

Global Bank Default Risk: A Cross-Regional Analysis of Financial Determinants Using the CAMELS Framework

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Abstract

This study evaluates the applicability of the CAMELS classification and related financial determinants for banks across countries. By analyzing 181 banks from North America, Oceania, Europe, and major Asian countries, using data from Bloomberg for the period 2006-2013, we aim to understand the global impact of financial shocks. Using financial distress dummy as the dependent variable and CAMELS variables as explanatory factors, our panel probit regressions reveal significant variations in how these financial variables react across different regions. The findings suggest that a one-size-fits-all global approach may be insufficient due to business cultural differences and legal frameworks that affect bank management and default risks. Thus, effective bank supervision requires tailored approaches at the country or regional level, while global regulatory institutions should strive for enhanced security and transparency in the banking sector.

JEL Classification Number: G01, G21, G28

Keywords: CAMELS, bank default prediction, banking supervision, financial distress, regulatory frameworks, financial crisis impact

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1. Introduction

The financial health and stability of banks have been a focal point of economic research for decades, with the CAMELS rating system being one of the most widely recognized frameworks for evaluating bank performance. Introduced by U.S. regulators in 1979 and later expanded to CAMELS in 1997 with the addition of a sixth component for Sensitivity to market risk, this system assesses Capital adequacy, Asset quality, Management competence, Earnings strength, Liquidity risk, and Sensitivity to market risks. It serves as a critical tool for regulatory authorities to monitor and supervise banking institutions, ensuring their soundness and stability.

Despite its widespread use, the CAMELS framework has predominantly been applied within the context of the United States banking sector. However, the global financial crisis of 2007-2009 has highlighted the interconnectedness of the international financial systems and the need for a broader application of such assessment tools. The crisis underscored that financial shocks could transcend borders, affecting banks in different regions in varying ways. This paper aims to fill this gap by applying the CAMELS framework to banks across multiple countries, including those in North America, Oceania, Europe, and major Asian economies.

Previous studies, such as those by Davis, Karim, and Liadze (2011), have shown that global samples may not always be relevant due to the diverse nature of banking systems and regulatory environments across regions. They find that assessing regions separately, such as Asia or Latin America, provided more accurate insights for policy objectives. This study builds on that premise, examining whether the CAMELS variables can provide a consistent and reliable measure of bank health across different global regions.

To this end, we selected a sample of 181 banks from these regions, ranked by total assets and covering the period from 2006 to 2013. The selection criteria ensured that our sample included banks with a significant market presence, with half of the sample comprising banks from the top 100 worldwide by assets. The financial data for these banks was obtained from Bloomberg, providing a robust dataset for our analysis.

Using panel probit regressions, we analyze the relationship between the CAMELS variables and the likelihood of a bank's financial distress. The dependent variable in our model is a dummy for financial distress, while the explanatory variables are the CAMELS components. This method allows us to capture the nuances of how different financial determinants affect bank stability across various regions.

Our results reveal significant regional differences in the impact of CAMELS variables on bank financial health. For instance, the Provision for Loan Losses to Total Assets, an indicator of asset quality, appears strongly significant in predicting financial distress in the North America-Oceania region but not in others. Similarly, the Total Equity to Total Assets ratio, indicative of capital adequacy, shows varying levels of significance across different regions. These findings suggest that while some CAMELS variables are universally relevant, others may have region-specific implications due to differing regulatory environments, business cultures, and market conditions.

The implications of these findings are twofold. First, they highlight the necessity for region-specific adjustments to the CAMELS framework to enhance its predictive accuracy and relevance. Regulatory bodies in different regions may need to tailor their supervisory practices based on the unique financial landscapes they oversee. Second, our study underscores the importance of global regulatory coordination in addressing the systemic risks arising from the interconnectedness of modern financial systems. Enhancing security and transparency in the banking sector requires a concerted effort from international regulatory institutions.

In conclusion, this research contributes to the ongoing discourse on bank supervision and financial stability by providing a more global perspective on the applicability of the CAMELS framework. It advocates for a nuanced approach considering regional specificities while promoting broader international cooperation in regulatory practices. Through this lens, we can better understand the complex dynamics that underpin global banking systems and work towards more resilient financial institutions.

2. Literature review

2.1 CAMELS and BOPEC ratings

The assessment of bank financial health has been a critical area of concern for decades, particularly in predicting bank defaults. To address these concerns, various systems have been developed to evaluate the financial soundness of banks, among which the CAMELS and BOPEC ratings are prominent. These rating systems have evolved over time to provide comprehensive frameworks for assessing different dimensions of bank health. The extant literature shows that these ratings provide valuable insights into bank safety and financial stability, underscoring the importance of rigorous regulatory frameworks and transparency in the banking sector.

Research in banking finance often focuses on specific regions, such as the US, which limits the ability to produce a global perspective that allows for comparisons between different countries or regions and the identification of key financial determinants. For example, Davis, Karim, and Liadze (2011) demonstrated that global samples can be inefficient when pooling data; instead, assessing regions like Asia or Latin America separately can better address policy objectives. Consequently, this research aims to examine the relevance of the CAMELS classification and its determinants, extending beyond American banks to provide a more international perspective.

The CAMEL rating system, formally known as the Uniform Financial Rating System, was introduced by US regulators in November 1979. This system evaluates banks based on five key components: Capital adequacy, Asset quality, Management competence, Earnings strength, and Liquidity risk exposure. Following an on-site examination by supervisory authorities such as the Federal Reserve, the Federal Deposit Insurance Corporation (FDIC), and the Office of the Comptroller of the Currency (OCC), bank examiners assign a score ranging from one (best) to five (worst) for each of the five CAMEL components. Additionally, a composite rating, derived from the analysis of the CAMEL components, is assigned, which remains strictly confidential. Banks with composite ratings of one or two are considered safe and sound, while those with ratings of three, four, or five are deemed unsatisfactory (Gilbert, Meyer, and Vaughan, 2002).

Bank supervision requires regular on-site examinations. In the USA, the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991 mandates most banks to undergo a full-scope federal or state examination every 12 months, with small, well-capitalized banks examined every 18 months (Gilbert, Meyer, and Vaughan, 2002). In January 1997, the CAMEL system evolved into CAMELS by adding the sixth component, “S” - Sensitivity, to market risk. The effectiveness of the CAMELS system largely depends on the accuracy and reliability of financial reporting, as it is primarily based on accounting numbers from regulatory filings (Jin, Kanagaretnam, Lobo, and Mathieu, 2013). Supervisory authorities tend to avoid using the Management component due to its qualitative nature, which is challenging to measure, unlike other components that can be proxied by accounting ratios (Capelle-Blancard and Chauveau, 2002).

CAMELS ratings, derived from on-site examinations, encompass a bank’s financial condition, management quality, internal control systems, regulatory policies, and legal compliance (Cole and Gunther, 1998). Regulators focus on early intervention and providing

appropriate responses to help troubled banks recover promptly. However, CAMELS ratings were not originally intended to predict bank failures. Cole and Gunther (1998) compared supervisory ratings with Call Report data in predicting future bank failures from 1988 to 1992. They found that CAMEL ratings improved forecast accuracy only if the examination occurred in the previous six months. This explains why a probit statistical model using publicly available financial data yields better results in predicting bank failure.

Similarly, Berger, Davies, and Flannery (2000) showed that only recently assigned BOPEC ratings outperform market-based measures for predicting the future performance of Bank Holding Companies (BHCs). Supervisory assessments appear less accurate than market indicators, such as stocks or bonds, in predicting future performance changes. They compared BOPEC ratings of BHCs with stock and bond market assessments for 184 banks from 1989:Q4 to 1992:Q2, using four indicators of market assessment: insider equity ownership, abnormal stock return, Moody's rating on outstanding debentures, and institutional investor equity ownership. They found that bond market ratings (market information) and BOPEC ratings (supervisory data) "Granger-cause" each other, indicating that both financial markets and supervisors possessed unique predictive information. Conversely, the "Granger-causality" between supervisory assessments and equity markets was weak to null, suggesting differing incentives about the future between these data sets.

In addition to the CAMELS system, the BOPEC rating system is used to evaluate Bank Holding Companies (BHCs). Assigned by the Federal Reserve, BOPEC ratings reflect the conditions of BHC's Bank subsidiaries, Other (nonbank) subsidiaries, Parent company, Earnings, and Capital adequacy. Similar to CAMELS, BOPEC ratings range from one (strongest) to five (weakest) for each component, with an overall rating indicating the BHC's management quality and financial health as satisfactory, fair, or unsatisfactory.

Along with on-site examinations, US bank supervisors use off-site surveillance to reduce costs and complement on-site examinations. By the late 1990s, the Federal Financial Institutions Examinations Council (FFIEC) required banks to issue quarterly Reports of Condition and Income, known as Call Reports. This led to the development of various tools based on CAMELS variables, using Call Report data for examination scheduling and planning, including econometric models.

Research shows that the added value of supervisory assessments deteriorates over time. Hirtle and Lopez (1999) employed CAMEL ratings assigned to banks from 1989 to 1995 by the FDIC, the Federal Reserve, the OCC, and state banking supervisors. They found that

information quality significantly decays within 18 to 36 months post-examination, especially during financial troubles.

Multiple research efforts have confirmed the utility of CAMELS ratings in assessing financial institutions. De Young, Flannery, Lang, and Sorescu (1998) demonstrated that government examinations yield valuable information about bank safety several quarters before markets internalize this information into debenture prices. Using quarterly data for national bank subsidiaries of BHCs with traded debentures from 1989 to 1995, their research showed that CAMELS ratings provided additional valuable information about the safety of publicly traded large banks. However, later findings by De Young, Flannery, Lang, and Sorescu (2001) found no clear evidence that CAMELS information adds value beyond market knowledge, likely due to the small sample size of large banks with traded debentures in their study.

