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

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Abstract

Detect bank distress events is one of the major goals of bank supervisors. 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 study 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. Particularly, this research focus on the introduction of the information requirements (Pillar 3) set by the Basel agreements.

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 implementation 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.

JEL-Codes: G21, G28, G33

Resumo

Prever eventos de *distress* nas instituições bancárias é um dos principais objetivos dos supervisores bancários. Num ambiente em constante mudança é essencial reavaliar se os modelos utilizados permanecem eficazes e perceber como melhorá-los. Tradicionalmente, a estabilidade financeira de uma instituição bancária é avaliada com base em rácios contabilísticos, porém, informação derivada do mercado de capitais pode complementar os modelos contabilísticos usados.

O presente estudo procura perceber se a informação proveniente do mercado de capitais pode ajudar supervisores bancários a detetar eventos de *distress* num banco em particular. Adicionalmente, procura avaliar se o poder de previsão dos sinais de mercado aumenta com a transaparência. Especificamente, após a introdução dos requisitos de divulgação de informação (Pillar 3) presentes nos Acordos de Basileia.

Para responder a estas questões, um total de 81 eventos de *distress* de uma amostra de 248 bancos europeus durante o período de 2008 a 2020 foram analisados. Primeiro, uma análise logística univariada foi usada para avaliar a relevância de cada variável contabilística e de mercado. De seguida, foi construído um modelo baseado só em rácios contabilísticos sendo este subsequentemente estendido para incluir as variáveis de mercado mais relevantes.

Os resultados suportam o uso de variáveis de mercado nos modelos de monitorização bancária. Adicionalmente, este estudo encontra evidências que apontam para um aumento do poder de previsão das variáveis de mercado após a introdução dos requisitos de informação no âmbito dos Acordos de Basileia. Em suma, esta dissertação suporta o uso de informação do mercado de capitais para monitorizar bancos sobretudo em mercados transparentes.

Palavras-chave: Falência de bancos; Modelos de monitorização; Avaliação de mercado; Acordos de Basileia.

JEL-Codes: G21, G28, G33

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1. 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 channels funds. If the banking system does not work well it can affect the investments and, consequently, negatively impact economic growth. Additionally, the banking sector's fragility can exacerbate the effects of a crisis. Grossman (1993) estimated that small bank failure can cause a 2% decline in real gross national product and a large bank 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 (2019) 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 and transparency of financial information were required (Curry, Fissel, & Hanweck, 2008; Flannery & Sorescu, 1996; Furlong & Williams, 2006; Jagtiani & Lemieux, 2001; Poghosyan & Cihak, 2011). Precisely, one of the most noteworthy bank regulations, the Basel agreements, have been focusing on enhancing banks' transparency by increasing both the quantity and the quality of the banks' information requirements.

Basel agreements are based on three pillars: minimum capital requirements (Pillar 1), supervisory review (Pillar 2), and market discipline (Pillar 3). Pillar 3 was only introduced in Basel II that was published in 2004. Basel III further structure Pillar 3 with the goal to guarantee that enough information about the bank's operations is disclosed to improve the market participants' ability to make an informed assessment of the bank's financial condition.

Hence, the introduction of Pillar 3 reveals the belief that market signals can help bank supervisors.

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

To accomplish the mentioned goals, it was analyzed a sample of 248 European banks 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 of this study suggest that market indicators add significant value to the accounting-based model.

Subsequently, the importance of individual variables and the performance of both the accounting and the extended model to predict bank distress events was assessed in two distinct periods. It was analyzed the observations from 2008 to 2012, representing the period before the implementation of the Pillar 3 disclosure requirements, and from 2013 to 2020, representing the period after its implementation. The findings indicate that the market variables have higher predictive power in the most recent period. Further, the accounting and extended model have a similar performance during 2008-12 but the second performs better during 2013-20. Therefore, 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.

It was not found any other research to date that seeks to understand if the introduction of Pillar 3 changed the predictive power of market variables in bank monitoring models. Thus, this empirical study 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 of this study 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 current dissertation will be as follows. After the current introductory part, the following chapter will discuss 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. Chapter 3 will describe the data and methodology used in this empirical study. Then, in chapter 4, the results will be presented and discussed and, in chapter 5, the robustness of the models will be assessed. Finally, in chapter 6, the conclusion will be presented taking into account the most relevant findings and the value added to current literature as well as further suggestions for future research.

2. Literature Review and Hypothesis Development

This dissertation focuses on the possibility of using market information to complement traditional accounting-based models to monitor banks. Therefore, the main literature regarding this topic will be presented and then the main hypothesis of the study will be introduced.

2.1. Distress Events

There are different approaches to identify bank distress events in the literature. In the studies that examined the United States (US) market, the authors used either explicit bank failures or supervisory ratings, such as the BOPEC[1] (Cole & White, 2011; Curry, Elmer, & Fissel, 2007; Curry et al., 2008; Gunther, Levonian, & Moore, 2001). 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 (Arena, 2008; Betz, Oprica, Peltonen, & Sarlin, 2013; Chiaramonte & Casu, 2017; Poghosyan & Cihak, 2011). 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 (Sironi, 2003).

To study bank distress based on ratings, Gropp, Vesala, and Vulpes (2006) selected European Union (EU) banks that had an individual rating from Fitch/IBCA and defined the bank's distress date as the month of the change in Fitch/IBCA's rating to C or below. This cut-off was based on the empirical findings that such a downgrade preceded all cases of serious bank problems in Europe on which public information is available. Alternatively, Distinguin, Rous, and Tarazi (2006) used any downgrading from the three rating agencies mentioned above. Using the three sources of ratings allowed the authors to choose the earliest event date possible, which is important when the goal is to test the predictive content of variables.

[1] BOPEC stands for the key areas of supervisory concern, BHC's Banks subsidiaries, Other nonbank subsidiaries, Parent company, Earnings, and Capital adequacy.

Further, Miller, Olson, and Yeager (2015) considered three different approaches to identify distress events, (1) explicit bank failure, (2) the Texas ratio, and (3) the Standard&Poor's Domestic Long Term Issuer Credit rating. The authors suggested that considering ratings is an alternative when there is no access to confidential supervisory ratings and there is not a sufficient number of failures during the period under analysis. Similarly, the present research will use a multi-criteria approach.

2.2. 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 CAMEL rating system[2], an internal supervisory tool for evaluating the soundness of financial institutions. As described in the Commercial Bank Examination Manual (Federal Reserve, 2017), the CAMEL rating system uses financial ratios to assess the overall financial soundness of banks and it focuses 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; and, lastly, (L) the adequacy of the bank's liquidity position.

Several studies show the effectiveness of using accounting indicators to assess the risk class of banks or predicting bank failure. Thomson (1991) showed that the majority of CAMEL factors are significantly connected with the probability of failure up to four years before a bank's failure. Further, Whalen and Thomson (1988) not only concluded that using a limited number of financial ratios does a good job classifying commercial banks into different risk classes but also assessed the relevance of each component used. The authors concluded that asset quality and earnings measures have a critical predictive role. Moreover, Cole and White (2011) revealed that CAMEL 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 1985-92 banking crisis.

[2] Its initial form has presented by the US regulators in 1979 as the Uniform Financial Rating System (UFIRS) but becomed known as the CAMEL rating system. Later on, in 1996 it was included the last component, the sensitivity to market risk, give rise to the CAMELS rating system.

Alternatively, Cole and Gunther (1995) 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. With a more recent sample, Cleary and Hebb (2016), using discriminant analysis to examine the failure of 132 US banks over 2002-09, stated that capital and loan quality and bank profitability appeared to be the most important variables.

Regarding European banks, Männasoo and Mayes (2009) showed that CAMEL's factors have an important role in distress detection and warning and Poghosyan and Cihak (2011) revealed that asset quality and earning profiles of EU banks are important determinants of bank distress, next to leverage. Additionally, Filippopoulou, Galariotis, and Spyrou (2020) suggested that specific banking variables are on average more important than macroeconomic variables for predicting systemic banking crisis in Eurozone.

2.3. Market indicators

Market information has desirable characteristics that are not present in accounting-based indicators. Market information is (1) forward-looking[3], (2) frequent and widely available[4], and (3) can be used in a diversity of ways to extract information and calculate risk measures from market prices (Persson & Blavarg, 2003).

Market participants have a strong incentive to collect and evaluate information to accurately assess the potential risks and rewards (Gunther et al., 2001). 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, Davies, and Flannery (2000) 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. Indeed, Pettway and Sinkey (1980), analyzing a sample

[3] Market prices depend on future cash flows, thus, they are inherently forward-looking.
[4] Prices can be updated daily and even intradaily, and are immediately made public.

of US banks, found that using both accounting and market measures in distress predicting models would allow having scheduled examinations at least one year earlier before the failure.

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 (Burton & Seale, 2005). But as Feldman and Levonian (2001) 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 (2006) 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.

2.3.1. 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[5] of the issuing bank. Flannery and Sorescu (1996) 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 (2001), 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 (2001) examined banks that failed during the period 1980-95 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

[5] Debt market can provide ex-ante and exp-post signals: before the debt issuance debt holder demand higher interest rates on riskier debt and after, in the secondary market, yield on the outstanding debt is expected to rise as default risk increases, i.e. the debt holders' claims declines (Furlong and Williams, 2006).

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 (2004) found that CDS and stock prices predict rating downgrades. In addition, Flannery, Houston, and Partnoy (2010) conclude that CDS spreads incorporate information more quickly than credit ratings and Ötker-Robe and Podpiera (2010) 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 (2011) examined the default risk sensitivity of yield spreads on bank-issued subordinated notes and debentures (SND) during the period 1994-99 for a sample of US banks. This period is marked by the return of implicit government guarantees, also known as a bailout. The authors concluded that SND yield spreads are sensitive to conventional firm-specific default risk measures before the bailout period but not after. Cutura (2018) 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.

2.3.2. Equity Signals

Assuming the market is reasonably efficient, the information about potential banks' problems will be translated into their stock prices. Hall, King, Meyer, and Vaughn (2002) 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. Similarly, Pettway and Sinkey (1980) analyzed US banks in the 1970s and concluded that equity price and returns provide signals about banks' condition.

Curry et al. (2007) analyzed 99 US banks during 1989-95, 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[6], 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 (Curry et al., 2008).

Alternatively, Gunther et al. (2001) used the expected default frequency (EDF). This equity variable represents an estimate of the percentage of firms in the same financial condition that historically defaulted on a financial obligation within the next twelve months. The authors tested 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 (2005) 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 (2018) as an equity signal, the authors concluded that short interest in the bank's equity increases before downgrades in supervisory ratings but does not decrease before upgrades in supervisory ratings. However, the use of the options market and short interest variable for monitoring purposes is limited given the lack of data.

[6] Not technically a market variable.

2.3.3. Debt and Equity Signals

Some researchers studied the value of using both debt and equity signals. Bliss and Flannery (2002) found that equity and bond prices move in the same direction more than half the time. Moreover, Krainer and Lopez (2003) 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 (Berger et al., 2000; Furlong & Williams, 2006; Gropp et al., 2006).

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, thus the bond spreads may be noisy (Gropp et al., 2006). Further, debt signals are affected by government implicit guarantees.

