–19

Each column presents the estimated coefficient for the respective explanatory variable, followed by the correspondent *p* value under brackets below it. *,**,***Means the value is significant at 10%, 5% and 1%, respectively. Huber White estimation was used

not only to strengthen the scientific research but also to the development of new bank monitoring models that can better detect distress events. These findings are pertinent to guide regulators in future discussions regarding information disclosure requirements and the introduction of market signals in the banking supervisory process.

A total of 81 distress events in a sample of 248 European banks from 2008 to 2020 were analyzed. Using univariate logistic analysis and a stepwise approach, an accounting model and an extended model were obtained that include market variables. Comparing the two models based on McFadden R-squared and AIC indicator, it is possible to observe that the extended model is superior. These findings suggest that market information adds significant predictive power to accounting-based bank monitoring models during the period analyzed even when the market information is not dated closer to distress event than the accounting information.

Moreover, two periods are analyzed separately, from 2008 to 2012, representing the period before Pillar 3 information requirements implementation, and from 2013 to 2020, being the period after its implementation. First, it is detected interesting trends in the accounting variables. In 2013–2020 all management variables are relevant and the earning indicators using noninterest information become more significant—align with the period of low-interest rates environment. Further, liquidity measures become more relevant.

Second, examining the accounting and extended model performance in both periods, it is possible to conclude that during 2013–2020 the extended model performs better than the accounting model. However, from 2008 to 2012 there are less noticeable differences in the McFadden R-squared and AIC indicator between the two models. These findings suggest that the market variable has more predictive power after the implementation of Pillar 3 information requirements.

This study has a few limitations. First, the classifications of distress events based on state intervention are to some extent subjective. Second, more frequent indicators were not available to most of the banks analyzed to allow a more diverse range of market variables. The use of annual data has limitations in terms of providing supervisors an effective warning mechanism. So, the use of higher frequency data—for instance, quarterly data—would thus be preferable.

Forthcoming studies can establish more objective criteria to classify distress banks and study different market indicators. Future research can also explore the change in the relevance of different accounting variables already detected in this study. Also, with access to more frequent market indicators, a similar analysis studying different time horizons and specific impacts can be conducted.

Namely, the ECB zero interest rate policy or the adoption of the Single Supervisory Mechanism could have influenced the relative contributions of accounting and market variables by changing supervisor's reaction function and/or the information content of banks' financial statements. Additionally, further research could study how state interventions prompted by Covid-19 (especially guarantee lines) impacted banking stability. Finally, a future revision of Pillar 3 is expected to be implemented on 1 January 2023, and consequently, similar studies after that implementation should be conducted.

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