Dahl, O’Keefe, and Hanweck (1998) demonstrated that examiners (government agencies) and auditors (private firms) influence loan-loss provisioning and timing differently. They found that bank examiners significantly impacted commercial and industrial loan-loss recognition timing, but not auditors. Conversely, auditors positively influenced provisions for loan losses between 1992 and 1997, while examinations had no significant effect. Similarly, Berger and Davies (1998) concluded that CAMEL downgrades were important for uncovering unfavorable information, suggesting that negative examination results were associated with poor financial conditions. Their sample included bank Call Report data, Federal bank examination data, BHC data, and stock return data from 390 bank examinations of large publicly traded banking organizations from January 1985 to June 1989. They found that banks with unsatisfactory ratings benefited more from auditing conclusions due to their poor financial conditions.

Billet, Garfinkel, and O’Neal (1998) indicated that insured deposit financing helped banks mitigate market discipline costs, suggesting that regulatory supervision is perceived as less costly than market supervision. They found that banks increased insured deposits during risky periods to lower regulatory costs compared to uninsured liabilities. Their study, covering credit rating changes for BHCs from January 1990 to December 1995, concluded that regulation might undermine market discipline's effectiveness in mitigating bank risk-taking.

Conversely, Jordan, Peek, and Rosengren (1999) examined the impact of mandatory disclosure on troubled banks during a crisis, finding it promoted market discipline without destabilizing the system, thus supporting greater transparency and disclosure to strengthen market discipline and resolve banking difficulties. Banks that have not fully disclosed financial

troubles may experience larger stock price reactions than those that have, highlighting the need to examine variables such as capital position, earnings, and loan loss provisioning (Jordan, Peek, and Rosengren 1999). Enhanced transparency and market discipline encourage management to avoid examiner intervention and take corrective actions.

Greater transparency, achieved through disclosure, can strengthen market discipline. Flannery & Sorescu (1996) analyzed debenture yields from 1983-1991 to show investor responsiveness to bank-specific risks due to policy shifts regarding government absorption of bank failure losses. Flannery (1998) documented the growing body of evidence suggesting market discipline can play a more significant role in governing large U.S. banks, challenging traditional justifications for extensive government oversight. While on-site examinations may lag in identifying troubled institutions, combining supervisory findings with market information (O'Keefe & Reidhill, 1997) could reduce this recognition delay. However, supervisors may require time to build a case before intervening, potentially creating a gap between identifying a problem bank and taking corrective action.

In conclusion, both CAMELS and BOPEC ratings play crucial roles in bank supervision and help combine supervisory data with market information to enhance the monitoring and control of banks and BHCs. Research shows that these ratings provide valuable insights into bank safety and financial stability, underscoring the importance of rigorous regulatory frameworks and transparency in the banking sector. Enhanced disclosure and transparency are essential for effective regulation and market discipline, helping to mitigate banking difficulties and ensuring financial stability.

2.2 Bank defaults and sophisticated Early Warning Systems

By the end of the 1990s, only a few researchers had focused on predicting bank defaults and banking crises. However, the last two decades of the 20th century witnessed a significant number of banking crises worldwide, where banks became insolvent, unable to perform their intermediary roles due to the value of their liabilities exceeding that of their assets.

Davis and Karim (2008a) noted that three-quarters of IMF countries experienced banking distress between 1980 and 1996. These decades were marked by financial liberalization, which coincided with the introduction of new financial products, further amplified by computerization and the internationalization of financial markets. A major development during this period was the significant revision of the American Glass-Steagall Act, adopted in 1999 under the Gramm-Leach-Bliley Act. This revision allowed commercial banks,

investment banks, and insurance companies to consolidate into universal banks, enabling diversified investments. While this diversification had some positive effects, it also increased risk-taking.

However, other factors also played crucial roles. Taylor (2008) argued that lenient monetary policies, particularly the fall in interest rates between 2002 and 2004, led to monetary excesses that contributed to the housing boom and subsequent burst and collapse. Reinhart and Rogoff (2008) corroborated this by showing that housing prices in the US grew far more rapidly than in other countries like Sweden (1991), Finland (1991), Spain (1977), Japan (1992), and Norway (1987) during their financial crises. The sudden lack of banking liquidity in credit markets further exacerbated the situation, leading to contagion effects. \

Demirgüç-Kunt and Detragiache (1998) found that banking crises were more likely in countries that had undergone financial liberalization, especially if these countries lacked strong institutional environments. Using a multivariate logit model to analyze data from 1980 to 1994, their study showed that in a weak macroeconomic context, low GDP growth, high real interest rates, high inflation, and an explicit deposit insurance system could increase the likelihood of a banking crisis. Paradoxically, while an explicit deposit insurance system should theoretically mitigate bank fragility (Diamond and Dybvig, 1983), it can also encourage risk-taking by bank decision-makers (i.e. a moral hazard), particularly in the post-1999 era following the Gramm-Leach-Bliley Act. Demirgüç-Kunt and Detragiache reinforced these findings in a 2005 study extending the analysis to 94 countries and 77 crises occurring between 1980 and 2002. They primarily focused on macroeconomic determinants due to the lack of data on potential microeconomic variables of banking and regulation, highlighting the need to further investigate bank-level information.

Kaminsky and Reinhart (1999) employed a different methodology, finding that financial liberalization often triggered banking crises, which then led to currency crises, creating a vicious cycle. Their study of 20 countries, covering 76 currency crises and 26 banking crises from 1970 to 1995, showed a significant increase in crises after the liberalization period of the 1980s and 1990s (50 currency crises and 23 banking crises) compared to the more regulated 1970s (26 and 3, respectively). Using a non-parametric signal extraction model, they established country-specific thresholds to create an Early Warning System¹ with univariate

¹ Kaminsky and Reinhart (1999) developed an Early Warning System by minimizing the Noise-to-Signal Ratio, defined as the Probability of Type II error divided by (1 – Probability of Type I error). This approach allowed them to establish country-specific thresholds, which served as benchmarks for generating univariate indicator signals. For each of the fifteen variables analyzed, they defined specific time intervals between signals and crises, creating

indicator signals. Their most effective predictive variables were related to capital accounts (e.g., reserves) and financial liberalization (e.g., real interest rates and domestic credit/GDP ratio).

Demirgüç-Kunt and Detragiache (2000) further refined crisis prediction models, revealing that their multivariate logit model produced fewer in-sample Type I and Type II errors than Kaminsky and Reinhart's signal extraction model. Their model involved selecting a probability threshold that minimized the loss function associated with either taking unnecessary action (no crisis) or failing to act when needed. They applied this model to six banking crises in the late 1990s, including the Jamaican crisis of 1996 and the East Asian countries crises of 1997. However, their predictions were overly optimistic for three of these crises, which the authors attributed to the novelty of their econometric tools and the challenge of accounting for new phenomena that could trigger crises, potentially limiting out-of-sample replication.

Comparing the multivariate logit models in Demirgüç-Kunt and Detragiache (2005) with Kaminsky and Reinhart's signal extraction method (1999), Davis and Karim (2008a) concluded that the multivariate logit model had better in-sample predictive accuracy. While the multinomial logit model aligned better with global Early Warning Systems, the signal extraction methodology was more suitable for country-specific Early Warning Systems. For their sample, changes in terms of trade and real GDP growth were the most reliable predictors of banking crises.

Binary Recursive Trees (BRT), or decision tree techniques commonly used in machine learning and medical research, have also been applied to banking crisis prediction. Davis and Karim (2008b) and later Davis, Karim, and Liadze (2011) used these techniques to classify banks using "If-Then" rules implemented in Early Warning Systems, using a proprietary software package ("CART", Salford Systems Inc.). Unlike multivariate logit models, BRT partitioning seeks to identify non-linear variable interactions that could signal economic vulnerability to banking crises. The non-parametric nature of BRT is advantageous, as it does not require specific statistical distributions for the variables, allowing for more flexibility.

However, when Davis and Karim (2008b) applied both BRT and logit models to OECD countries, including emerging markets, neither method provided robust predictions for the potential increase in crisis probability for the two years preceding the subprime crisis. The logit

time series data that indicated either a "1" (signal of crisis) or a "0" (no signal) whenever a variable exceeded its threshold. They then compared these signals with actual crisis events to assess the predictive accuracy of their model.

model performed better for the UK and the US. This led Davis, Karim, and Liadze (2011) to suggest that pooling global data may not be effective. Instead, they recommended using both models to assess specific regions, such as Asia or Latin America, to better align with policy objectives.

Wilson (1998) and McKinsey & Company proposed the CreditPortfolioView model, a discrete-time multi-period model that measures default risk. This model generates default probabilities through a logit model based on macroeconomic variables, which are specific to each country and follow an autoregressive model of order 2 (AR(2)). The key idea is to link these macroeconomic factors to default and migration probabilities. However, the model requires reliable default data for each country and industrial sector (Crouhy et al., 2000), as well as a specified procedure to adjust the migration matrix. Due to the limited historical data, it is challenging to cover multiple credit cycles and test the model's robustness during crises.

Other sophisticated tools, such as Case-based reasoning, Neural Networks, Trait Recognition, and Multicriteria decision aid, have also been developed in the empirical literature (Demyanyk and Hasan, 2009). However, none of these methods consistently outperforms the others, suggesting that combining different approaches may be more effective. Davis and Karim (2008a) and Davis, Karim, and Liadze (2011) demonstrated the benefits of combining models depending on whether the focus is on global or country/zone-specific Early Warning Systems.

3. Data

3.1 Sample analysis and data collection

This study analyzes a sample of 181 globally systemically important banks (GSIBs) from 2006 to 2013. Banks were selected based on total assets, with a focus on the top 150 institutions within three geographic regions: North America-Oceania (Anglo-Saxon countries - USA, Canada, and Australia, 62 banks), Europe (57 banks), and Asia (major countries - India, China, Japan, 62 banks). We have not included Russian banks for historical, political, and economic considerations.