To illustrate, Gropp et al. (2006) 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 (1996) studied the relationship between stock and bonds and concluded that stocks lead bonds in reflecting firm-specific information. Further, Gropp and Richards (2001), 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 (2001) 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 (2003) claimed their preference for equity signs due to the better quality of data and the absence of too big to fail problems. Similarly, Levonian (2001) consented that equity information is preferable as a source of meaningful information about bank risk although the subordinated-debt market could contain complementary information.

In contrast, Bongini, Laeven, and Majnoni (2002) found that in Asia during the crisis of mid-1997 and mid-1998 neither stock prices nor credit rating information add value to accounting

information in assessing bank fragility. The researchers argued that it is advisable to use different sources of information, especially where information processing is quite costly, as in most developing countries.

Krainer and Lopez (2004) 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 argue 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 (2003) also supported the idea that market indicators are important to complement and provide a reference point for conventional analysis.

2.4. 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 2008-14 the accumulated assistance amounted to 8% of GDP (ECB, 2015).

Given its systemic importance, banks are highly regulated. 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[7], 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 (Basel Commitee on Baking Supervision, 2004). 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 –

[7] Basel I was published in 1998, Basel II in 2004, and Basel III in 2010.

adding macroprudential elements and introducing minimum leverage ratio – and tried to mitigate liquidity and maturity transformation issues (Ingves, 2018).

The purpose of Basel III is to make failure resolution less disruptive. To ensure that a distressed bank can be re-organized without neither disrupting the financial system nor require government rescues, Basel III redefined the capital requirements[8] 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 (2017) 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.

Flannery and Bliss (2019) believed that short-term debt holders provide the most effective market discipline because they represent a large proportion of total bank funding and are capable to understand changes in a bank's condition. The short-term debt holders' protection reduces their incentive to monitoring banks which in turn may negatively affect market discipline. On the other side, with relatively higher capital ratios, equity holders have more weight in the capital structure. As the equity holders' exposure increases, the equity investors are encouraged to close monitor a bank's risk profile which creates incentives for managers to act prudently (King, Nuxoll, & Yeager, 2005).

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 (Furlong & Williams, 2006). However, equity holders continue to have incentives to monitor banks' risk since they are not fully protected by the TBTF policy.

[8] Some of the changes include higher capital requirements (various situational buffers), liquidity requirements, reduction in risky trading for a bank's account, central clearing of OTC derivatives, and ex-post assessments on surviving financial firms to pay any costs incurred by the public entities.

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 of 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. On the other side, the cost decrease of obtaining information and the increased of equity holders exposure may positively affect the equity market discipline.

As is shown by Charalambakis and Garrett (2016), we cannot use a common model to predict corporate financial distress regardless of the stage of development of the economy. [9] 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, is relevant to take into account not only the changes caused by the regulatory framework but also their time of implementation.

The Progress Report on Basel III as of March 2012 shows that the EU has completely implemented Basel II and Basel 2.5 and it has draft regulations for Basel III (Basel Commitee on Baking Supervision, 2012). The Progress Report published in October 2014 demonstrates that the EU is well advanced in implementing Basel III (Basel Commitee on Banking Supervision, 2014). More recently, in 2017, the Basel Committee presented Basel III reforms to complement the initial phase of Basel III (Basel Committee on Banking Supervision, 2017). Further, in a press release in December 2018, 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 (Basel Committee on Banking Supervision, 2020).

Further, EBA analyses Pillar 3 reports for a sample of European banks in terms of compliance with the Basel requirements since 2008. EBA is an institution that aims to promote the convergence of supervisory practices and performs regular assessments and

[9] They compare US with another developed economy, UK, and with an emerging economy, India. Conclude that for India the market-based variables do not impact the probability of financial distress when are combined with accounting information, i.e. market-based variables do not add value to the traditional model.

stress tests. When evaluating the bank's transparency in 2010, EBA stated that banks have made an effort to improve their disclosures, nevertheless, noted some room for improvement (European Banking Authority, 2011). In the EBA Report on banks' transparency assessing the year 2014, it is noted development in the standardization of formats and the consistency of information disclosed (European Banking Authority, 2015). The last report available assesses the year 2019 and it shows that there are still some aspects that need further improvement (European Banking Authority, 2020). In conclusion, even though there are still improvements to be made, the transparency in European banks has improved. 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.

2.5. Hypothesis Development

The goal of the present study is to examine the value of extending accounting-based monitoring models to include market variables. This research does not aim to test models only based on market variables.

Models are simplifications of reality and, for that reason, it is important to keep reassessing and improving them. It is critical to understand how regulatory, financial, or other relevant factors[10] may affect bank monitoring models. It was not found any other research to date that seeks to understand if the introduction and development of Pillar 3 changed the predictive power of market variables in bank monitoring models. However, some empirical studies concluded that information disclosure is useful for market investors. Namely, Giner, Allini, and Zampella (2020) created several indexes based on the specific requirements in IFRS 7 – that overlap with some established in Pillar 3 – and evaluate its relevance for the market participants of European listed banks during 2007-14.

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.

[10] Such as TBTF policies, implicit guarantees, requirements in information disclosure.

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 introduction and development of information disclosure requirements.

3. Data and Methodology

This section provides information related to the sample that will be used, including the source of data. Then, it is presented the methodology that will be applied.

3.1. Data

This study will use a sample that includes both active and non-active banks, similarly to Chiaramonte and Casu (2017). Including banks that failed or were liquidated during the considered period avoids the survivorship bias. The sample was collected in the BankFocus database.

First, concerning location, the EU[27], United Kingdom, Norway, Liechtenstein, and Iceland were selected. The United Kingdom 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 (Poghosyan & Cihak, 2011). 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 companies were chosen. Lastly, following the approach of Distinguin et al. (2006), 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, table 3.1 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 compare to Distinguin et al. (2006) study.

Table 3.1 Distribution of banks by country and specialization

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

In terms of the period under analysis, using the identifiers Bank name and Year is possible to observe that before 2006 the percentage of missing values in key accounting and market variables[11] is higher than 90% in the BankFocus database. More specifically, in the year 2004, only one bank has missing values below 90%. Following, in 2005, 127 banks present more than 90% of missing values, and in 2006 124 banks are in the same situation. Finally, in 2007 approximately 63% of the sample has missing values below 90% and in the subsequent years the percentage of banks with a high level of missing values decreases.

Additionally, a preliminary analysis detected that some banks including Mediocredito Europeo SPA and Illimity Bank SPA only have data for one or two years, thus, it's important

[11] These variables are presented in a subsequent section.

to point out that the number of banks is not constant over time[12]. As expected, there are changes in the sample size due to missing values or market entries and exits. After deleting the years for which a certain bank had no information available remained a total of 2929 observations.

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. (2006) analyze from January 1991 to March 2001 a sample of 86 EU banks to assess equity signals and Distinguin et al. (2006) for the 1995-02 period studies 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 study considers that the data available before 2007 is 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 this research considers one year prediction windows.

Table 3.2 presents descriptive statistics on the sample of banks use in this study where it is possible to observe the sample's heterogeneity. Heterogeneity is valuable to investigate the robustness of the indicators since it allows to investigate the probability of distress events for banks with different capital structure, size, and earning profile. Compared to Distinguin et al. (2006), 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. Summary of these ratios per country can be found on Annex II.

Table 3.2 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)	3 390.21	8 999.18	0.00	82 859 .44

Units are indicated in front of the indicators between parentheses.
In this table is computed the average of each indicator in the total sample from 2007 to 2019.

[12] For the used econometric program (Eviews), the change in sample size across years does not represent a problem. Using panel data the sample size per set of identifiers can change.

3.1.1. Distress Events

In the present study, distress events are defined using a three-criteria approach, similar to Miller et al. (2015). The first criterion is banks that undergo explicit bankruptcy or liquidation. This information was collected from BankFocus by selecting the inactive banks. However, instead of immediately classify it as a distress event, the bank will be flagged. Then, analogous to Poghosyan and Cihak (2011) approach, was performed individual research using news, articles, 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 (2008) and Chiaramonte and Casu (2017) 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. (2006), this study considers any category downgrading in the speculative-grade, following an approach more similar to the one used by Distinguin et al. (2006). 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 decrease from BB to CCC it was considered another event but from BBB to BB it was not. To accomplish this step, the Orbis database was used to analyze the S&P and Fitch ratings since they were not present in the BankFocus database, and Moody's ratings were extracted from BankFocus. However, note that Orbis has fewer data available, namely for a longer time horizon[13]. Given the desirable qualities of the Financial Strength Moody's rating mention in the literature review, a greater emphasis is put on this rating but the number of banks with this rating available is very limited.

The last criterion is banks that benefit from state interventions. As Chiaramonte and Casu (2017) 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 (2013) document and European Commision (2017) report were analyzed. Then, a further

[13] More than 10 years, before 2010 there is significant missing information.

investigation was performed for each state intervention to obtain a deeper understanding, namely through ECB press releases. Annex I contains a summary table of the sources used.

Is frequent to observe multiple state interventions in the same bank, thus, 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 extend 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.

Table 3.3 describes the distribution of distressed banks and the number of distress events per country. Italy and Greece are the most affected countries during 2008-20, presenting the highest number of distress events. Other peripheral countries, such as Spain and Portugal were also harshly affected. To illustrate, the total sample has only three Portuguese banks and two of them experience distress events but from a total of twenty-six Italian banks, only eleven of them experience distress. Note that this study only considers quoted banks thus some countries are misrepresented compared to others.

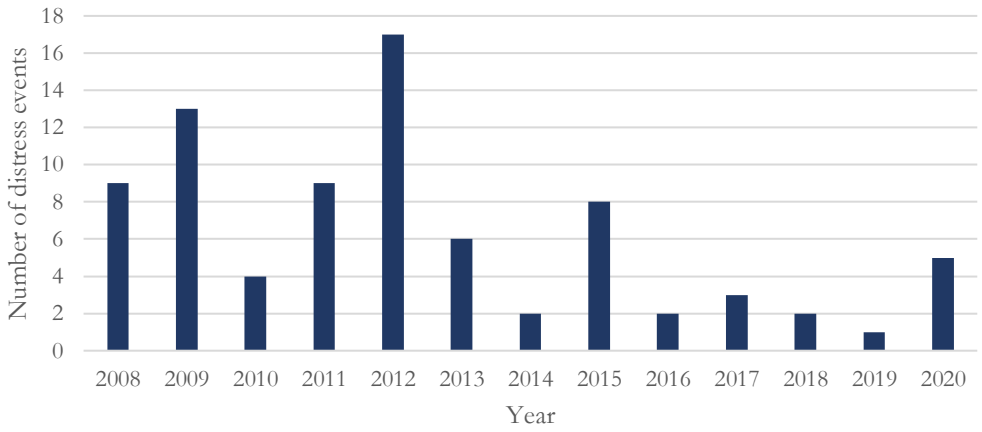
Table 3.3 Distribution of distressed banks and number of distress events across countries

Countries	Number Distressed Banks	Number Events	Percentage of distressed banks
Austria	2	2	20%
Belgium	2	4	67%
Bulgaria	1	1	25%
Croatia	2	3	25%
Cyprus	1	1	50%
Denmark	3	3	12%
Germany	3	3	23%
Greece	6	14	100%
Hungary	1	1	33%
Ireland	3	7	75%
Italy	11	17	42%
Netherlands	2	4	50%
Poland	3	7	23%
Portugal	2	3	67%
Slovenia	1	2	100%
Spain	2	2	22%
United Kingdom	6	7	30%
Total	**51**	**81**	

Percentage of distressed banks is computed by dividing the number of distressed banks by the total number of banks in the sample per country.

As figure 3.1. shows, exists 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.

Figure 3.1 Distress events distributed through time



Further, table 3.4 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. Comparing with the sample used by Poghosyan and Cihak (2011), the liquid assets to total assets ratio shows less discrepancy between distressed and non-distressed banks.

Table 3.4 Summary of accounting statistics of distressed and non-distressed banks from 2007-2019

	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)	7 268.23	2 119.22

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.

3.1.2. Explanatory Variables

Most of the accounting variables found in the literature are based on CAMEL proxies. Distinguin et al. (2006) 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 (Berger et al., 2000; Curry et al., 2008; Gunther et al., 2001; Thomson, 1991). 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. Table 3.5 describes the accounting variables analyzed and the authors that use them.[14] The accounting data was collected from BankFocus on a yearly basis.

Table 3.5 Accounting early warning indicators

Panel A: Capital variables

Name	Description	Literature reference
Total capital ratio	total equity/risk-weighted assets	(Chiaramonte & Casu, 2017; Cleary & Hebb, 2016; Climenta, Momparlerb, & Carmonac, 2019; Distinguin et al., 2006; Jing & Fang, 2018; Otker & Podpiera, 2001; Poghosyan & Cihak, 2011)
Equity-to-net loans*	equity/net loans	(Arena, 2008; Jing & Fang, 2018)
Equity-to-gross loans*	equity/gross loans	(Distinguin et al., 2006)
Equity-to- dep. and st term funding	equity/deposits & short-term funding	(Climenta et al., 2019; Distinguin et al., 2006)
Equity-to-liabilities	equity/liabilities	(Climenta et al., 2019; Distinguin et al., 2006)
Equity-to-assets also known as Leverage ratio	equity/total assets	(Arena, 2008; Curry et al., 2008; Distinguin et al., 2006; Ötker-Robe & Podpiera, 2010; Parrado-Martinez, Gomez-Fernandez-Aguado, & Partal-Urena, 2019; Sironi, 2003)
Capital funds-to-assets	(equity+debt)/total assets	(Climenta et al., 2019; Distinguin et al., 2006)
Capital funds-to-gross loans*	(equity+debt)/gross loans	(Distinguin et al., 2006)

Panel B: Adequacy variables

Name	Description	Literature reference
Impaired loans-to-equity	impaired loans/equity	(Betz et al., 2013)
Non perf. loans-to-gross loans	non-performing loans/total gross loans	(Chiaramonte & Casu, 2017; Parrado-Martinez et al., 2019; Poghosyan & Cihak, 2011)
Loan loss res.-to- non perf. loans	loans loss reserves/non-performing loans	(Ötker-Robe & Podpiera, 2010)
Coverage ratio*	loans loss reserves/impaired loans	(Betz et al., 2013; Parrado-Martinez et al., 2019)
Loan loss res.-to-gross loans	loans loss reserves/gross loans	(Climenta et al., 2019; Cole & White, 2011; Distinguin et al., 2006)
Loan loss res.-to- total loans*	loans loss reserves/total loans	(Arena, 2008; Ötker-Robe & Podpiera, 2010; Sironi, 2003)
Loan loss res.-to-assets*	loan-loss-reserves/assets	(Avino, Conlon, & Cotter, 2019; Betz et al., 2013; Cole & White, 2011; Curry et al., 2008; Milne, 2014)
Loan loss res.-to-interest revenue	loan loss reserves/net interest revenue	(Climenta et al., 2019; Distinguin et al., 2006)
ROA	net income/total assets	(Betz et al., 2013; Cleary & Hebb, 2016; Cole & White, 2011; Curry et al., 2008; Distinguin et al., 2006; Jing & Fang, 2018; Ötker-Robe & Podpiera, 2010; Parrado-Martinez et al., 2019; Sironi, 2003)
ROAA	net income/average assets	(Chiaramonte & Casu, 2017; Climenta et al., 2019; Krainer & Lopez, 2004)
Past due loans*	past due loans(>90 days)/total assets	(Curry et al., 2008; Jing & Fang, 2018)
Loans-to-assets*	total loans/total assets	(Arena, 2008; Climenta et al., 2019)

[14] In the literature, sometimes the same ratio is attributed to a different CAMEL elements. Hence, this classification is to some extend subjective.

Panel C: Management variables

Name	Description	Literature reference
ROE	net income/equity	(Betz et al., 2013; Distinguin et al., 2006; Ötker-Robe & Podpiera, 2010; Parrado-Martinez et al., 2019; Poghosyan & Cihak, 2011)
ROEA	net income/average equity	(Avino et al., 2019; Climenta et al., 2019; Milne, 2014)
Cost to income ratio	loans/deposit ratio	(Betz et al., 2013; Chiaramonte & Casu, 2017; Climenta et al., 2019; Filippopoulou et al., 2020; Milne, 2014; Ötker-Robe & Podpiera, 2010; Poghosyan & Cihak, 2011)
Operating expenses-to-revenues*	operating expenses/operating revenues	(Ötker-Robe & Podpiera, 2010)
Net interest income ratio*	net interest income/operational revenue	(Betz et al., 2013; Jing & Fang, 2018; Ötker-Robe & Podpiera, 2010)
Noninterest expenses-to-total assets	noninterest expenses/total aveg. assets	(Climenta et al., 2019; Jing & Fang, 2018)

Panel D: Earning variables

Name	Description	Literature reference
Net interest margin		(Climenta et al., 2019)
Net interest-to-assets*	net interest revenue/total assets	(Climenta et al., 2019; Distinguin et al., 2006; Jing & Fang, 2018)

Panel E: liquidity variables

Name	Description	Literature reference
Liquidity ratio	liquid assets/total assets	(Arena, 2008; Avino et al., 2019; Curry et al., 2008; Jing & Fang, 2018; Ötker-Robe & Podpiera, 2010; Parrado-Martinez et al., 2019)
Liquid assets-to- dep. and st funding	liquid assets /customer(deposits) and short term funding	(Climenta et al., 2019; Distinguin et al., 2006; Filippopoulou et al., 2020; Sironi, 2003)
Liquid assets-to-dep. and borrowings	liquid assets/total deposits and borrowings	(Climenta et al., 2019; Distinguin et al., 2006)
NCO-to-gross Loans	net charge offs/gross loans	(Cleary & Hebb, 2016)
St funding-to-total liabilities*	short term funding/total liabilities	(Betz et al., 2013; Filippopoulou et al., 2020; Ötker-Robe & Podpiera, 2010)
Interbank ratio	interbank assets/interbank liabilities	(Climenta et al., 2019; Distinguin et al., 2006)
Net loans-to-total assets	net loans/total assets	(Cleary & Hebb, 2016; Climenta et al., 2019)
Net loans-to-dep. and st funding	net loans/deposits & short term funding	(Cleary & Hebb, 2016; Climenta et al., 2019)
Net loans-to-dep. and borrowings	net loans/deposits & borrowings	(Climenta et al., 2019)

* Variable is calculated using data extracted from Bank Focus.

From BankFocus were additionally collected the market monthly data. Monthly stock returns[15] are expected to have a negative relation with the probability of distress event (Avino et al., 2019; Balasubramnian & Palvia, 2018; Distinguin et al., 2006). 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

[15] Returns are computed using log of price, $r_i = \log\left(\frac{price\ i}{price_{i-1}}\right)$

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 (Curry et al., 2008; Furlong & Williams, 2006). Moreover, variables compose of both market and accounting information were analyzed, including market-to-book of equity (Curry et al., 2008; Sironi, 2003), market-to-book of assets (Curry et al., 2008), and stock price-to-earnings (Furlong & Williams, 2006). These variables allow the detection of divergences between market and accounting assessments.

3.2. Methodology

3.2.1. Model specification

This study will use a binary dependent variable DIS, which assumes the value one if there is a distress event and zero otherwise. In this case, the use of linearity probability such as ordinal least squares (OLS) is not appropriate since the resulting model will not produce values bounded from zero to one. In the econometric literature is noted that when the dependent variable is binary the most frequently used functional forms are probit and logit, which are bounded between zero to one. The first follows a standard normal distribution and the second a logistic distribution (Amemiya, 1981). [16]

In a univariate model, the choice between the probit or logit model is not very often relevant[17] since the results of the two models are very similar. However, in a multivariate model such as the one that will be used in this study, there are significant distinctions between the two functional forms. Typically, logit tends to be preferable when there are an extreme independent variable level and probit in random effect models (Maddala, 1987). An extreme independent variable respects the following three criteria: (1) the extreme level occurs at the upper or lower range of the independent variable, (2) the extreme level should contain a significant proportion of the total sample, and (3) the probability of success at this level should itself be extreme(>99%)(Chambers & Cox, 1967). In this research, the non-distress event is much more frequent, represents a significant portion of the sample, and is a lower range of the independent variable. Therefore, similar to previous studies, logit regression will be used to estimate the probability of distress as a function of lagged explanatory variables,

[16] Logistic distribution has slightly heavier tails compared to normal distribution.
[17] Except in the cases where data are concentrated on the tails.

as equation 3.1 shows (Cole & White, 2011; Distinguin et al., 2006; Poghosyan & Cihak, 2011).

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

Equation 3.1 Logistic model

The sign of the coefficients (β) indicates the direction of the relationship between the respective explanatory variable and the probability of distress, all else being equal. If the coefficient is positive (negative) a bank with that early warning indicator is more (less) likely to experience a distress event. Regarding the magnitude of the effect, each coefficient shows the effect of one unit change in the predictor variable. However, notice that a coefficient can seem small in absolute terms but if the predictor variable has a very large range it can represent a strong effect.

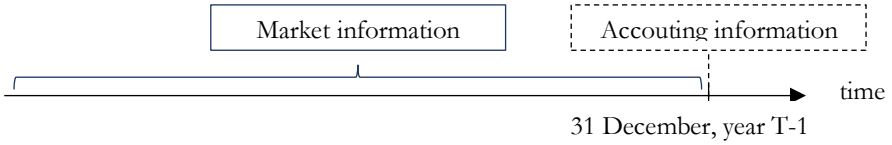
A simple logit model assumes independence of errors across individual banks and through time. Nevertheless, in the present study, this assumption is likely to be violated. Failing to acknowledge this dependence of errors leads to downward biased estimations of the standard errors of the coefficients. To account for the dependence of errors within banks, the heteroskedasticity robust variance-covariance matrix will be used, similar to Poghosyan and Cihak (2011) and Distinguin et al. (2006)[18].

Further, as argued by Curry et al. (2007), there is a synchronize issue that must be addressed. In other words, the market and accounting information is not available at the same time. The present research will follow the approach of Distinguin et al. (2006). Starting from the disclosure date of accounting information, 31 December for European banks, and then consider subsequent events. To clarify, 31 December is considered the prediction date and so cannot be introduced information in the model after that date. As figure 3.2 shows, 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

[18] Using Huber–White method.