Data were primarily sourced from Bloomberg, supplemented by Relbanks and Fitch Connect for bank rankings and additional financial information.² Half of the sample included

² It is crucial to note that consolidated financial data were employed, necessitating adjustments to align with research requirements.

the world's top 100 banks by assets in 2008, as defined by Relbanks.³ To ensure sample representativeness, smaller institutions were included, with The South Indian Bank Ltd. (total assets at €2.35bn in 2006) and the Signature Bank (€4bn in 2007) in the US, the lower asset benchmarks. These banks remained the smallest in 2008 by total assets. According to Bloomberg, the Royal Bank of Scotland Group PLC (total assets: € 2,508 bn) and the Deutsche Bank (total assets: € 2,202 bn) represented the largest banks in the sample in 2008.

The European banking sector exhibited a remarkable consolidation during the study period (2006-2013). No European bank in the sample possessed total assets below €10 billion. However, European global dominance waned over time. While all five of the world's largest banks by assets were European in 2008, this figure declined to two by 2013, with a corresponding rise in Chinese (4 banks) and Japanese (1 bank) representation in 2016.

The initial sample of European banks comprised the top 100 institutions by total assets in 2008, as identified by Fitch Ratings, covering 31 countries within the EU and EFTA (European Free Trade Association, including Iceland, Norway, Switzerland, and Liechtenstein). The dynamic nature of the European banking industry during the 2006-2013 period posed significant challenges to sample selection. Numerous bank failures, mergers, and nationalizations occurred, necessitating careful sample refinement. Spanish cajas, in particular, experienced widespread distress, of them went bankrupt or were taken over (e.g. with the creation of the Bankia on 3/12/2010). Additionally, data limitations affected the inclusion of smaller and non-listed banks, such as French savings banks (“caisses d’épargne”) and mutual banks.

The initial sample of 100 European banks was significantly reduced due to various factors. Several high-profile bank failures and nationalizations occurred during the study period. Notable examples include the nationalization of Northern Rock and Bradford & Bingley in the UK, as well as the acquisition of Alliance & Leicester by Santander. The collapse of Anglo-Irish Bank and the merger of HBOS with Lloyds also impacted the sample. On the continental European landscape, significant restructuring took place. ABN Amro was acquired by a consortium, while Sachsen LB and WestLB encountered severe financial difficulties. The merger of Dresdner Bank with Commerzbank and the formation of BPCE through the

³ At the end of 2008, our 12 Chinese banks belonged to the Top 20 in China, and our 20 Indian banks belonged to the Top 50 in India. Because Australian banks had not been really impacted by the financial crisis, there was no real shift in asset ranking after 2008 (even until 2016) hence our 7 Australian banks remain in the 14 top banks in Australia.

combination of Banques Populaires and Caisses d'Epargne further reduced the pool of eligible institutions. We also excluded Natixis from the sample due to its specialized business model.

3.2 Financial distress and explanatory variables

3.2.1 Dependent variables

In this study, our dependent variable, financial distress, is a dummy variable that takes a value of 1 or 0 for a given year. Wheelock and Wilson (2000) defined bank failure in the U.S. as either closure by the FDIC or a scenario where total equity capital (less goodwill) divided by total assets falls below 2%. Similarly, Gilbert, Meyer, and Vaughan (2002) employed the SEER (System to Estimate Examination Ratings) risk rank probit model to classify a bank as distressed if its tangible capital (equals total equity capital less goodwill) falls below 2% of total assets within the next 24 months. Given that this condition may not always be as apparent as a formal bank closure, we define financial distress using two other widely recognized financial ratios, thereby simplifying the identification process.

The first variable is the Tier 1 Capital Ratio (TIER1_CAP_RATIO), defined as the ratio of Tier 1 capital to risk-weighted assets. This ratio is frequently used to gauge the financial strength of banks, as demonstrated by Jin, Kanagaretnam, and Lobo (2011), Aebi, Sabato, and Schmid (2011), and Minton, Taillard and Williamson (2012). According to Beltratti and Stulz (2012), banks with higher capital ratios are more resilient to adverse shocks. Thus, we set a threshold where if the Tier 1 Capital Ratio falls below 6%, the dummy variable for financial distress equals 1; otherwise, it equals 0. This threshold aligns with the Basel Committee's post-crisis regulations, which raised the minimum Tier 1 Capital Ratio to 6%.

The second variable is the Return on Assets (ROA), a common measure of bank performance (Berger, Imbierowicz and Rauch, 2013; Ellul and Yerramilli, 2013). Jin, Kanagaretnam, and Lobo (2011) used ROA as part of a set of conditions to categorize a bank as troubled ⁴, Jin, Kanagaretnam, Lobo and Mathieu (2013) referred to a large loss, while Krishnan (2005) suggested using a dummy variable indicating a loss (net income < 0) to measure financial distress. Accordingly, we define that if ROA is less than 0, the dummy variable for financial distress equals 1; otherwise, it equals 0. Financial distress (FD) is therefore defined as follows:

$$FD = 1 \text{ if } (Tier\ 1\ Capital\ Ratio < 6\%) \text{ or } (ROA < 0); \text{ otherwise, } FD = 0.$$

⁴ Jin, Kanagaretnam, and Lobo (2011) employed a three-condition criterion to identify troubled banks: return on assets (ROA) below -5%, Tier 1 capital ratio under 4%, and a loan loss provision to total loan ratio exceeding 1%.

3.2.2 Explanatory variables

To explain financial distress, we selected explanatory variables from Bloomberg that align with the six CAMELS dimensions. We also included a dummy variable indicating whether a bank is European (1 for European, 0 otherwise).

SELECTED BLOOMBERG VARIABLES

CAPITAL PROTECTION

TOT_EQ_TO_TOT_ASSET(%) (*)

ASSET QUALITY

LOG(TOT_ASSET)

TOT_LOAN_TO_TOT_ASSET (%)

PROV_FOR_LOAN_LOSS_TO_TOT_ASSET(%) (*)

MANAGEMENT COMPETENCE

OPER_MARGIN(%)

RETURN_COM_EQY(%)

EARNINGS STRENGTHS

RETURN_TOT_EQY (%)

NET_REV_TO_TOT_CAP (*)

LIQUIDITY RISK EXPOSURE

CUSTOMER_DEPOSIT_TO_TOT_ASSET(%) (*)

CASH_TO_TOT_ASSET

ST_BORROW_TO_TOT_ASSET(%) (*)

SENSITIVITY TO MARKET RISKS

BOOK_VAL_PER_SH

Source: Bloomberg. We compute the Log of TOT_ASSET with TOT_ASSET in Euro thousands (knowing that they are given in Euro million in Bloomberg). () stand for Bloomberg variables that we scaled by assets (or by capital for the Net Revenue). Table 0 in the Appendix details the description of the variables.*

Capital protection

Capital adequacy is pivotal, as undercapitalized banks are more susceptible to acquisition or failure (Wheelock and Wilson, 2000; Cole and Gunther, 1998). We employ the Total Equity to Total Assets ratio (TOT_EQ_TO_TOT_ASSET) as a proxy for capital protection, following Arena (2008) and Demirgüç-Kunt, Detragiache, and Gupta (2000). We expect this variable to have a negative relationship with financial distress, as higher capitalization should correlate with greater resilience.

Asset quality

The Total Assets variable (LOG(TOT_ASSET)) is a proxy for bank size (Aebi, Sabato and Schmid, 2011; Adams and Mehran, 2011; Berltratti and Stulz, 2012; Berger, Imbierowicz and Rauch, 2013; Cole and White, 2012). Empirical studies present mixed findings regarding the impact of bank size. Bhattacharyya and Purnanandam (2011) posited that larger banks may

hedge their risks more effectively and anticipate governmental bailouts during crises (too-big-to-fail facilities). Cole and White (2012) suggested that younger, smaller banks are more prone to failure, acknowledging that larger banks' investments in toxic RMBS (Residential Mortgage Backed Security) complicated the risk attribution purely based on size. Prior literature suggests a nuanced impact of bank size on risk-taking behaviors. Jin, Kanagaretnam, Lobo, and Mathieu (2013) considered bank size a risk driver, differentiating between large and small banks by incorporating non-linear size determinants in their models. Ellul and Yerramilli (2013) employed similar size metrics in constructing their Risk Management Index for US Bank Holding companies, emphasizing the relevance of both linear and squared logarithmic transformations of total assets. Consequently, the effect of bank size on financial distress remains an open question, requiring further investigation.

The ratio of Total Loans to Total Assets (TOT_LOAN_TO_TOT_ASSET) is another critical indicator (Aebi, Sabato and Schmid, 2011; Ellul and Yerramilli, 2013). While higher values of this ratio suggest a focus on traditional lending activities over securities investments, interpretations vary. Aebi, Sabato, and Schmid (2011) noted the complexity of associating this ratio with performance during crises, whereas Beltratti and Stulz (2012) found that banks holding government securities instead of loans fared better.

To assess loan quality, we incorporate the Provision for Loan Losses to Total Assets ratio (PROV_FOR_LOAN_LOSS_TO_TOT_ASSET), following Betz, Oprica, Peltonen, and Sarlin (2013) and Jin, Kanagaretnam, and Lobo (2011). An abnormal increase in this provision often signals an impending failure, as it reflects anticipated future loan losses (O'Keefe and Wilcox, 2009).

Management competence

Management competence is evaluated using the Return on Common Equity (RETURN_COM_EQY) and Operating Margin (OPER_MARGIN). These metrics assess profitability and operational efficiency, respectively. They are hypothesized to exhibit a negative correlation with financial distress. It is worth noting that Betz, Oprica, Peltonen, and Sarlin (2013) employed a distinct calculation for operating margin, defining it as the ratio of operating costs to operating income.

Earnings strengths

Earnings strength is represented by the Return on Total Equity (RETURN_TOT_EQY) (Berger and Bouwman, 2013) and the Net Revenue to Total Capital ratio

(NET_REV_TO_TOT_CAP). These variables measure a bank's capability to generate income relative to its capital base. Consistent with prior research (e.g., Cole and Gunther, 1998), robust earnings are presumed to mitigate financial difficulties, suggesting a negative association with financial distress.