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.

Figure 3.2 Market and accounting variables – Synchronize issue



The 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 study, several explanatory variables will be analyzed to construct the most powerful model. Similar to Curry et al. (2007) and Distinguin et al. (2006), it will be conducted a logistic univariate analysis to assess the relevance of both accounting and market variables, as equation 3.2 shows.

$$DIS_T = \text{intercept} + \beta \text{Accounting}_{T-1}$$

Equation 3.2 Univariate logit analysis

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 equation 3.3. in which distress and non-distress banks are analyzed simultaneously[19]. The dependent variable, $DIS_{B,T}$, is considered for each bank (B) and year (T). It is taken into consideration accounting and market information at the previous year (T-1).

$$DIS_{B,T} = \text{Intercept} + \beta \text{Control variable}_{B,T-1} + \beta \text{Accounting}_{B,T-1} + \beta \text{Market}_{B,T-1} + \varepsilon_{B,T-1}$$

Equation 3.3 Multivariate logistic model

Several criteria will be used to compare and assess the most superior model in the stepwise approach. McFadden's R-squared, also known as pseudo R-squared, takes values from zero

[19] It is argued by Curry et. al (2007) that this approach reduces de potential spurious result caused by different macroeconomic environments. Additionally, it helps to deal with the reduce number of distress events.

to one with higher values indicating a better model. This statistic is only useful when compared to other models fit to the same data, in other words, it does not have its own interpretation. Moreover, the Akaike information criterion (AIC) will also be used. All else constant, the model with lower AIC is better. Further, AIC takes into consideration the complexity of the model, by favoring simpler models, making it generally a better indicator than McFadden's R-squared. Simpler models are preferable since they avoid overfitting problems and have fewer parameters to estimate. Finally, the likelihood ratio (LR) will be used to test if the model is jointly significant. These indicators are used by several authors in the literature including Curry et al. (2007), Poghosyan and Cihak (2011), and Cleary and Hebb (2016).

3.2.2. Robustness

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

An univariate analysis of both accounting and market variables will be performed from 2007 to 2012 and then from 2013 to 2020. Analyzing the different variables for the different periods will allow examining if there are some trends in the predictive power of the explanatory variables. Then, the optimal accounting models and the extended model will be estimated for the two periods. The results will provide an indication of the extended model power through time in comparison to the accounting model.

4. Results

4.1. Accounting model

Each of the 36 accounting variables will be individually analyzed, starting with a simple univariate analysis as equation 3.2 shows. A variable will be considered significant if presents a p-value lower than 10%, in other words, if it is relevant with a 90% confidence level.

Table 4.1 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-value equal to zero. Moving to the capital adequacy proxies, just loan loss reserves-to-total loans and loan loss reserves-to-interest revenues are irrelevant. Concerning the management variables only cost to income ratio suggests some importance but it is low. Further, for the earnings profile component, noninterest 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 (2017) concluded that liquidity is relevant, contrasting to other results using older data that did not found liquidity proxies significant (Cleary & Hebb, 2016; Cole & Gunther, 1995; Poghosyan & Cihak, 2011; Whalen & Thomson, 1988).

Table 4.2 is a summary of the relevant variables, 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. [20]

In the literature, the capital, asset quality, and earnings proxies are critical to predictive distress and failure events (Cleary & Hebb, 2016; Cole & Gunther, 1995; Poghosyan & Cihak, 2011; Whalen & Thomson, 1988). Similarly, in this empirical study, most of the relevant variables (65%) are capital and asset quality proxies. The liquidity component is the third more represented CAMEL component.

[20] In the literature, sometimes the same ratio is attributed to a different CAMEL elements. Hence, this classification is to some extend subjective. Can consult the classification of each accounting variable used on this study in Tabel 3.5.

Table 4.1 Univariate analysis of accounting early indicators from 2007 to 2019

Panel A	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	1 844	2 113	2 026	2 026	2 073	2 113	1 281	1 281	1 850	1 841	1 837	1 837	1 956

Panel B	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	Net interest margin
Coefficient	0.072	1.244	0.001	-0.025	-0.031	0.000	0.897	-0.002	-0.002	0.001	0.002	-0.017
p-value	0.248	0.027	0.196	0.007	0.026	0.016	0.144	0.239	0.226	0.075	0.728	0.223
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	0.001
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
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	0.226
Schwarz criterion	0.244	0.243	0.244	0.230	0.230	0.251	0.237	0.231	0.231	0.231	0.231	0.231
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	0.228
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	0.616
Dep=1	51	51	51	51	51	35	51	51	51	51	51	51
Dep=0	1 956	1 956	1 956	2 106	2 106	1 309	2 026	2 106	2 106	2 096	2 107	2 098

Panel C

	Noninterest expenses-to-total assets	Net interest income ratio	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	-0.024	0.322	-7.056	-0.017	-0.048	-0.058	-0.027	1.860	0.000	0.009	-0.004	-0.001
p-value	0.045	0.039	0.216	0.065	0.000	0.000	0.625	0.017	0.457	0.144	0.074	0.606
McFadden R-squared	0.002	0.002	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	0.152	0.153	0.154	0.161	0.153	0.155	0.155	0.155	0.156
Akaike info criterion	0.225	0.226	0.226	0.224	0.214	0.218	0.247	0.226	0.233	0.232	0.232	0.236
Schwarz criterion	0.230	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	0.227	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)	0.276	0.309	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	51	50	44	51	48	51	51	50
Dep=0	2 107	2 099	2 099	2 113	2 073	2 000	1 614	2 073	1 895	2 026	2 016	1 942

Huber White estimation was used.

Table 4.2 Relevant accounting indicator per CAMEL element

	C	A	M	E	L
Significant at 99%	Total capital ratio Equity-to-assets 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 ROA			Liquid assets-to-dep. and st funding Liquid assets-to-dep. and borrowings
Significant at 95%		Loan loss res.-to-assets ROAA Past due loans		Noninterest expenses-to-total assets Net interest income ratio	St funding-to-total funding
Significant at 90 %			Cost to income ratio		Liquidity ratio Net loans-to-dep. and st funding

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 (2009), 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 ratio 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, it will be analyzed the noninterest expenses-to-total assets and net interest income ratio since are the only relevant variables of this component. Concerning the liquidity variables, this study 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 use combined is expected to create multicollinearity problems in the multivariate model. The correlation matrix can be found in Annex III.

As table 4.3 shows, a model with all the 14 variables do 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 (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 Model 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 mention 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.

Table 4.3 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	1 157	1 221	1 225	1 225	1 225
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, in other words, the p-value is lower than the indicated percentages.
Huber White estimation was used.

4.2. Extended model

Each of the market variables is individually analyzed through a univariate analysis, as illustrated by equation 3.2 previously presented. Table 4.4 presents the results obtained. Observing the p-value, it is possible to conclude that all return variables tested show significance. 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. (2007).

Table 4.4 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	2 206	2 166	2 120	1 933	1 697	2 164	2 105	2 049	1 961	1 714	1 722	1 715

Huber White estimation was used.

Turnover= Trading shares/Number of shares

Table 4.5 reveals the results of the extended models. Comparing 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 4.5 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 of the present study 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 the ones found in the literature such as Burton and Seale (2005), Curry et al. (2007), and Pettway and Sinkey (1980).

Table 4.5 Multivariate logistic models – Extended model

Model 5 represents the best accounting model found in the previous step. Model I, II, and III include market variables.

	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	1 225	7 92	807	948
Obs with Dep=1	26	11	14	15

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, in other words, the p-value is lower than the indicated percentages. Huber White estimation was used.

5. Robustness test

To assess if a higher information disclosure conducts to a higher ability of market signals to foreseen bank distress events, this study will compare the result from the univariate and multivariate logit analysis in two periods. Table 5.1 contains a summary of the univariate analysis of the accounting variables. See in Annex IV all the results.

Overall, more variables are significant in 2013-20 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 2007-12 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 2007-12. 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 2013-20, 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 2007-12 only operating expenses to total revenues is significant and in 2013-20 only noninterest expenses to total assets and net interest ratio are relevant.

In table 5.2 it is possible to observe the univariate analysis of the market variables. For both periods, all the return measures are significant, but in 2013-20 all have p-value equal to zero. For the period 2008-12, there is no relevant turnover indicator, nonetheless, in the most recent period, 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 2008-12 but not in 2013-20.

Table 5.1 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
M	Loans-to-assets	0.897	0.144	-0.626	0.507	2.365	0.000
	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
E	Operating expenses-to-revenues	0.002	0.728	0.619	0.000	0.000	0.970
	Net interest margin	-0.017	0.223	-0.097	0.162	-0.010	0.418
	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
	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

Table 5.2 Univariate analysis of market variables: 2007-2012 and 2013-2019

Panel A: Period 2007-2012	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	-2.610	-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	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	-2.865	-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	1 507	1 487	1 461	1 418	1 317	1 493	1 457	1 424	1 366	1 256	1 471	1 465

Huber White estimation was used.

Turnover= Trading shares/Number of shares

Analyzing the model performance output in table 5.3, 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 period 2007-12 the differences between the extended and accounting model are less noticeable, with an AIC of 0.336 compared to 0.344, respectively.

Table 5.3 Accounting and extended model: 2007-12 and 2013-20

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

	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

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, in other words, p-value is lower than the indicated percentages.
Huber White estimation was used.

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.

6. Conclusions and future research

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 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, it was obtained an accounting model and an extended model that includes 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 2013-20 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 2013-20 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.

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. Additionally, with access to more frequent market indicators, a similar analysis studying different time horizons can be conducted. 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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8. Annex

8.1. Annex I

Panel A: Explicit Failure or liquidation

Bank	Country	No. Events	Criteria	Year	Quarter	Description	Sources
LOCINDUS S.A.	France	0	Dissolved	N.a.		Restructuring not caused by distress.	https://creditfoncier.com/cfcontent/uploads/2018/10/2018-half-year-financial-report.pdf; https://www.globenewswire.com/news-release/2018/06/26/1529865/0/en/Proposed-delisting-offer-on-Locindus.html; https://www.globenewswire.com/news-release/2019/01/25/1705431/0/fr/LOCINDUS-Offre-publique-de-retrait-visant-les-actions-de-la-soci%C3%A9t%C3%A9-Locindus-SA-initi%C3%A9e-par-le-Cr%C3%A9dit-Foncier-Autres-informations.html
BRABANK ASA	Norway	0	Dissolved	N.a.		Merger without distress.	https://news.cision.com/brabank/r/key-dates-relating-to-merger-between-easybank-asa-and-brabank-asa,c3204847
OESTJYDSK BANK A/S	Denmark	1	Bankruptcy	2017	4	Following an inspection of Østjydsk Bank at the end of 2017, the bank established a recovery plan and agree on a potential sale, merger and/or recapitalization. As part of the transaction, the bank filled a petition for bankruptcy proceedings and its board of directors and executive board resigned.	https://www.spglobal.com/marketintelligence/en/news-insights/trending/0avzalxcllstscqazfoyw2
NAVA BANKA DD	Croatia	1	Bankruptcy	2014	1	The bank first received a capital injection in 2013, however, in 2014 was identified significant deficiencies and illegalities in the operation.	https://thebanks.eu/banks/9828; https://www.hnb.hr/en/-/hnb-predlozio-otvaranje-stecajnog-postupka-nad-nava-bankom
DEVIN BANKA AS	Slovakia	N.a.	Accounting information not available	N.a.		The bank was put under forced administration on August 24 after running into severe liquidity problems.	https://spectator.sme.sk/c/20007913/nbs-devin-bank-investor-a-fraud.html

Panel B: Rating and State intervention criteria – Austria, Belgium, Bulgaria, Croatia, Cyprus, and Denmark

Bank	Country	No. Events	Criteria	Year	Quarter	Description	Sources
ERSTE GROUP BANK AG	Austria	1	State Intervention	2009	1	Guarantee on new bonds and underwriting of shares and capitalization financial instruments.	Mediobanca Document
BAWAG GROUP AG	Austria	1	State Intervention	2009	1	Capital increase and guarantee line.	Mediobanca Document
KBC GROEP NV/ KBC GROUPE SA	Belgium	1	State Intervention	2009	4	Restructuring plan caused by financial distress.	ECB (https://ec.europa.eu/commission/presscorner/detail/en/MEX_12_1221)
DEXIA SA	Belgium	3	State Intervention State Intervention State Intervention	2008 2011 2017	3 4 4	Underwriting of shares and convertible bonds and guarantee line in 2008. After recovery observed in the financial statements in 2010, on 21 December 2011, the European Commission approved the intervention with a joint guarantee of the three states, which grant part of the guarantee and then extend it in 2012. Then, receive again help in 2017.	Mediobanca; ECB (https://ec.europa.eu/competition/state_aid/cases/270969/270969_1935120_121_2.pdf)
BULGARIAN-AMERICAN CREDIT BANK	Bulgaria	1	Rating	2010	4	The Fitch LT Issuer default rating decreased to B in 2010.	Orbis
ZAGREBACKA BANKA DD	Croatia	2	Rating Rating	2012 2020	2 2	The S&P ICR Local LT shows a decreased to BB+ in 2012 and to BB in 2014. After recovery, the Fitch LT Issuer default rating decreased to BB+ in 2020.	Orbis
HELLENIC BANK PUBLIC COMPANY LIMITED	Cyprus	1	Rating	2013	1	Moody's Financial Strength decreased to b- in 2013, also foreign rating decreased to SD.	BankFocus
DANSKE BANK A/S	Denmark	1	State Intervention	2009	3	Guarantee line.	Mediobanca Document
ALM. BRAND A/S	Denmark	1	State Intervention	2010	1	Guarantee line.	Mediobanca Document

Panel C: Rating and State intervention criteria – Germany and Greece (Part I)

Bank	Country	No. Events	Criteria	Year	Quarter	Description	Sources
DEUTSCHE BANK AG	Germany	1	State Intervention	2009	1	Issue of shares for the acquisition of the banking.	Mediobanca Document
AAREAL BANK AG	Germany	1	State Intervention	2009	1	Underwriting of shares.	Mediobanca Document
COMMERZBANK AG	Germany	1	State Intervention	2009	2	Restructuring plan approved on 7 May 2009.	EBC (https://ec.europa.eu/commission/presscorner/detail/en/IP_12_337)
ATTICA BANK SA	Greece	3	State Intervention | Rating	2009	2	Share subscription in 2009. Further, analyzing Moody's Financial strength rating, there is a decreased to B+ in 2012 and to C- in 2015.	Mediobanca Document; BankFocus
			Rating	2012	3		
			Rating	2015	3		
NATIONAL BANK OF GREECE SA	Greece	2	State Intervention	2009	1	Underwriting of shares and convertible securities and guarantee on bonds in 2009. In 2014, "The Commission approved restructuring plans for National Bank of Greece in July 2014." Further, the decreased to C+ Financial Strength rating of Moody's in 2015 validates that there is a deterioration in 2014/2015. Thus, the second distress event date is considered 2015(3) as the distress date since the Long-term Foreign rating from Moody's decreased to SD (S&P ICR Local LT and Fitch LT Issuer default rating support this decision).	Mediobanca Document; ECB (https://ec.europa.eu/commission/presscorner/detail/fr/IP_15_6255); Orbis; BankFocus.
			State Intervention | Rating	2015	3		
PIRAEUS BANK SA	Greece	3	State Intervention	2008	4	Underwriting of shares and convertible securities, guarantee, and credit lines in 2008, further increased in 2010 and at the end of 2011 as part of the same program. On May 20, 2012, the Hellenic Financial Stability Fund subscribed a capital increase of 4.7 billion. Additionally, in 2015 the Moody's Financial Strength decreased to C, and long-term foreign rating to SD.	Mediobanca Document; ECB; BankFocus
			State Intervention	2012	2		
			Rating	2015	3		

Panel D: Rating and State intervention criteria – Greece (Part II) and Hungary

Bank	Country	No. Events	Criteria	Year	Quarter	Description	Sources
ALPHA BANK AE	Greece	3	State Intervention | Rating	2009	2	After a share subscription and guarantee line in 2010, the institution intended to reimburse the intervention until May 21, 2010, however did not. In May 2012, the Hellenic Financial Stability Fund subscribed to an increased capital of 1.9 bln. Additionally, in 2015 the Moody's Financial strength rating decreased to C+, and other long-term foreign ratings decreased to SD, signalizing another relevant distress event (S&P ICR Local LT and Fitch LT Issuer default rating changes support these 3 events).	Mediobanca Document; ECB (https://ec.europa.eu/commission/presscorner/detail/en/IP_14_790); BankFocus; Orbis
			State Intervention | Rating	2012	2		
			Rating	2015	3		
MARFIN INVESTMENT GROUP HOLDINGS SA	Greece	1	Rating	2011	2	S&P ICR Local LT decreased to BB 2007 and B+ 2011 (no ratings available after 2011).	Orbis
EUROBANK ERGASIAS SERVICES AND HOLDINGS SA	Greece	2	State Intervention | Rating	2010	2	Benefited from significant state aid, "including state guarantees and capital support granted by the State in 2009 and the HFSF in 2012 and 2013". European Commission approved restructuring plans in April 2014. The S&P ICR Local LT decreased to BB in 2010 and B+ in 2011, then to RD 2015; Fitch LT Issuer default rating decreased to BB+ 2011 and RD 2015. Since the specific date of the 2009 intervention is not available the dates of ratings were the ones used.	ECB (https://ec.europa.eu/commission/presscorner/detail/en/IP_15_6184); Orbis
			State Intervention | Rating	2015	2		
MKB BANK ZRT	Hungary	1	State Intervention	2014	4	In December 2014, the Hungarian resolution authority decided to put the bank into resolution.	ECB (https://ec.europa.eu/commission/presscorner/detail/en/IP_15_6347)

Panel E: Rating and State intervention criteria – Ireland and Italy (Part I)

Bank	Country	No. Events	Criteria	Year	Quarter	Description	Sources
BANK OF IRELAND GROUP PLC	Ireland	2	State Intervention	2008	1	Subscription of shares and warrants and guarantee line in 2008. The first intervention was a recapitalization of 2 billion in February 2008, and a further 1.5 billion in 2009. In December 2011, the European Commission approved the second restructuring plan.	Mediobanca Document; ECB (https://ec.europa.eu/commission/presscorner/detail/en/IP_13_669)
			State Intervention	2011	4		
AIB GROUP PUBLIC LIMITED COMPANY	Ireland	2	State Intervention	2009		In 2009, the bank received repeated State support in the form of guarantees, recapitalizations, and asset relief. In 2011, when AIB and EBS were merged, the merged entity also received capital support. Further, in September 2012, Ireland submitted a restructuring plan for AIB which was complemented by several additional submissions.	ECB (https://ec.europa.eu/commission/presscorner/detail/en/IP_14_524)
			State Intervention	2012	3		
PERMANENT TSB GROUP HOLDINGS P.L.C	Ireland	3	Rating	2012	1	The Fitch LT Issuer default rating goes to BB+ in 2012, to B in 2013, and, after recovery in between, decreased again to B in 2020. After the Guarantee line, at the end of 2013 Single Supervisory Mechanism revealed that the bank still lacked capital, and a restructuring plan was set.	Mediobanca Document; ECB (https://ec.europa.eu/commission/presscorner/detail/en/IP_15_4755); Orbis
			State Intervention | Rating	2013	4		
			Rating	2020	3		
MEDIOBANCA– BANCA DI CREDITO FINANZIARIO SOCIETA PER AZIONI	Italy	1	State Intervention	2012	1	Guarantee on bond issues.	Mediobanca Document
BPER BANCA S.P.A.	Italy	1	Rating	2013	3	The S&P ICR Local LT decreased to BB+ 2012 and again to BB- 2013 (with a recovery in between). The Fitch LT Issuer default rating decreased to BB+ in 2013 and BB in 2015, in 2020 is put on rating watch on.	Orbis

Panel F: Rating and State intervention criteria – Italy (Part II)

Bank	Country	No. Events	Criteria	Year	Quarter	Description	Sources
INTESA SANPAOLO	Italy	1	State Intervention	2011	4	Guarantee on bond issues in December 2011 and March 2012.	Mediobanca Document
BANCA POPOLARE DI SONDRIO SOCIETA COOPERATIVA PER AZIONI	Italy	1	Rating	2019	2	Fitch LT Issuer default rating decreased to BB+ in 2019.	Orbis
BANCA GENERALI	Italy	2	Rating Rating	2008 2012	4 4	Moody's Financial Strength rating decreased to BB in 2008, and after recovery, decreased to BB+ in 2012 and BB in 2014.	BankFocus
BANCO DI DESIO E DELLA BRIANZA SPA	Italy	2	Rating Rating	2012 2020	3 2	Moody's Financial Strength rating decreased to BB+ in 2012, and BB- in 2013 maintaining this level until 2015. Analyzing other ratings is observed a negative change starting from 2012 but only in 2013 decreased to category BB occur. The Fitch LT Issuer default rating shows a decreased to BB+ on May 19, 2020.	BankFocus
CREDITO EMILIANO SPA	Italy	1	State Intervention	2011	4	Guarantee on bond issues	Mediobanca Document
BANCA SISTEMA SPA	Italy	2	Rating Rating	2012 2015	3 3	The bank presents a low Financial strength rating (BB category) before 2012, however, in 2012 decreased to B+ and in 2015 decreased to C-.	BankFocus
BANCA IFIS SPA	Italy	1	State Intervention | Rating	2012	1	Guarantee in bond issues in 2012. Moody's Financial Strength decreased to BB+ in 2012.	Mediobanca Document; BankFocus
BANCA CARIGE SPA	Italy	3	State Intervention | Rating Rating State Intervention | Rating	2011 2016 2018	4 4 4	Guarantee on bond issues in 2011. Additionally, the Fitch LT Issuer default rating shows a decreased to BB+ in 2012, to B in 2016, to CCC+ in 2018, and CC 2019 (2018 and 2019 decreased was considered the same event).	Mediobanca Document; Orbis
BANCA MONTE DEI PASCHI DI SIENA SPA	Italy	2	State Intervention State Intervention	2009 2017	1 1	Recapitalization plan in 2009 and a second recapitalization plan in 2017.	ECB (https://ec.europa.eu/commission/presscorner/detail/en/IP_17_1905); https://www.globaltradealert.org/intervention/11327/capital-injection-and-equity-stakes-including-bailouts/italy-state-aid-to-monte-dei-paschi-di-siena