Liquidity risk exposure

Liquidity risk is measured using several ratios. The Customer Deposit to Total Assets ratio (CUSTOMER_DEPOSIT_TO_TOT_ASSET) indirectly captures the extent of retail banking activities, reflecting a bank's reliance on deposit funding. We anticipate a negative relationship between this ratio and financial distress, as a higher deposit-to-asset ratio is associated with greater bank stability due to the reduced reliance on potentially volatile interbank funding (Berltratti and Stulz, 2012; Aebi, Sabato, and Schmid, 2011; Ellul and Yerramilli, 2013; and Bhattacharyya and Purnanandam, 2011). However, Merton (1977) cautions that deposit insurance may incentivize shareholders to undertake greater risks.

The Cash to Total Assets ratio (CASH_TO_TOT_ASSET) is another important metric. While cash reserves enable banks to manage unexpected deposit withdrawals, an excessive accumulation may signal underlying issues, such as impending financial distress or agency problems. Studies like Arena (2008), Cole and White (2012), or Demirgüç-Kunt, Detragiache and Gupta (2000) utilized similar ratios to proxy for liquidity risk (Liquid Assets or Cash divided by Total assets). Notably, excessive cash holdings may necessitate the divestment of specific activities or assets and could be linked to agency problems, making this ratio potentially connected with financial distress. Acharya and Mora (2011) and Bennet, Hwa, and Kwast (2014) observed that banks on the brink of failure in early 2009 raised deposit rates to counteract outflows. To prevent such scenarios, Basel III mandates that the Liquidity Coverage Ratio (high-quality liquid assets divided by total net cash outflows over 30 days) exceed 100%.

Additionally, the Short-Term Borrowing to Total Assets ratio (ST_BORROW_TO_TOT_ASSET) is incorporated, adhering to Betz, Oprica, Peltonen, and Sarlin's (2013) findings that reliance on short-term funding is positively associated with financial distress. For consistency, we scale this variable by total assets in our analysis.

Sensitivity to market risks

In the CAMELS framework, **Sensitivity to Market Risks** assesses a bank's exposure to adverse market conditions, such as fluctuations in interest rates, exchange rates, or equity prices. This dimension is often evaluated using market-based metrics like the price-to-book

ratio, which compares a company's market price to its book value per share (BOOK_VAL_PER_SH). This ratio serves as a proxy for the market's growth expectations and risk assessment, (Aebi, Sabato, and Schmid, 2011; Campbell, Hilscher, and Szilagyi, 2008).

However, our dataset faced a frequent absence of share price information, particularly for Asian banks. This constraint rendered the computation of market-oriented ratios like the price-to-book ratio infeasible. Consequently, we incorporated Book Value per Share (BOOK_VAL_PER_SH) as an alternative, acknowledging its nature as an accounting-based measure rather than a direct indicator of market sensitivity.

While Book Value per Share does not capture market dynamics explicitly, it provides insights into the bank's capital structure. The importance of robust capital levels in mitigating market risks is underscored by Berger and Bouwman (2013), who found that capital enhances the survival probability and market share of small U.S. banks under all conditions and enhances the performance of medium and large banks, especially during banking crises. This linkage emphasizes the interplay between capital adequacy and market risk sensitivity. Although Book Value per Share is not a perfect proxy for sensitivity to market risks, its inclusion serves as a practical compromise given data constraints, offering partial insights into the bank's capacity to withstand adverse market conditions.

European dummy variable

As our study particularly focuses on European banks, we include a European dummy variable (1 for a European bank, 0 otherwise) to account for regional heterogeneity. This consideration stems from evidence that legal protections and ownership concentration vary across countries, influencing financial distress risk (Shleifer and Vishny, 1997; La Porta, Lopez-de-Silanes, Shleifer and Vishny, 1998). Laeven and Levine (2008) and Beltratti and Stulz (2012) found that banks with powerful owners face higher risks but exhibit greater resilience under stronger protection laws. Beltratti and Stulz (2012) further demonstrated that large banks in countries with stricter legal protection on bank activities outperformed their peers during the financial crisis, despite the lack of a consistent correlation between national regulatory stringency and overall bank performance. Moreover, Aggarwal, Erel, Stulz, and Williamson (2008) suggested that firms in countries with weaker investor protections are less inclined to invest in robust governance mechanisms. Therefore, the European dummy variable is a crucial control in our analysis.

3.3 Summary statistics

Table A shows the main summary statistics for our variables for the 181 banks from which we get detailed financial data from 2006 to 2013. We obtained 1,242 observations.

Table A: Summary statistics - All banks

Variable	Obs	Mean	SD	Min	Max
TOT_LOAN_TO_TOT_ASSET	1,242	56.660	15.753	1.519	88.728
RETURN_TOT_EQY	1,242	8.459	12.374	-141.453	64.367
CASH_TO_TOT_ASSET	1,242	4.042	4.203	0.002	29.590
OPER_MARGIN	1,242	17.698	192.039	-6,632.044	94.830
TOT_EQ_TO_TOT_ASSET	1,242	7.138	3.921	0.863	45.770
ST_BORROW_TO_TOT_ASSET	1,242	9.606	9.353	0.000	67.174
NET_REV_TO_TOT_CAP	1,242	14.628	9.670	0.148	81.247
PROV_FOR_LOAN_LOSS_TO_TOT_ASSET	1,242	0.416	0.597	-0.366	5.770
CUSTOMER_DEPOSIT_TO_TOT_ASSET	1,242	61.572	22.014	1.245	94.137
Log_TOT_ASSET	1,242	8.053	0.642	6.371	9.399
RETURN_COM_EQY	1,242	8.452	13.055	-141.453	64.367
BOOK_VAL_PER_SH	1,242	19.664	44.776	0.020	617.840

Table B of summary statistics: European banks

This table shows the main summary statistics for our variables for the 57 banks from which we get detailed financial data from 2006 to 2013. We obtained 387 observations.

Variable	Obs	Mean	SD	Min	Max
TOT_LOAN_TO_TOT_ASSET	387	55.016	17.037	9.929	84.585
RETURN_TOT_EQY	387	5.531	16.644	-141.453	64.367
CASH_TO_TOT_ASSET	387	2.686	2.470	0.013	15.319
OPER_MARGIN	387	12.789	52.198	-663.830	94.830
TOT_EQ_TO_TOT_ASSET	387	5.355	2.227	0.863	14.504
ST_BORROW_TO_TOT_ASSET	387	15.482	10.399	0.478	57.130
NET_REV_TO_TOT_CAP	387	6.669	4.953	0.228	40.134
PROV_FOR_LOAN_LOSS_TO_TOT_ASSET	387	0.451	0.554	-0.136	5.770
CUSTOMER_DEPOSIT_TO_TOT_ASSET	387	38.825	14.359	2.316	87.492
Log_TOT_ASSET	387	8.429	0.496	6.995	9.399
RETURN_COM_EQY	387	5.367	16.947	-141.453	64.367
BOOK_VAL_PER_SH	387	33.361	73.701	0.020	617.840

Table C of summary statistics: US, Canadian, and Australian banks

This table shows the main summary statistics for our variables for the 62 banks from which we get detailed financial data from 2006 to 2013. We obtained 415 observations.

Variable	Obs	Mean	SD	Min	Max
TOT_LOAN_TO_TOT_ASSET	415	57.426	18.402	5.147	88.728
RETURN_TOT_EQY	415	9.099	10.788	-49.258	55.080
CASH_TO_TOT_ASSET	415	2.922	4.020	0.002	29.590
OPER_MARGIN	415	8.584	327.820	-6,632.044	73.610
TOT_EQ_TO_TOT_ASSET	415	9.269	3.328	3.130	32.796
ST_BORROW_TO_TOT_ASSET	415	7.780	7.919	0.000	67.174
NET_REV_TO_TOT_CAP	415	18.055	10.146	0.148	81.247
PROV_FOR_LOAN_LOSS_TO_TOT_ASSET	415	0.555	0.800	-0.366	5.667
CUSTOMER_DEPOSIT_TO_TOT_ASSET	415	65.255	15.077	8.822	89.576
Log_TOT_ASSET	415	7.894	0.647	6.603	9.252
RETURN_COM_EQY	415	8.969	12.310	-72.660	55.080
BOOK_VAL_PER_SH	415	22.351	22.025	2.205	183.352

Table D of summary statistics: Asian banks

This table shows the main summary statistics for our variables for the 62 banks from which we get detailed financial data from 2006 to 2013. We obtained 440 observations.

Variable	Obs	Mean	SD	Min	Max
TOT_LOAN_TO_TOT_ASSET	440	57.383	11.112	1.519	79.010
RETURN_TOT_EQY	440	10.431	8.224	-27.476	35.772
CASH_TO_TOT_ASSET	440	6.292	4.632	0.059	22.068
OPER_MARGIN	440	30.611	15.619	-65.704	71.724
TOT_EQ_TO_TOT_ASSET	440	6.697	4.622	2.530	45.770
ST_BORROW_TO_TOT_ASSET	440	6.160	6.898	0.064	34.084
NET_REV_TO_TOT_CAP	440	18.396	8.031	1.032	48.171
PROV_FOR_LOAN_LOSS_TO_TOT_ASSET	440	0.253	0.294	-0.358	1.449
CUSTOMER_DEPOSIT_TO_TOT_ASSET	440	78.105	15.210	1.245	94.137
Log_TOT_ASSET	440	7.873	0.610	6.371	9.355
RETURN_COM_EQY	440	10.679	8.531	-29.608	35.772
BOOK_VAL_PER_SH	440	5.083	6.981	0.099	46.793

4. Methodology

4.1 Models

The dependent variable in our analysis is binary, taking a value of 0 or 1 to indicate the occurrence of financial distress. Our explanatory variables consist of various accounting and financial metrics observed on an annual basis.