Panel G: Rating and State intervention criteria – Netherlands, Poland and Portugal

Bank	Country	No. Events	Bank	Cou ntry	No. Events	Bank	Country
ABN AMRO BANK NV	Netherlands	2	State Intervention	2008	3	Support package and restructuring plan in 2008. In April 2011, the Commission approves another restructuring subject to conditions.	ECB (https://ec.europa.eu/commission/presscorner/detail/en/IP_11_406)
			State Intervention	2011	2		
ING GROEP NV	Netherlands	2	State Intervention	2008	3	Recapitalization aid in the autumn of 2008 followed by further state aid in March 2009. On 19 November 2012, it is approved a restructuring plan, in the press release mention is mention: "This new plan addresses the Commission's concerns".	ECB (https://ec.europa.eu/commission/presscorner/detail/en/IP_12_1226)
			State Intervention	2012	2		
BANK HANDLOWY W WARSZAWIE S.A.	Poland	2	Rating	2008	4	Moody's Financial Strength rating decreased to BB in 2008. After recuperation, the rating decreased to BB+ in 2012 and BB in 2014.	BankFocus
			Rating	2012	4		
BANK OCHRONY SRODOWISKA SA– BOS SA	Poland	2	Rating	2009	3	Moody's Financial Strength rating decreased to BB+ in 2009. The Fitch LT Issuer default rating goes decreased to BB on 18/5/2015, B+ on 29/2/2016.	BankFocus
			Rating	2015	2		
GETIN NOBLE BANK SA	Poland	3	Rating	2016	1	The Fitch LT Issuer default rating decreased to BB- on February 29, 2016, then to B+on February 4, 2018, to B- on November 14, 2018, and then to CCC+ on April 14, 2020.	Orbis
			Rating	2018	1		
			Rating	2020	2		
BANCO COMERCIAL PORTUGUES, SA	Portugal	2	State Intervention	2010	2	On 15 April 2010, the Bank of Portugal revoked BPP's banking license and initiated the process for its liquidation. Further, the rating S&P ICR Local shows a decreased to BB+ in 2012 and to B in 2013, and the Fitch LT issuer default rating decreased to B- in 2015 (2012 and 2013 were considered the same event of 2010).	ECB (https://ec.europa.eu/commission/presscorner/detail/en/IP_10_972)
			State Intervention	2015	2		
BANCO BPI SA	Portugal	1	Rating	2011		The S&P ICR Local LT decreased to BB+ in 2011, also, the Fitch LT Issuer default rating decreased to BB+ in 2011 and to BB in 2015.	Orbis

Panel H: Rating and State intervention criteria – Slovenia, Spain and United Kingdom

Bank	Country	No. Events	Bank	Cou ntry	No. Events	Bank	Country
NOVA LJUBLJANSKA BANKA D.D.	Slovenia	2	State Intervention | Rating State Intervention | Rating	2011 2013	1 4	In 2011 occurred an emergency recapitalization and subsequent reinforcement in 2012. In 2013 a new restructuring plan: "The Commission approved the restructuring plans (...) based on the transfer a pool of non-performing loans and a list of equities". Analyzing the ratings is observed a deterioration in October 2013, reinforcing the idea that a new distress event takes place.	ECB (https://ec.europa.eu/commission/presscorner/detail/en/IP_13_1276; https://ec.europa.eu/commission/presscorner/detail/en/IP_11_264); Orbis
BANKIA, SA	Spain	1	State Intrevention	2012	4	Restructuring plan.	ECB (https://ec.europa.eu/commission/presscorner/detail/en/IP_12_1277)
LIBERBANK SA	Spain	1	State Intervention | Rating	2012	4	Restructuring plan. The Fitch LT Issuer default rating also signals a distressing event in 2012.	ECB (https://ec.europa.eu/commission/presscorner/detail/en/IP_12_1432); Orbis
ARBUTHNOT BANKING GROUP PLC	United Kingdom	1	State Intervention	2013	3	Loan.	Mediobanca
LLOYDS BANKING GROUP PLC	United Kingdom	1	State Intervention	2008	3	Underwriting of shares, guarantee on assets and loans.	Mediobanca Document; ECB (https://ec.europa.eu/commission/presscorner/detail/en,en/IP_09_1728)
BARCLAYS PLC	United Kingdom	1	State Intervention	2008	4	Guarantee line and loans. The plan submitted to the Commission on 16 July 2009 and that contained additional state aid measures, yet, is not considered a different distress event in this study.	Mediobanca Document
VIRGIN MONEY UK PLC	United Kingdom	1	State Intervention	2012	4	Loan.	Mediobanca Document
ONESAVINGS BANK PLC	United Kingdom	1	State Intervention	2013	4	Loan.	Mediobanca Document
METRO BANK PLC	United Kingdom	2	State Intervention Rating	2012 2020	4 3	Loan in 2012. Further, Fitch LT Issuer default rating decreased to B+ in 21/08/2020, representing a decreased from the category BBB to B.	Mediobanca Document; Orbis

8.2. Annex II – Sample Description

a. List of banks

Bank	Country
MEDIOCREDITO EUROPEO SPA	Italy
ILLIMITY BANK SPA	Italy
APRILA BANK ASA	Norway
INSTABANK ASA	Norway
DWS GROUP GMBH & CO. KGAA	Germany
NORDEA BANK ABP	Finland
ASA INTERNATIONAL GROUP PLC	United Kingdom
SKUE SPAREBANK	Norway
BANK OF GEORGIA GROUP PLC	United Kingdom
BANK2 ASA	Norway
AVIDA HOLDING AB	Sweden
SPAREBANKEN TELEMARK	Norway
SHORE CAPITAL GROUP LIMITED	United Kingdom
DEN JYSKE SPAREKASSE A/S	Denmark
AIB GROUP PUBLIC LIMITED COMPANY	Ireland
BANK OF CYPRUS HOLDINGS PUBLIC LIMITED COMPANY	Ireland
ROMSDAL SPAREBANK	Norway
TYSNES SPAREBANK	Norway
BRABANK ASA	Norway
ADDIKO BANK AG	Austria
TBC BANK GROUP PLC	United Kingdom
NIDAROS SPAREBANK	Norway
NAVA BANKA DD	Croatia
BANCO BPM SPA	Italy
OMA SAASTOPANKKI	Finland
BAWAG GROUP AG	Austria
DOVALUE S.P.A.	Italy
KOMPLETT BANK ASA	Norway
MKB BANK ZRT	Hungary
VOLKSBANK VORARLBERG E.GEN.	Austria
CMC MARKETS PLC	United Kingdom
TF BANK AB	Sweden
BANCO BPI SA	Portugal
AMUNDI SA	France
SURNADAL SPAREBANK	Norway
RESURS HOLDING AB	Sweden
MELHUS SPAREBANK	Norway
SOGN SPAREBANK	Norway

KVIKA BANKI HF	Iceland
VIRGIN MONEY UK PLC	United Kingdom
BLUE MARLIN HOLDINGS S.A.	Luxembourg
SUNNDAL SPAREBANK	Norway
PARETO BANK ASA	Norway
SPAREBANK 1 NORDVEST	Norway
FINECOBANK BANCA FINECO SPA	Italy
GRONG SPAREBANK	Norway
SPAREBANKEN MORE	Norway
SPAREBANK1 BV	Norway
MONETA MONEY BANK, A.S	Czech Republic
AS LHV GROUP	Estonia
TCS GROUP HOLDING PLC	Cyprus
AASEN SPAREBANK	Norway
AKTIA BANK PLC	Finland
EVLI BANK PLC	Finland
BANCA PICCOLO CREDITO VALTELLINESE	Italy
SBANKEN ASA	Norway
LILLESTROMBANKEN	Norway
ABN AMRO BANK NV	Netherlands
IDEA BANK S.A.	Poland
UNICAJA BANCO SA	Spain
AUTOBANK AG	Austria
METRO BANK PLC	United Kingdom
DEXIA SA	Belgium
FERAX CAPITAL AG	Germany
BANCA SISTEMA SPA	Italy
NORWEGIAN FINANS HOLDING ASA	Norway
CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL ATLANTIQUE VENDEE SC	France
BANK OF IRELAND GROUP PLC	Ireland
CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL TOULOUSE 31 SC	France
SOCIEDADE COMERCIAL OREY ANTUNES, S.A.	Portugal
FISKE PLC	United Kingdom
SCHNIGGE WERTPAPIERHANDELSBANK SE	Germany
BANCA MEDIOLANUM SPA	Italy
ARION BANKI HF	Iceland
SPAREBANK 1 OESTLANDET	Norway
TEXIMBANK	Bulgaria
AGRAM BANKA DD ZAGREB	Croatia
GRUPPO MUTUIONLINE S.P.A.	Italy
NOVA LJUBLJANSKA BANKA D.D.	Slovenia

ONESAVINGS BANK PLC	United Kingdom
FYNSKE BANK A/S	Denmark
LOLLANDS BANK A/S	Denmark
NIBC HOLDING NV	Netherlands
LONDON FINANCE & INVESTMENT GROUP P.L.C.	United Kingdom
SOFIBUS PATRIMOINE SA	France
LIECHTENSTEINISCHE LANDESBANK AG	Liechtenstein
POSTE ITALIANE SPA	Italy
LIBERBANK SA	Spain
EUROBANK ERGASIAS SERVICES AND HOLDINGS SA	Greece
NEWCAP HOLDING A/S	Denmark
AURSKOG SPAREBANK	Norway
CENTRAL COOPERATIVE BANK AD	Bulgaria
ALIOR BANK SPOLKA AKCYJNA	Poland
ISTARSKA KREDITNA BANK UMAG D.D.	Croatia
SPAREBANK 1 RINGERIKE HADELAND	Norway
BREWIN DOLPHIN HOLDINGS PLC	United Kingdom
OESTJYDSK BANK A/S	Denmark
SECURE TRUST BANK PLC	United Kingdom
BANCO COMERCIAL PORTUGUES, SA	Portugal
GETIN NOBLE BANK SA	Poland
HOELAND OG SETSKOG SPAREBANK	Norway
EUWAX AKTIENGESELLSCHAFT	Germany
SPAREBANKEN OST	Norway
HELGELAND SPAREBANK	Norway
MARFIN INVESTMENT GROUP HOLDINGS SA	Greece
RMS MEZZANINE	Czech Republic
SPAREBANKEN SOR	Norway
SPAREKASSEN SJALLAND-FYN A/S	Denmark
SPAREBANK 1 SR-BANK ASA	Norway
DEUTSCHE PFANDBRIEFBANK AG	Germany
SPAREBANK 1 NORD-NORGE	Norway
BNP PARIBAS BANK POLSKA SA	Poland
BANKIA, SA	Spain
SPAREBANKEN VEST	Norway
SPAREBANK 1 SMN	Norway
PODRAVSKA BANKA	Croatia
GROUPE BRUXELLES LAMBERT SA	Belgium
PATRIA BANK S.A.	Romania
PRIMA BANKA SLOVENSKO A.S.	Slovakia
DANSKE ANDELSKASSERS BANK A/S	Denmark

ABG SUNDAL COLLIER HOLDING ASA	Norway
LOCINDUS S.A.	France
SLATINSKA BANKA DD	Croatia
PARAGON BANKING GROUP PLC	United Kingdom
VARENGOLD BANK AG	Germany
MLP SE	Germany
AZIMUT HOLDING SPA	Italy
CONAFI S.P.A	Italy
SPAREBANK 1 OSTFOLD AKERSHUS	Norway
BANCA INTERMOBILIARE DI INVESTIMENTI E GESTIONI	Italy
BULGARIAN-AMERICAN CREDIT BANK	Bulgaria
KARLOVACKA BANKA D.D.	Croatia
ALM. BRAND A/S	Denmark
BANCA CARIGE SPA	Italy
LOMBARD BANK (MALTA) PLC	Malta
SANDNES SPAREBANK	Norway
CAIXABANK, S.A.	Spain
JAEREN SPAREBANK	Norway
CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL DU LANGUEDOC SC	France
MEDIOBANCA– BANCA DI CREDITO FINANZIARIO SOCIETA PER AZIONI	Italy
ING GROEP NV	Netherlands
TOTENS SPAREBANK	Norway
FIRST INVESTMENT BANK AD	Bulgaria
BANCA MONTE DEI PASCHI DI SIENA SPA	Italy
JUTLANDER BANK A/S	Denmark
COMMERZBANK AG	Germany
NORDFYNS BANK A/S	Denmark
ALPHA BANK AE	Greece
PIRAEUS BANK SA	Greece
BAADER BANK AG	Germany
NATIONAL BANK OF GREECE SA	Greece
UNICREDIT SPA	Italy
BANK OF GREENLAND	Denmark
BANCA GENERALI SPA	Italy
NATWEST GROUP PLC	United Kingdom
SVENSKA HANDELSBANKEN AB	Sweden
DJURSLANDS BANK A/S	Denmark
KREDITBANKEN A/S	Denmark
HVIDBJERG BANK AKTIESELSKAB	Denmark
WIENER PRIVATBANK SE	Austria
SALLING BANK A/S	Denmark

OTP BANK PLC	Hungary
BANCO DE SABADELL SA	Spain
BANCO DI SARDEGNA SPA	Italy
ING BANK SLASKI S.A.– CAPITAL GROUP	Poland
BARCLAYS PLC	United Kingdom
SKANDINAVISKA ENSKILDA BANKEN AB	Sweden
KBC GROEP NV/ KBC GROUPE SA	Belgium
TOTALBANKEN A/S	Denmark
UMWELTBANK AG	Germany
KOMERCNI BANKA	Czech Republic
BANCO BILBAO VIZCAYA ARGENTARIA SA	Spain
BRD-GROUPE SOCIETE GENERALE SA	Romania
SIAULIU BANKAS	Lithuania
WUSTENROT & WURTTEMBERGISCHE AG	Germany
BANCO DI DESIO E DELLA BRIANZA SPA	Italy
BANCA FINNAT EURAMERICA SPA	Italy
BPER BANCA S.P.A.	Italy
BANCA POPOLARE DI SONDRIO SOCIETA COOPERATIVA PER AZIONI	Italy
CREDITO EMILIANO SPA	Italy
CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL DE LA TOURAINE ET DU POITOU SC	France
BANCA IFIS SPA	Italy
INTESA SANPAOLO	Italy
NATIXIS SA	France
CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL DE NORMANDIE-SEINE	France
CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL DE L'ILLE-ET-VILAINE SA	France
MOENS BANK A/S	Denmark
SYDBANK A/S	Denmark
BNP PARIBAS	France
ERSTE GROUP BANK AG	Austria
CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL LOIRE HAUTE-LOIRE SC	France
DANSKE BANK A/S	Denmark
POWSZECHNA KASA OSZCZEDNOSCI BANK POLSKI SA– PKO BP SA	Poland
SWEDBANK AB	Sweden
ALANDSBANKEN ABP	Finland
JYSKE BANK A/S	Denmark
CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL SUD RHONE ALPES	France
HSBC HOLDINGS PLC	United Kingdom
LAAN & SPAR BANK A/S	Denmark
MBANK SA	Poland
CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL D'ALPES-PROVENCE SC	France

DEUTSCHE BANK AG	Germany
LLOYDS BANKING GROUP PLC	United Kingdom
BANK MILLENNIUM	Poland
BANCO SANTANDER SA	Spain
STANDARD CHARTERED PLC	United Kingdom
CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL DU MORBIHAN SC	France
SOCIETE GENERALE	France
SKJERN BANK	Denmark
CREDIT AGRICOLE S.A.	France
BANKINTER SA	Spain
CLOSE BROTHERS GROUP PLC	United Kingdom
PRIVREDNA BANKA ZAGREB D.D	Croatia
PERMANENT TSB GROUP HOLDINGS P.L.C	Ireland
INVESTEC PLC	United Kingdom
AVANZA BANK HOLDING AB	Sweden
GETIN HOLDING SA	Poland
TRANSILVANIA BANK	Romania
BANK FUR TIROL UND VORARLBERG AG	Austria
OBERBANK AG	Austria
BANKNORDIK P/F	Denmark
OTP BANKA SLOVENSKO, AS	Slovakia
RENTA 4 BANCO, S.A.	Spain
CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL NORD DE FRANCE SC	France
CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL BRIE PICARDIE SC	France
TATRA BANKA A.S.	Slovakia
ROTHSCHILD & CO	France
CAISSE REGIONALE DE CREDIT AGRICOLE MUTUEL DE PARIS ET D'ILE-DE-FRANCE SC	France
BKS BANK AG	Austria
ATTICA BANK SA	Greece
TAKAREK MORTGAGE BANKPLC	Hungary
VSEOBECNA UVEROVA BANKA A.S.	Slovakia
HELLENIC BANK PUBLIC COMPANY LIMITED	Cyprus
RINGKJOEBING LANDBOBANK	Denmark
HSBC BANK MALTA PLC	Malta
ZAGREBACKA BANKA DD	Croatia
BANK HANDLOWY W WARSZAWIE S.A.	Poland
BANK POLSKA KASA OPIEKI SA	Poland
VESTJYSK BANK A/S	Denmark
BANK OF VALLETTA PLC	Malta
BANK OCHRONY SRODOWISKA SA– BOS SA	Poland
AAREAL BANK AG	Germany

RAIFFEISEN BANK INTERNATIONAL AG	Austria
VAN LANSCHOT KEMPEN NV	Netherlands
SPAR NORD BANK	Denmark
SANTANDER BANK POLSKA S.A.	Poland
DNB ASA	Norway
ARBUTHNOT BANKING GROUP PLC	United Kingdom

b. Sample Description per country

Country	Average of Total assets (000)	Average of Net Loans / Total assets (%)	Average of Liquid assets / Total assets (%)	Average of Total Capital Ratio (%)	Average of ROA(%)	Average of Loan Loss Res. / Gross Loans (%)	Average of Non Perf. Loans / Gross Loans (%)	Average of Impaired loans (000)
Austria	43 035.88	62.04	22.99	23.77	0.60	3.32	5.44	2 129.68
Belgium	230 943.37	48.80	39.46	17.98	0.86	1.92	3.88	5 444.91
Bulgaria	1 959.05	49.69	33.15	19.27	-0.04	9.59	19.21	221.97
Croatia	4 768.68	56.11	29.63	17.54	-0.12	11.32	14.10	380.29
Cyprus	7 081.72	52.94	33.50	17.03	1.75	17.13	24.04	1 104.76
Czech Republic	15 785.78	67.34	21.67	18.41	1.74	3.55	6.50	541.22
Denmark	23 065.75	56.71	34.01	17.98	0.31	7.88	13.10	494.90
Estonia	1 306.50	52.47	44.94	21.39	1.52	1.24	2.89	11.05
Finland	34 980.41	57.03	32.69	17.56	0.71	0.54	1.09	395.81
France	263 085.98	62.79	26.46	18.22	1.14	2.64	3.08	4 047.44
Germany	203 005.07	38.06	33.93	20.78	-1.62	2.52	3.40	2 780.53
Greece	47 693.80	64.62	11.62	13.26	-2.56	16.96	34.93	15 648.86
Hungary	14 488.47	59.07	29.06	14.98	-0.24	9.05	13.34	1 391.51
Iceland	4 294.37	54.13	36.72	21.37	1.56	3.63	10.99	325.74
Ireland	86 721.68	63.57	22.99	14.92	-0.24	6.50	13.31	5 572.42
Italy	101 283.81	48.46	36.24	17.44	0.24	7.86	16.47	9 642.99
Liechtenstein	17 397.08	50.44	45.37	20.35	0.51	1.09	2.53	245.28
Lithuania	1 358.07	63.19	10.55	14.13	0.83	3.67	6.64	53.41
Luxembourg	48.88	10.97	9.31	N.a.	-0.70	N.a.	N.a.	N.a.
Malta	5 638.36	49.48	36.94	14.88	0.81	2.84	5.39	154.43
Netherlands	288 100.95	58.63	30.37	18.35	0.35	1.41	3.46	4 573.23
Norway	14 631.18	77.98	15.07	19.27	0.99	0.93	1.95	178.81
Poland	20 118.67	65.31	24.55	14.77	0.96	4.97	7.65	943.96
Portugal	43 081.18	50.38	19.44	13.91	-0.72	4.93	5.22	2 384.78
Romania	7 976.08	49.53	38.23	16.91	0.87	12.19	18.65	660.34
Slovakia	6 807.70	69.77	13.46	14.85	0.52	4.63	6.57	240.80
Slovenia	14 839.34	60.55	21.98	13.85	-0.64	10.70	27.98	3 085.32
Spain	310 437.15	51.12	31.83	13.82	0.33	4.62	8.60	11 071.71
Sweden	131 364.17	53.18	19.93	19.71	1.11	1.47	2.85	665.86
United Kingdom	384 359.95	56.49	27.97	18.27	1.84	1.76	3.68	7 952.65
Total	**2 329 659.09**	**1 660.85**	**834.06**	**504.97**	**12.65**	**160.85**	**286.96**	**82 344.65**