The marginal probability of financial distress can be modeled using a Binomial Logit model, which is expressed as:

$$P(Y_{i,t+1} = 1) = \frac{1}{1 + \exp(-\alpha - \beta x_{i,t})}$$

Here, $Y_{i,t+1} = 1$ if the bank experiences financial distress in the subsequent year $t+1$, incorporating a one-year lag. The term $x_{i,t}$ represents the vector of explanatory variables from the previous year, while α is the intercept and β is the vector of coefficients associated with these variables.

Alternatively, using a Probit model, the equation is:

$$P(Y_{i,t+1} = 1) = F(\alpha + \beta x_{i,t})$$

where F denotes the standardized normal cumulative distributive function.

We conducted panel probit regressions for the period 2006-2013, extending to 2014 for models incorporating the lagged dependent variable to predict financial distress. Tables 1 to 5 present regression results.

We opted for the probit model due to its suitability for calculations involving random effects, as econometricians such as Piroette (2011) recommended. The probit model with random effects is particularly advantageous as it simplifies the integration process using marginal non-conditional likelihood after computing the conditional likelihood, providing more detailed and reliable results.

4.2 Main results

Tables 1 to 5 present the results of panel probit regressions analyzing the determinants of financial distress (FD) for the whole sample and different sub-samples. The models include various financial ratios from Bloomberg, with the dependent variable being either a one-year lead (FD_{t+1}) or contemporaneous (FD) measure of financial distress.

4.2.1. Regressions on the whole sample (181 banks)

First, Table 1 provides lagged and contemporaneous regressions with all 181 banks in the sample. The regressions incorporate variables categorized under the CAMELS framework.

[Insert ***Table 1***]

The panel probit regressions presented in Table 1 provide valuable insights into the determinants of bank financial distress. By examining both lagged (employing a one-year lead for the dependent variable) and non-lagged models, we can identify the predictive power of various financial indicators at different time horizons.

In terms of *Capital adequacy*, TOT_EQ_TO_TOT_ASSET emerges as a potent indicator of financial distress, but only in non-lagged models. This ratio shows a strongly significant negative association with the dependent variable, emphasizing the importance of maintaining adequate capital buffers to avoid imminent financial distress.

A key finding from these models is the substantial association between *Asset quality* and financial distress. Specifically, the PROV_FOR_LOAN_LOSS_TO_TOT_ASSET variable consistently emerges as a strong predictor in all models, indicating that increasing provisions for loan losses are a reliable indicator of both near and future financial difficulties. This result is consistent with prior research indicating that increasing loan loss provisions often signal deteriorating financial conditions within banks, especially in the U.S. context. This suggests that deteriorating asset quality is a leading driver of bank vulnerability. In the meantime, Log_TOT_ASSET shows a weakly negative association with the dependent variable in non-lagged models (5% and 10% significance levels), confirming the too-big-too-fail hypothesis over big banks' failures.

Management competence also plays a crucial role. The RETURN_COM_EQY variable, representing return on common equity, is consistently negatively associated with financial distress (5% significance), emphasizing the importance of efficient management practices in mitigating vulnerability. OPER_MARGIN has a consistently negative relationship with financial distress, but this association is strongly significant (1% significance) only in non-lagged models, suggesting a short-term effect of this aspect of efficient management on mitigating financial risks. In contrast, these whole-sample regressions show no evidence of *Earning strength* as a potential financial distress predictive indicator.

Regarding *Liquidity risk*, the ST_BORROW_TO_TOT_ASSET variable demonstrates a positive relationship with financial distress in the lagged model. This implies that reliance on short-term borrowings can increase a bank's vulnerability to liquidity shocks in the future. Furthermore, CASH_TO_TOT_ASSET is a significant predictor (1% significance) in non-lagged models, suggesting that excessive liquidity may be indicative of underlying problems. Conversely, CUSTOMER_DEPOSIT_TO_TOT_ASSET is weakly (10% significance) and negatively associated with distress, suggesting that deposit-based funding is a more stable source of financing. Finally, BOOK_VAL_PER_SH (*Sensitivity to market risk*) shows no explanatory power in this models.

While the models in Table 1 do not explicitly explore regional differences, the inclusion of a Europe dummy variable, which was non-significant, suggests that there may not be

substantial regional variations within the overall sample. However, to gain a more nuanced understanding of regional determinants of bank vulnerability, we carry out further analysis of sub-samples. Subsequent regressions will examine the specific characteristics of European, Asian, and North American-Oceanian banks to identify any regional disparities in the factors influencing financial distress.

The overall robustness of the models is confirmed by the highly significant Wald chi-squared test statistics. This suggests that the included variables provide a strong explanation for bank financial distress. In conclusion, the findings from Table 1 highlight the significance of asset quality, liquidity management, and efficient management practices in predicting bank financial distress. These insights can inform regulatory policies and risk management strategies to enhance bank stability.

Regressions on the whole sample with a modified Europe dummy

The analysis in Table 2 replicates the previous regressions but introduces a modified Europe dummy variable that is set to zero for the period 2011-2013. This allows us to assess the potential impact of the European financial crisis on the determinants of bank financial distress.

[Insert ***Table 2***]

The overall findings from Table 2 are largely consistent with those from Table 1. The inclusion of the modified Europe dummy variable examines the potential impact of the financial crisis on European banks. The coefficient of this variable remains non-significant, suggesting that the overall impact of the crisis on bank vulnerability was not substantial. The Wald chi-squared test statistics for both lagged and non-lagged models remain highly significant, confirming the overall robustness of the specifications.

4.2.2. Regressions on North American-Oceanian banks (62 banks)

The panel probit regressions in Table 3, focusing on the 62 banks from the United States, Canada, and Australia, provide insights into the determinants of financial distress within this region and variations from the overall sample. The p-value linked to the Wald test result for this lag regression with column (1) is very low (0.000) indicating that our model is robust.

[Insert ***Table 3***]

First, the chosen ***Capital Protection*** criteria, TOT_EQ_TO_TOT_ASSET shows no clear effect in both lagged and non-lagged models, whereas the findings for the overall sample

indicate it as a significant predictor of distress in the non-lagged model. While this result may sound counter-intuitive, it may signify important government's interventions in weakly capitalized banks in case of financial difficulties.

Regarding banks' *Asset Quality*, PROV_FOR_LOAN_LOSS_TO_TOT_ASSET is still a prominent predictor in the lagged model (1% significance level), but shows no significance in the non-lagged models, highlighting the difference in predicting financial distress of this region compared to the overall sample. More importantly, Log_TOT_ASSET is consistently insignificant, unlike the finding for the whole sample, suggesting that bank size may have a limited impact on financial distress prediction within this region.

In terms of *Management Competence*, there is evidence of regional variations: OPER_MARGIN is no more significant in any model setting, implying its limited role in predicting financial distress in North American-Oceanian banks. Nevertheless, RETURN_COM_EQY still shows its significant (1% level) and negative impact on the dependent variable in the non-lagged model, consistent with the findings for the whole sample.

Next, we observe that NET_REV_TO_TOT_CAP (*Earnings strengths*) is negatively associated with distress in the lagged model (5% significance level), suggesting that strong earnings generation can be a protective factor for the bank's future. It is worth noting that this variable displays no significance in the regressions for the whole sample, indicating another regional difference for financial distress predictions.

Another variation lies in *Liquidity Risk Exposure*, where both variables CUSTOMER_DEPOSIT_TO_TOT_ASSET and CASH_TO_TOT_ASSET lose all significance found in the regressions for the whole sample. We find significance at the 5% level again for ST_BORROW_TO_TOT_ASSET in the lagged model, confirming similar pattern found for the whole sample between short-term borrowings and an increase a bank's financial distress risk in the future.

Finally, BOOK_VAL_PER_SH (*Sensitivity to market risk*) is positively associated with distress in the lagged model (significant at the 5% level), suggesting that a higher book value per share may be indicative of underlying vulnerabilities. However, further analysis is needed to fully understand its implications.

In conclusion, while some determinants of financial distress for North American-Oceanian banks are consistent with the broader sample, there are notable regional variations. This region exhibits distinct patterns in terms of the impact of capital protection, bank size,

operating margin, liquidity risk, and sensitivity to market risks, suggesting different market and government's reaction to banks financial characteristics in these areas.

4.2.3. Regressions on European banks (57 banks)

Table 4 displays probit regression results for European banks over the period 2006 to 2013 from both lagged (Column 1) and non-lagged (Column 2) models, focusing on financial distress (FD) as the dependent variable. The Wald chi-squared test statistics for both lagged and non-lagged models are highly significant, suggesting that the overall specifications are robust.

[Insert **Table 4**]

Unlike the overall sample and the North American-Oceanian sub-sample, for **Capital Protection** criteria, TOT_EQ_TO_TOT_ASSET appears a significant predictor of distress in the lagged model (positive sign at 5% significance level), but shows no clear effect in the non-lagged model. This finding is surprising, as Total Equity is supposed to behave as a buffer role against losses by protecting a bank's solvency. An explanation could be that as European banks resorted to equity issues far less than US banks did, then, when there is an increase of the ratio one year before a financial distress, it may be a real sign of forthcoming difficulties. As the coefficient becomes negative in the non-lagged model, though insignificant, we conjecture that a strong equity buffer in the past alone is not an absolute guarantee for a bank against financial distress and can even backfire in the following year if the bank cannot manage well other criteria.

In this table, we observe that both **Asset quality** variables have no power of explanation. Log_TOT_ASSET is consistently insignificant, indicating that bank size has limited predictive power. PROV_FOR_LOAN_LOSS_TO_TOT_ASSET is also insignificant, suggesting that provisions for loan losses may not be a primary driver of financial distress in this region.

In terms of **Management Competence**, RETURN_COM_EQY is a significant predictor (1% significance level) of financial distress in the non-lagged model, similar to the overall sample and the North American-Oceanian sub-sample. Furthermore, this ratio is also significant in the lagged model (5% significance level), emphasizing the importance of efficient return management practices. Otherwise, OPER_MARGIN is not significant in either model, suggesting that operational efficiency may be less critical for European banks (similar to the North American-Oceanian group).

Regarding **Earnings Strength** aspect, NET_REV_TO_TOT_CAP is negatively associated with distress in the lagged model, but only at 10% significance level, suggesting that

strong earnings generation may be a protective factor. In addition, none of the **Liquidity Risk Exposure** variables (CUSTOMER_DEPOSIT_TO_TOT_ASSET, CASH_TO_TOT_ASSET, ST_BORROW_TO_TOT_ASSET) are significant in either model, suggesting that liquidity factors may not be major determinants of distress in this region. Similarly, **Sensitivity to Market Risks** variable, BOOK_VAL_PER_SH is not significant at all, indicating that it may not be a primary concern for European banks.

Overall, the regressions reveal that financial distress in European banks is primarily driven by management competence, as measured by return on common equity. While earnings strength may play some role, its impact is less pronounced. Asset quality, liquidity risk factors and sensitivity to market risks appear to be less significant determinants for European banks during the study period.

4.2.4. Regressions on Asian banks (62 banks)

The panel probit regressions in Table 5, focusing on 62 Asian banks, provide valuable insights into the determinants of financial distress within this region.

[Insert **Table 5**]

Regarding **Capital Protection**, TOT_EQ_TO_TOT_ASSET is a significant predictor of financial distress (5% significance level) in the non-lagged model, reinforcing the importance of adequate capital buffers.

Asset Quality group exhibits some differences compared to other regions. Log_TOT_ASSET is a significant predictor of financial distress in the non-lagged model (5% significance level), implying a too-big-too-fail effect in this region, though it is not the case in the lagged-model. PROV_FOR_LOAN_LOSS_TO_TOT_ASSET does not seem to be a decisive factor determining financial distress, similarly to European banks.

Unlike the results in previous regressions for **Management Competence**, in this table, OPER_MARGIN is a significant predictor of financial distress in both lagged and non-lagged models, at 5% and 1% significance levels, respectively, calling attention to the role of efficient operating management practices in Asian banks. In contrast, RETURN_COM_EQY shows no significant association with the dependent variable. NET_REV_TO_TOT_CAP (**Earnings Strength**) also seems to have no impact on financial distress in this region.

In terms of **Liquidity Risk Exposure**, ST_BORROW_TO_TOT_ASSET is positively associated with financial distress in both lagged and non-lagged model, at 5% and 10%

significance level, respectively, indicating that reliance on short-term borrowings may contribute to increased vulnerability. CASH_TO_TOT_ASSET strongly and positively associated with the dependent variable (1% significance level), but only in the non-lagged model, confirming that a surplus of cash may alert serious underlying problems. CUSTOMER_DEPOSIT_TO_TOT_ASSET, nevertheless, shows no significance in both models. Finally, as in most models, BOOK_VAL_PER_SH (*Sensitivity to Market Risks*) exhibits no explanatory power.

Overall, the regressions reveal that Asian banks are more sensitive to operating management competence and asset size compared to the broader sample. While capital adequacy and liquidity risk factors may also play a role, their impact is less pronounced. These findings highlight the importance of effective operating management and adequate capital buffers for mitigating financial distress in Asian banks.

5. Conclusion

In this paper, we have explored the impact of various financial determinants on the likelihood of bank defaults across different regions, utilizing the CAMELS framework to assess its applicability beyond the United States and in a more global context. The analysis included 181 banks from North America-Oceania Anglo-Saxon countries, Europe, and major Asian countries, focusing on the period from 2006 to 2013. We aimed to evaluate whether CAMELS variables could consistently predict financial distress across different zones, considering that financial shocks may affect banks differently depending on their region.

Our findings reveal that the significance of financial variables varies notably by region, which can be attributed to differing business cultures, legal environments, and bank management practices. **Capital adequacy** and **management competence** emerge as significant predictors of financial distress in multiple regions. However, the specific aspects of these factors that drive vulnerability differ. For example, Return on Common Equity was a significant predictor only in the European and North America-Oceania Anglo-Saxon regions, but not in Asia, where Cash to Total Assets and Operating Margin were more critical. Interestingly, in the non-lagged regression, Total Equity to Total Assets (global sample), Operating Margin (global and Asian samples), and Cash to Total Assets (global and Asian samples), were strongly significant at the 1% level, although their significance was not uniformly observed across all regions. **Asset quality** and **liquidity risk** factors exhibit mixed results across regions. While

provisions for loan losses are important in North America-Oceania, it is not the case in Europe or Asia. Similarly, the influence of bank size and liquidity indicators differs across regions. **Earnings strength** is a significant predictor in some regions, particularly in North America-Oceania, suggesting its importance in mitigating financial distress.

These disparities suggest that while certain CAMELS variables have global relevance, their predictive power can differ significantly depending on the region. This highlights the complexity of applying a universal model for bank oversight and suggests that a more nuanced approach, tailored to regional specificities, may be more effective. Consequently, while global regulatory bodies like the IMF and the Basel Committee play a crucial role in promoting transparency and security in the banking sector, the importance of robust, region-specific supervisory mechanisms cannot be overstated. Institutions such as the European Banking Authority (EBA) and the U.S. Federal Reserve, the FDIC and the OCC, alongside others, remain essential for effective financial oversight tailored to local conditions.

In summary, our study underscores the need for both global and regional approaches in financial regulation, with CAMELS variables offering valuable insights but requiring adaptation to account for regional variations in banking operations and risks.

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Table 1: Probit Regression Results for the whole sample (181 Banks)

This table presents the results of panel probit regressions conducted on 181 banks, using variables sourced from Bloomberg data covering the period from 2006 to 2013 with financial distress (FD) as the dependent variable. Columns (1) and (3) include a one-year lead for financial distress (FD_{t+1}), while columns (2) and (4) are contemporaneous. The variable Log_TOT_ASSET is expressed in Euro/1000. The Europe dummy variable is 1 for banks located in geographical Europe, 0 otherwise. Standard errors are provided in parentheses beneath the coefficient estimates, with significance levels indicated as follows: *** for 1%, ** for 5%, and * for 10%.

VARIABLES	(1) FD _{t+1}	(2) FD	(3) FD _{t+1}	(4) FD
<i>CAPITAL PROTECTION</i>				
TOT_EQ_TO_TOT_ASSET	0.000643 -0.0187	-0.140*** -0.0417	-0.000491 -0.0185	-0.142*** -0.0423
<i>ASSET QUALITY</i>				
Log_TOT_ASSET	-0.105 -0.141	-0.535* -0.3	-0.165 -0.13	-0.631** -0.28
TOT_LOAN_TO_TOT_ASSET	0.00513 -0.00512	0.00831 -0.0106		
PROV_FOR_LOAN_LOSS_TO_TOT_ASSET	0.328*** -0.106	0.469** -0.22	0.357*** -0.101	0.538*** -0.208
<i>MANAGEMENT COMPETENCE</i>				
OPER_MARGIN	-0.00192 -0.00202	-0.0379*** -0.00867	-0.00183 -0.00197	-0.0375*** -0.00871
RETURN_COM_EQY	-0.00122 -0.0235	-0.129** -0.0594	-0.0114** -0.00544	-0.118*** -0.0207
<i>EARNINGS STRENGTHS</i>				
RETURN_TOT_EQY	-0.0115 -0.025	0.0118 -0.0614		
NET_REV_TO_TOT_CAP	-0.0162 -0.0133	-0.0247 -0.0242	-0.02 -0.0129	-0.0296 -0.0237
<i>LIQUIDITY RISK EXPOSURE</i>				
CUSTOMER_DEPOSIT_TO_TOT_ASSET	-0.0106* -0.0061	-0.0144 -0.0122	-0.00839 -0.00565	-0.0112 -0.0115
CASH_TO_TOT_ASSET	0.000464 -0.0169	0.116*** -0.0272	-0.00239 -0.0166	0.110*** -0.0264
ST_BORROW_TO_TOT_ASSET	0.0179** -0.0072	0.0131 -0.015	0.0165** -0.00704	0.0109 -0.0149
<i>SENSITIVITY TO MARKET RISKS</i>				
BOOK_VAL_PER_SH	0.000493 -0.00117	-0.00176 -0.00221	0.000662 -0.00115	-0.00134 -0.00215
<i>CONTROL</i>				
EUROPE	-0.115 -0.204	-0.692 -0.438	-0.054 -0.194	-0.588 -0.418
Constant	-0.237 -1.408	4.888 -3.04	0.44 -1.255	5.967** -2.793
Wald chi2	94.62	87.8	93.84	86.18
p-value	0.000	0.000	0.000	0.000
Observations	1,242	1,242	1,242	1,242
Number of banks	181	181	181	181

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2: Probit Regression Results for the whole sample (181 Banks) with a modified Europe dummy

This table presents the results of panel probit regressions conducted on 181 banks, using variables sourced from Bloomberg data covering the period from 2006 to 2013, with financial distress (FD) as the dependent variable. Column (1) includes a one-year lead for financial distress (FD_t+1), while column (2) is contemporaneous. The variable Log_TOT_ASSET is expressed in Euro/1000. The Europe dummy variable is set to 0 for the period from 2011 to 2013 in both columns. Standard errors are provided in parentheses beneath the coefficient estimates, with significance levels indicated as follows: *** for 1%, ** for 5%, and * for 10%.