8.3. Annex III – Correlation matrix

	Total capital ratio	Equity-to-assets	Equity-to-liabilities	Equity-to-dep. and st funding	Capital funds-to-assets	Capital funds-to-gross loans	Loan loss res.-to-gross loans	Impaired loans-to-equity	ROA	Non perf. Loans-to-gross loans	Noninterest expenses-to-total assets	Net interest income ratio	Liquid assets-to-dep. and st funding	Liquid assets-to-dep. and borrowings
Total capital ratio	1													
Equity-to-assets	0.378	1												
Equity-to-liabilities	0.377	0.997	1											
Equity-to-dep. and st funding	0.550	0.739	0.747	1										
Capital funds-to-assets	0.346	0.950	0.959	0.702	1									
Capital funds-to-gross loans	0.378	0.533	0.547	0.636	0.562	1								
Loan loss res.-to-gross loans	-0.136	0.152	0.166	0.073	0.221	0.226	1							
Impaired loans-to-equity	-0.185	-0.017	-0.023	-0.094	0.035	-0.024	0.477	1						
ROA	0.348	0.501	0.501	0.428	0.473	0.279	-0.229	-0.217	1					
Non perf. Loans-to-gross loans	-0.175	0.110	0.117	0.040	0.144	0.203	0.810	0.524	-0.242	1				
Noninterest expenses-to-total assets	-0.087	0.337	0.372	0.186	0.445	0.341	0.522	0.181	0.051	0.405	1			
Net interest income ratio	-0.049	0.058	0.056	-0.031	0.083	-0.207	0.070	0.078	-0.073	0.077	0.083	1		
Liquid assets-to-dep. and st funding	0.318	-0.068	-0.059	0.411	-0.072	0.590	0.105	-0.044	0.012	0.111	-0.006	-0.248	1	
Liquid assets-to-dep. and borrowings	0.298	0.070	0.077	0.404	0.072	0.689	0.225	-0.002	0.059	0.226	0.116	-0.218	0.905	1

8.4. Annex IV – Univariate analysis accounting variables

a) From 2007 to 2012

	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	-0.21337	-0.08597	-0.00253	-0.00254	-0.04926	-0.04704	-0.26608	-0.19096	0.00185	0.02639	-0.00441	-0.30721	0.03844
p-value	0.00430	0.38980	0.55790	0.59300	0.55820	0.57860	0.00110	0.00030	0.25940	0.13930	0.19630	0.42580	0.13750
McFadden R-squared	0.07824	0.01897	0.00308	0.00285	0.01843	0.01157	0.11182	0.12510	0.00938	0.00860	0.00979	0.00979	0.00545
S.D. dependent var	0.24512	0.23531	0.23591	0.23591	0.23561	0.23531	0.22952	0.22952	0.24034	0.24034	0.24069	0.24069	0.23925
Akaike info criterion	0.45179	0.44876	0.45765	0.45776	0.44988	0.45207	0.39701	0.39131	0.46927	0.46964	0.47014	0.47014	0.46671
Schwarz criterion	0.47666	0.46971	0.47868	0.47878	0.47087	0.47301	0.42502	0.41932	0.49251	0.49287	0.49343	0.49343	0.48821
Hannan-Quinn criterion	0.46175	0.45708	0.46600	0.46611	0.45822	0.46038	0.40828	0.40258	0.47855	0.47891	0.47944	0.47944	0.47526
Prob(LR statistic)	0.00089	0.07473	0.47287	0.49010	0.07904	0.16402	0.00051	0.00024	0.23499	0.25553	0.22524	0.22524	0.33967
Dep=1	19	22	22	22	22	22	14	14	20	20	20	20	22
Dep=0	278	353	351	351	352	353	238	238	306	306	305	305	340

	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	Net interest margin
Coefficient	1.73285	3.85015	0.18638	-0.26144	-0.25965	0.00000	-0.62601	-0.00037	-0.00022	0.00619	0.61884	-0.09717
p-value	0.24550	0.20900	0.02420	0.00090	0.00090	0.26440	0.50680	0.63540	0.76860	0.00010	0.00010	0.16160
McFadden R-squared	0.00236	0.00407	0.02475	0.06000	0.05931	0.00522	0.00207	0.00070	0.00021	0.02963	0.02963	0.00475
S.D. dependent var	0.23925	0.23925	0.23925	0.23561	0.23561	0.23112	0.23591	0.23561	0.23561	0.23531	0.23531	0.23531
Akaike info criterion	0.46815	0.46737	0.45789	0.43129	0.43160	0.45006	0.45811	0.45782	0.45804	0.44400	0.44400	0.45511
Schwarz criterion	0.48965	0.48887	0.47939	0.45227	0.45258	0.48162	0.47913	0.47881	0.47902	0.46495	0.46495	0.47606
Hannan-Quinn criterion	0.47670	0.47592	0.46644	0.43962	0.43993	0.46281	0.46646	0.46615	0.46637	0.45232	0.45232	0.46343
Prob(LR statistic)	0.53142	0.41157	0.04275	0.00153	0.00163	0.48745	0.55628	0.73299	0.85050	0.02591	0.02591	0.37246
Dep=1	22	22	22	22	22	12	22	22	22	22	22	22
Dep=0	340	340	340	352	352	201	351	352	352	353	353	353

	Nonintere st expenses-to-total assets	Net interest income ratio	Net interest-to-assets	Liquidity ratio	Liquid assets-to-dep. and st funding	Liquid assets-to-dep. and borrowin gs	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 borrowin gs
Coefficient	0.00447	-0.18060	-26.41444	0.00314	-0.05058	-0.07967	0.13450	0.32554	-0.00938	-0.00626	-0.00509	-0.00678
p-value	0.89160	0.80000	0.15430	0.81950	0.00620	0.00490	0.73010	0.73530	0.02010	0.50680	0.39010	0.43270
McFadden R-squared	0.00005	0.00027	0.00975	0.00029	0.06878	0.08423	0.00120	0.00057	0.05234	0.00207	0.00719	0.00336
S.D. dependent var	0.23531	0.23531	0.23531	0.23531	0.23561	0.23199	0.24408	0.23561	0.23594	0.23591	0.23620	0.23258
Akaike info criterion	0.45721	0.45711	0.45288	0.45711	0.42736	0.41081	0.48586	0.45788	0.43612	0.45811	0.45671	0.44793
Schwarz criterion	0.47815	0.47806	0.47382	0.47805	0.44834	0.43201	0.51155	0.47886	0.45789	0.47913	0.47778	0.46921
Hannan-Quinn criterion	0.46552	0.46543	0.46119	0.46542	0.43569	0.41923	0.49616	0.46621	0.44478	0.46646	0.46508	0.45639
Prob(LR statistic)	0.92528	0.83229	0.20122	0.82705	0.00069	0.00023	0.68834	0.75832	0.00385	0.55628	0.27321	0.46239
Dep=1	22	22	22	22	22	21	18	22	21	22	22	21
Dep=0	353	353	353	353	352	348	266	352	335	351	350	346

Note: Huber White estimation was used.

b) From 2013 to 2019

	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	-0.21150	-0.05108	-0.02514	-0.03544	-0.00592	-0.07346	-0.16389	-0.17550	0.00246	0.02838	-0.02160	-2.16004	0.04028
p-value	0.00000	0.00000	0.00010	0.07230	0.00060	0.00000	0.00230	0.00000	0.00630	0.00590	0.00160	0.00160	0.00000
McFadden R-squared	0.07222	0.02723	0.02819	0.03614	0.01313	0.04033	0.03188	0.07547	0.04488	0.03746	0.02721	0.02721	0.02598
S.D. dependent var	0.13365	0.12632	0.12938	0.12938	0.12770	0.12632	0.11032	0.11048	0.13231	0.13268	0.13281	0.13281	0.13164
Akaike info criterion	0.17113	0.16352	0.16988	0.16851	0.16883	0.16135	0.13229	0.12680	0.17331	0.17544	0.17756	0.17756	0.17515
Schwarz criterion	0.17787	0.16966	0.17627	0.17490	0.17507	0.16748	0.14169	0.13622	0.18013	0.18230	0.18442	0.18442	0.18172
Hannan-Quinn criterion	0.17364	0.16578	0.17225	0.17088	0.17114	0.16361	0.13585	0.13037	0.17585	0.17799	0.18011	0.18011	0.17759
Prob(LR statistic)	0.00001	0.00449	0.00401	0.00112	0.04894	0.00054	0.03452	0.00115	0.00038	0.00118	0.00572	0.00572	0.00591
Dep=1	29	29	29	29	29	29	13	13	28	28	28	28	29
Dep=0	1566	1760	1675	1675	1721	1760	1043	1043	1544	1535	1532	1532	1616

	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	Net interest margin
Coefficient	0.09692	1.40266	0.00158	-0.02069	-0.02581	0.00000	2.36506	-0.00218	-0.00236	0.00055	-0.00017	-0.01012
p-value	0.11990	0.01610	0.10900	0.00480	0.00910	0.01470	0.00010	0.00550	0.01930	0.07980	0.96960	0.41770
McFadden R-squared	0.00054	0.00843	0.00050	0.00341	0.00442	0.00989	0.01625	0.00372	0.00418	0.00156	0.00000	0.00028
S.D. dependent var	0.13164	0.13164	0.13164	0.12653	0.12653	0.14121	0.12938	0.12653	0.12653	0.12691	0.12653	0.12684
Akaike info criterion	0.17966	0.17826	0.17967	0.16792	0.16775	0.20026	0.17194	0.16787	0.16779	0.16907	0.16849	0.16913
Schwarz criterion	0.18623	0.18484	0.18624	0.17408	0.17391	0.20916	0.17833	0.17402	0.17395	0.17525	0.17464	0.17531
Hannan-Quinn criterion	0.18210	0.18070	0.18211	0.17019	0.17003	0.20362	0.17431	0.17014	0.17007	0.17135	0.17076	0.17141
Prob(LR statistic)	0.69035	0.11688	0.70177	0.31498	0.25248	0.13605	0.02890	0.29344	0.26597	0.49626	0.99477	0.77456
Dep=1	29	29	29	29	29	23	29	29	29	29	29	29
Dep=0	1616	1616	1616	1754	1754	1108	1675	1754	1754	1743	1754	1745

	Noninterest expenses-to-total assets	Net interest income ratio	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	-0.02914	0.38729	-4.17469	-0.03295	-0.04745	-0.04976	-0.05300	3.78298	0.00000	0.02365	-0.00405	-0.00029
p-value	0.01400	0.01430	0.45210	0.00300	0.00140	0.00460	0.37280	0.00360	0.41740	0.00010	0.04950	0.02030
McFadden R-squared	0.00334	0.00426	0.00060	0.01904	0.06036	0.04714	0.00121	0.03364	0.00076	0.01625	0.00314	0.00042
S.D. dependent var	0.12653	0.12681	0.12681	0.12632	0.12770	0.13025	0.13630	0.12770	0.12936	0.12938	0.12972	0.13243
Akaike info criterion	0.16793	0.16839	0.16900	0.16488	0.16086	0.16845	0.19032	0.16536	0.17474	0.17194	0.17494	0.18145
Schwarz criterion	0.17409	0.17457	0.17518	0.17101	0.16710	0.17490	0.19792	0.17161	0.18151	0.17833	0.18136	0.18809
Hannan-Quinn criterion	0.17021	0.17067	0.17128	0.16714	0.16317	0.17084	0.19316	0.16767	0.17725	0.17431	0.17732	0.18392
Prob(LR statistic)	0.32005	0.26162	0.67324	296.6101 0	0.00002	0.00020	0.57611	0.00162	0.64786	0.02890	0.33680	0.72612
Dep=1	29	29	29	29	29	29	26	29	27	29	29	29
Dep=0	1754	1746	1746	1760	1721	1652	1348	1721	1560	1675	1666	1596

Note: Huber White estimation was used.