VARIABLES	(1) FD_t+1	(2) FD
<i>CAPITAL PROTECTION</i>		
TOT_EQ_TO_TOT_ASSET	0.00392	-0.124***
	-0.0177	-0.039
<i>ASSET QUALITY</i>		
Log_TOT_ASSET	-0.113	-0.607**
	-0.141	-0.308
TOT_LOAN_TO_TOT_ASSET	0.00444	0.00516
	-0.00495	-0.0101
PROV_FOR_LOAN_LOSS_TO_TOT_ASSET	0.329***	0.480**
	-0.106	-0.222
<i>MANAGEMENT COMPETENCE</i>		
OPER_MARGIN	-0.00192	-0.0400***
	-0.00204	-0.00899
RETURN_COM_EQY	-0.00159	-0.125**
	-0.0235	-0.0591
<i>EARNINGS STRENGTHS</i>		
RETURN_TOT_EQY	-0.0107	0.0171
	-0.0251	-0.0611
NET_REV_TO_TOT_CAP	-0.016	-0.0239
	-0.0133	-0.0244
<i>LIQUIDITY RISK EXPOSURE</i>		
CUSTOMER_DEPOSIT_TO_TOT_ASSET	-0.00909*	-0.00773
	-0.00549	-0.0102
CASH_TO_TOT_ASSET	0.000515	0.112***
	-0.017	-0.0276
ST_BORROW_TO_TOT_ASSET	0.0182**	0.0172
	-0.00719	-0.0153
<i>SENSITIVITY TO MARKET RISKS</i>		
BOOK_VAL_PER_SH	0.000542	-0.000958
	-0.00117	-0.00216
<i>CONTROL</i>		
EUROPE (0 for 2011-2013)	-0.0264	-0.512
	-0.164	-0.317
Constant	-0.288	4.886
	-1.411	-3.11
Wald chi2	94.56	83.7
p-value	0.000	0.000
Observations	1,242	1,242
Number of banks	181	181

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Probit Regression Results for U.S., Canadian, and Australian Banks

This table presents the results of panel probit regressions conducted on 62 banks from the U.S., Canada, and Australia, using variables sourced from Bloomberg data covering the period from 2006 to 2013, with financial distress (FD) as the dependent variable. Column (1) includes a one-year lead for financial distress (FD_t+1), while column (2) is contemporaneous. The variable Log_TOT_ASSET is expressed in Euro/1000. Standard errors are provided in parentheses beneath the coefficient estimates, with significance levels indicated as follows: *** for 1%, ** for 5%, and * for 10%.

VARIABLES	(1) FD_t+1	(2) FD
<i>CAPITAL PROTECTION</i>		
TOT_EQ_TO_TOT_ASSET	0.0216 -0.0395	-0.0279 -0.193
<i>ASSET QUALITY</i>		
Log_TOT_ASSET	-0.359 -0.23	-0.625 -1.058
PROV_FOR_LOAN_LOSS_TO_TOT_ASSET	0.497*** -0.163	0.389 -0.596
<i>MANAGEMENT COMPETENCE</i>		
OPER_MARGIN	-0.000232 -0.000618	-0.0443 -0.0324
RETURN_COM_EQY	-0.0102 -0.0108	-0.488*** -0.158
<i>EARNINGS STRENGTHS</i>		
NET_REV_TO_TOT_CAP	-0.0583** -0.0258	-0.00382 -0.111
<i>LIQUIDITY RISK EXPOSURE</i>		
CUSTOMER_DEPOSIT_TO_TOT_ASSET	0.00758 -0.0121	0.0285 -0.0798
CASH_TO_TOT_ASSET	0.0253 -0.026	0.0252 -0.0774
ST_BORROW_TO_TOT_ASSET	0.0386** -0.0154	0.0776 -0.0999
<i>SENSITIVITY TO MARKET RISKS</i>		
BOOK_VAL_PER_SH	0.0108** -0.00504	0.0014 -0.0145
Constant	0.716 -2.253	1.886 -11.82
Wald chi2	45.49	13.62
p-value	0.0000	0.1909
Observations	415	415
Number of banks	62	62

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Probit Regression Results for European Banks

This table presents the results of panel probit regressions conducted on 57 European banks, using variables sourced from Bloomberg data covering the period from 2006 to 2013, with financial distress (FD) as the dependent variable. Column (1) includes a one-year lead for financial distress (FD_{t+1}), while column (2) is contemporaneous. The variable Log_TOT_ASSET is expressed in Euro/1000. Standard errors are provided in parentheses beneath the coefficient estimates, with significance levels indicated as follows: *** for 1%, ** for 5%, and * for 10%.

VARIABLES	(1) FD _{t+1}	(2) FD
<i>CAPITAL PROTECTION</i>		
TOT_EQ_TO_TOT_ASSET	0.118**	-0.0183
	-0.0583	-0.0815
<i>ASSET QUALITY</i>		
Log_TOT_ASSET	0.337	-0.198
	-0.257	-0.422
PROV_FOR_LOAN_LOSS_TO_TOT_ASSET	0.181	-0.348
	-0.211	-0.534
<i>MANAGEMENT COMPETENCE</i>		
OPER_MARGIN	-0.000357	-0.0167
	-0.00223	-0.014
RETURN_COM_EQY	-0.0146**	-0.189***
	-0.00687	-0.0357
<i>EARNINGS STRENGTHS</i>		
NET_REV_TO_TOT_CAP	-0.0959*	-0.0536
	-0.0543	-0.08
<i>LIQUIDITY RISK EXPOSURE</i>		
CUSTOMER_DEPOSIT_TO_TOT_ASSET	0.00378	0.00866
	-0.0132	-0.0179
CASH_TO_TOT_ASSET	-0.0418	0.0596
	-0.0455	-0.074
ST_BORROW_TO_TOT_ASSET	0.00653	0.00196
	-0.00961	-0.0155
<i>SENSITIVITY TO MARKET RISKS</i>		
BOOK_VAL_PER_SH	-2.97E-05	9.38E-05
	-0.00135	-0.00169
Constant	-4.140*	1.279
	-2.411	-4.002
Wald chi2	24.82	53.58
p-value	0.0057	0.0000
Observations	387	387
Number of banks	57	57

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Probit Regression Results for Asian Banks

This table presents the results of panel probit regressions conducted on 62 Asian banks, using variables sourced from Bloomberg data covering the period from 2006 to 2013, with financial distress (FD) as the dependent variable. Column (1) includes a one-year lead for financial distress (FD_{t+1}), while column (2) is contemporaneous. The variable Log_TOT_ASSET is expressed in Euro/1000. Standard errors are provided in parentheses beneath the coefficient estimates, with significance levels indicated as follows: *** for 1%, ** for 5%, and * for 10%.

VARIABLES	(1) FD _{t+1}	(2) FD
<i>CAPITAL PROTECTION</i>		
TOT_EQ_TO_TOT_ASSET	-0.0164	-0.174**
	-0.0449	-0.0838
<i>ASSET QUALITY</i>		
Log_TOT_ASSET	-0.529	-1.139**
	-0.323	-0.577
PROV_FOR_LOAN_LOSS_TO_TOT_ASSET	-0.338	-0.372
	-0.463	-0.62
<i>MANAGEMENT COMPETENCE</i>		
OPER_MARGIN	-0.0244**	-0.0767***
	-0.0111	-0.0196
RETURN_COM_EQY	0.0101	-0.0158
	-0.0229	-0.0311
<i>EARNINGS STRENGTHS</i>		
NET_REV_TO_TOT_CAP	0.0222	0.0283
	-0.0234	-0.0355
<i>LIQUIDITY RISK EXPOSURE</i>		
CUSTOMER_DEPOSIT_TO_TOT_ASSET	-0.00933	-0.0288
	-0.0156	-0.0267
CASH_TO_TOT_ASSET	0.0171	0.226***
	-0.0397	-0.0586
ST_BORROW_TO_TOT_ASSET	0.0713**	0.0737*
	-0.0281	-0.0415
<i>SENSITIVITY TO MARKET RISKS</i>		
BOOK_VAL_PER_SH	0.0169	0.00924
	-0.0159	-0.027
Constant	2.742	9.650*
	-3.202	-5.702
Wald chi2	20.59	25.48
p-value	0.0241	0.0045
Observations	440	440
Number of banks	62	62

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix A: Variable Definition

VARIABLES (source: BLOOMBERG)	VARIABLES DEFINITION
TOTAL_EQUITY_TO_TOT_ASSET	<p>Total Equity: firm's total assets minus its total liabilities.</p> <p>INDUSTRIALS, BANKS, FINANCIALS, UTILITIES, & REITS Common Equity + Minority Interest + Preferred Equity</p> <p>Where: Common Equity is RR010, TOT_COMMON_EQY Minority Interest is BS062, MINORITY_NONCONTROLLING_INTEREST Preferred Equity is BS061, BS_PFD_EQY. TOT_ASSET: cf. below.</p>
TOT_COMMON_EQY	<p>The amount that all common shareholders have invested in a company. Calculated as: Share Capital & APIC + Retained Earnings and Other Equity</p> <p>Where: Share Capital & APIC is BS064, BS_SH_CAP_AND_APIC Retained Earnings and Other Equity is BS065, BS_RETAIN_EARN</p> <p>Figure is reported in millions; the Scaling Format Override (DY339, SCALING_FORMAT) can be used to change the display units for the field.</p>
TOT_ASSET	<p>BANKS</p> <p>Total Assets: This is the sum of Cash & bank balances, Fed funds sold & resale agreements, Investments for Trade and Sale, Net loans, Investments held to maturity, Net fixed assets, Other assets, Customers' Acceptances and Liabilities.</p> <p>Canada: This is the sum of Cash & Bank Balances, Short Term Investments, Interbank Assets, Securities Purchased with Resale Agreements, Net loans, Investments Held to Maturity, Net fixed assets, Other assets, Customers' Acceptances and Liabilities.</p>
RETURN_TOT_EQY	<p>Calculated as Net Income (IS050) divided by the sum of average Total Common Equity (RR010) and average Preferred Equity (BS061). Available for all industry types.</p>
RETURN_COM_EQY	<p>Measure of a corporation's profitability by revealing how much profit a company generates with the money shareholders have invested, in percentage.</p> <p>Calculated as: (T12 Net Income Available for Common Shareholders / Average Total Common Equity) * 100 Where: T12 Net Income Available for Common Shareholders is T0089, TRAIL_12M_NET_INC_AVAI_COM_SHARE Average Total Common Equity is the average of the beginning balance and ending balance of RR010, TOT_COMMON_EQY If either the beginning or ending total common equity is negative, Return on Equity will not be calculated. Please reference Return on Common Equity Adjusted (F1169, RETURN_ON_COMMON_EQUITY_ADJUSTED) for the adjusted value that excludes the impact of abnormal items.</p>
CUSTOMER_DEPOSIT_TO_TOT_ASSET	<p>BANKS</p> <p>Customer Deposits: Total deposits received from customers. Amounts due to banks are shown in borrowings. TOT_ASSET: cf. above.</p>

TOT_LOAN_TO_TOT_ASSET	<p>BANKS</p> <p>Total Loans: Includes Commercial loans, Consumer loans and Other loans.</p> <p>France: Loans are not separated into commercial and consumer. Some banks break out mortgage loans and lease financing.</p> <p>China: Includes financial lease receivables.</p> <p>TOT_ASSET: cf. above</p>
BOOK_VAL_PER_SH	<p>Measure used by owners of common shares in a firm to determine the level of safety associated with each individual share after all debts are paid accordingly. Units: Actual Calculated as:</p> <p>Total Common Equity / Number of Shares Outstanding</p> <p>Where: Total Common Equity is RR010, TOT_COMMON_EQY Shares Outstanding is BS081, BS_SH_OUT</p>
CASH_NEAR_CASH_ITEM	<p>BANKS</p> <p>Cash & Near Cash: Includes cash in vaults and non-interest earning deposits in banks. Includes receivables from the central bank and postal accounts. Includes cash items in the process of collection and unposted debits. Interest bearing deposits in other banks are included in interbank assets. Includes statutory deposits with the central bank.</p> <p>Japan: Excludes collateral. Semi-annual and consolidated reports include deposits to central bank and other institutions.</p> <p>Netherlands: Includes cash, checks and short-term investments.</p>
CASH_TO_TOT_ASSET	<p>Ratio to measure the percentage of cash and near cash over total assets. Calculated as:</p> <p>Cash and Near Cash * 100 / Total Assets Cash and Near Cash is BS010, BS_CASH_NEAR_CASH_ITEM Total Assets is BS035, BS_TOT_ASSET i.e. TOT_ASSET here, cf. above.</p>
OPER_MARGIN	<p>Ratio used to measure a company's pricing strategy and operating efficiency, in percentage.</p> <p>BANKS & FINANCIALS</p> <p>Calculated as: Operating Income (Losses) / Net Income * 100 Where: Operating Income is IS033, IS_OPER_INC Net Revenue is RR209, NET_REV.</p>
ST_BORROW_TO_TOT_ASSET	<p>ST_BORROW includes bank overdrafts, short-term debts and borrowings, repurchase agreements (repos) and reverse repos, short-term portion of long-term borrowings, current obligations under capital (finance)leases, current portion of hire purchase creditors, trust receipts, bills payable, bills of exchange, bankers acceptances, interest bearing loans, and short term mandatory redeemable preferred stock. Net with unamortized premium or discount on debt and may include fair value adjustments of embedded derivatives.</p> <p>For banks and financials, includes call money, bills discounted, federal funds purchased, and due to other banks or financial institutions.</p> <p>For Real Estate Investment Trusts (REITs), includes all unsecured borrowings regardless of length of term. This field is used either for unsecured debt or short term borrowing. Unsecured debt refers to mortgage and other secured debt which is not collateralized by property or assets of the company.</p> <p>Available for all formats. TOT_ASSET: cf. above.</p>

NET_REV_TO_TOT_CAP	<p>BANKS & FINANCIALS</p> <p>SUM OF INTEREST INCOME, TRADING ACCOUNT PROFITS (LOSSES), INVESTMENT INCOME (LOSSES), COMMISSIONS AND FEES EARNED, AND OTHER OPERATING INCOME, MINUS INTEREST EXPENSE.</p> <p>CALCULATED AS: NET INTEREST INCOME + TRADING ACCT. PROFITS + COMMISSIONS & FEES EARNED + OTHER OPERATING INCOME (LOSSES)</p> <p>WHERE: NET INTEREST INCOME IS RR016, NET_INT_INC TRADING ACCT. PROFITS IS IS017, IS_TRADING_ACCT_PROF COMMISSIONS & FEES EARNED IS IS019, IS_COMM_AND_FEE_EARN_INC_REO OTHER OPERATING INCOME (LOSSES) IS IS020, IS_OTHER_OPER_INC_LOSSES</p> <p>PLEASE REFERENCE NET REVENUE ADJUSTED (IM392, IS_ADJUSTED_NET_REVENUE) FOR THE ADJUSTED VALUE THAT EXCLUDES THE IMPACT OF ABNORMAL ITEMS.</p>
TOT_CAP	<p>Total investment that shareholders and debtholders have made in a company. Figure is reported in millions.</p> <p>BANKS & FINANCIALS</p> <p>Calculated as:</p> <p>Short Term Borrowings + Securities Sold with Repo Agreements + Long Term Borrowings + Preferred Equity + Minority Interest + Total Common Equity</p> <p>Where: Short Term Borrowing is BS047, BS_ST_BORROW Securities Sold with Repo Agreements is BS049, BS_SEC_SOLD_REPO_AGRMNT Long Term Borrowings is BS051, BS_LT_BORROW Preferred Equity is BS061, BS_PFD_EQY Minority Interest is BS062, MINORITY_NONCONTROLLING_INTEREST Total Common Equity is RR010, TOT_COMMON_EQY</p>
PROV_FOR_LOAN_LOSS_TO_TOT_ASSET	<p>BANKS</p> <p>Provision for loan losses: The periodic expense for possible future loan losses. Could be negative when there is a recovery of loan losses. May include other provisions if they are not disclosed separately.</p> <p>FINANCIALS</p> <p>Provision for loan losses: Provision allocated for uncollectible interest income and principal on loans granted to customers. Could be negative when there is a recovery of loan losses. May include other provisions if they are not disclosed separately. TOT_ASSET: cf. above.</p>
RETURN_ON_ASSET	<p>Indicator of how profitable a company is relative to its total assets, in percentage. Return on assets gives an idea as to how efficient management is at using its assets to generate earnings.</p> <p>INDUSTRIALS, BANKS, FINANCIALS, UTILITIES, & REITS</p> <p>Calculated as:</p> <p>$(\text{Trailing 12M Net Income} / \text{Average Total Assets}) * 100$</p> <p>Where: Trailing 12M Net Income is RR813, TRAIL_12M_NET_INC Average Total Assets is the average of the beginning balance and ending balance of BS035. TOT_ASSET (Cf. above).</p>

<p>TIER1_CAP_RATIO</p>	<p>BANKS Tier 1 Capital Ratio: Tier 1 or Core capital ratio. Tier 1 is used for commercial banks and core capital is used for savings and loans in the United States (U.S.).</p> <p>The ratio of Tier 1 capital to risk-weighted assets. For Core Tier 1 Capital Ratio see Core Tier 1 Capital Ratio (BS895, BS_CORE_TIER1_CAPITAL_RATIO).</p> <p>Common stockholders' equity: Qualifying perpetual preferred stock. Minority Interest in consolidated subsidiaries less Goodwill and other disallowed intangibles.</p> <p>Core capital for savings and loans: Common stockholders' equity. Noncumulative perpetual preferred and surplus. Minority interests less intangible assets (other than PMSR).</p> <p>The ratios are discussed in the Cooke Committee and adopted by each country. The information is provided in terms of absolute numbers and percentages. If the absolute amounts are disclosed, the percentages should be computed for this account. Slightly different ratios are defined for commercial banks and savings and loans. The minimum ratios set by the U.S. Federal Reserve and OTC are 4% for commercial banks and 3% for savings and loans, respectively.</p> <p>Canada: Computed in accordance with the Office of Superintendent of Financial Institutions (OSFI) based on standards issued by the Bank for International Settlements. Since 1992, Canadian deposit-taking institutions are required to maintain a minimum Tier 1 capital ratio of 4%.</p> <p>Europe: The Bank of International Settlements in Basel requires a Tier I ratio of 4.4% (and now 6%). In Europe it is referred to as the BIS ratio, the European Solvency ratio, or the Cooke ratio as the Cooke committee established it.</p> <p>Japan: Discloses only international standards.</p>
<p>EUROPE</p>	<p>Dummy variable which is equal to 1 if a bank belongs to geographical Europe (0 otherwise).</p>

Appendix B: Pearson correlations matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1 TOT_LOAN_TO_TOT_ASSET	1,000											
2 RETURN_TOT_EQY	-0,058	1,000										
3 CASH_TO_TOT_ASSET	-0,138	0,209	1,000									
4 OPER_MARGIN	-0,017	0,238	0,032	1,000								
5 TOT_EQ_TO_TOT_ASSET	0,051	-0,017	0,007	0,027	1,000							
6 ST_BORROW_TO_TOT_ASSET	-0,284	-0,017	-0,050	-0,017	-0,231	1,000						
7 NET_REV_TO_TOT_CAP	0,110	0,191	0,165	0,067	0,184	-0,561	1,000					
8 PROV_FOR_LOAN_LOSS_TO_TOT_ASSET	0,243	-0,425	-0,026	-0,121	0,166	-0,045	0,071	1,000				
9 CUSTOMER_DEPOSIT_TO_TOT_ASSET	0,271	0,085	0,218	0,032	0,012	-0,574	0,716	-0,027	1,000			
10 Log_TOT_ASSET	-0,417	0,023	0,084	0,012	-0,376	0,417	-0,471	-0,081	-0,453	1,000		
11 RETURN_COM_EQY	-0,056	0,989	0,201	0,231	-0,027	-0,017	0,182	-0,448	0,087	0,023	1,000	
12 BOOK_VAL_PER_SH	-0,051	-0,028	-0,156	-0,021	-0,059	0,145	-0,077	-0,023	-0,199	0,089	-0,031	1,000