Path modeling to bankruptcy: causes and symptoms of the banking crisis


This paper studies the bankruptcy of USA banks since 2009. It first analyzes the financial symptoms that precede bankruptcy, such as low profitability, insufficient revenue, or low solvency ratios. It also goes into the causes of these symptoms. It poses several hypotheses on causes of failure, such as loans growth (some of them risky), specialization (in this case concentration in real estate), and the pursuit of a turnover-driven strategy neglecting margin. It presents and tests a path modeling to bankruptcy based on structural equations, hypotheses tests and logistic regression. Results show that, five years before the crisis, failed banks had, compared to solvent banks, the following: higher loan growths, higher concentration on real estate loans, higher risk ratios, higher turnover, but lower margins. A relationship is found between symptoms and causes. Failed banks present a significant relationship between the percentage of real estate loans and risk. This relationship is negative in excellent banks, confirming that they allocated less real estate loans with higher quality. Non-failed banks compensated increases in risk by strengthening their core capital.

Keywords: Bankruptcy, financial ratios, banking crisis, solvency, PLS-Path modeling.

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Path modeling to bankruptcy: causes and symptoms of the banking crisis

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ABSTRACT

This paper studies the bankruptcy of USA banks since 2009. It first analyzes the financial symptoms that precede bankruptcy, such as low profitability, insufficient revenue, or low solvency ratios. It also goes into the causes of these symptoms. It poses several hypotheses on causes of failure, such as loans growth (some of them risky), specialization (in this case concentration in real estate), and the pursuit of a turnover-driven strategy neglecting margin. It presents and tests a path modeling to bankruptcy based on structural equations, hypotheses tests and logistic regression. Results show that, five years before the crisis, failed banks had, compared to solvent banks, the following: higher loan growths, higher concentration on real estate loans, higher risk ratios, higher turnover, but lower margins. A relationship is found between symptoms and causes. Failed banks present a significant relationship between the percentage of real estate loans and risk. This relationship is negative in excellent banks, confirming that they allocated less real estate loans with higher quality. Non-failed banks compensated increases in risk by strengthening their core capital.

KEYWORDS

Bankruptcy, financial ratios, banking crisis, solvency, PLS-Path modeling.

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1. INTRODUCTION

In 2009, 140 out of around 8,000 USA banks went bankrupt. A logistic regression with several financial ratios allows for the failure symptoms, and even successfully predicting failed banks in 2010, with an accuracy rate around 75%. Insufficient revenue to cover costs, lack or profitability and low solvency are financial symptoms to predict the crisis when it is about to happen. This is similar to the physician who, taking the blood pressure and the high temperature of the moribund, predicts the worst. But the good doctor knows the origin of the sickness from its symptoms. This paper models a path to bankruptcy, which poses hypotheses on some of the causes of these low profitability and low solvency. The causes analyzed are the specialization in real estate, loans growth (some of them risky) following a turnover-driven strategy, and neglecting aspects such as the preservation of adequate margins or saving costs.

It is important to distinguish between symptoms and causes. Financial ratios have excelled in the assessment of the symptoms of failure. Beaver [1] pioneered in showing that particular financial ratios predict companies’ bankruptcy some years before they happen. Ratio analysis has been a fruitful research line, see state of the art revisions by Zavgren [2], Ravi Kumar and Ravi [3], and Demyanyk and Hasan [4]. The aim of most studies is to obtain the highest percentage of correctly classified firms. Argenti [5] does emphasize the causality, but his study is of a theoretical nature. He provides bankruptcy causes such as managers’ personality, management deficiencies, or losing touch with their customers. The empirical study by Cooper et al [6] incorporates qualitative causes by using variables such as human capital measures. Ooghe and De Prijcker [7] emphasize the errors made by management, errors in the corporate policy and the importance of external factors. In the banking industry, Heffernan [8] analyzes causes such as fraud, weak asset management or managerial problems. Many authors look for the roots of banking crisis in macroeconomic policies. For example, Kaminsky and Reinhart [9] affirm that financial liberalization often precedes banking crisis.

This paper analyzes information from banks’ annual accounts to determine the non-financial causes revealed on the financial statements. Balance sheets and profit and loss accounts contain information that somehow reveals the firm’s strategy. For example, specialization has been a common cause of banks’ failure [10]. This specialization strategy can be identified by analyzing the breakdown of the loans account. Another recurrent cause of bank failure is the overextension of credit. This is true since the time of ancient medieval bankers, whose failure was studied by De
Roover [11]. Here the growth of loans accounts can be analyzed. A bank’s strategic decision can be to achieve a higher turnover, while other banks look for higher margins. This strategy can be discovered by disaggregating the profitability ratio into turnover and margin ratios. Banks decide to provide loans to customers, previously classified according to their risk levels, following banking rules by Bank for International Settlements [12] and Federal Register [13]. By analyzing the risk-weighted assets composition, which banks are prudent and which are risky can be assessed.

The paper models the symptoms that precede bank failure and its causes. It proposes a structural equations model to illustrate the path to failure. The model has been tested with USA banks data, from 2003 to 2010. Partial Least Squares Path Modeling (PLS-PM) is applied. This technique is commonly used in Marketing [14] or Information Systems [15], but hardly using accounting data. To the best of our knowledge, corporate failure has not been studied with this technique. In addition to the conventional procedure of two group analysis (failed and non-failed), we have extracted a third sample of the best banks (excellent), that identifies the path to excellence. A multigroup analysis tests the existence of significant differences among the groups.

The following section presents the model, which incorporates the financial symptoms that precede bankruptcy, and provides hypotheses on its causes. Third section tests the path modeling. Finally, conclusions are provided.

2. CONCEPTUAL BACKGROUND

Periodically, banking sector goes into crisis. Crises are associated with the peaks of business cycles [16]. From 2008 on, USA banks went into crisis. According to the International Monetary Fund [17] macroeconomic policies did not take into account the buildup of systemic risks in the housing markets. More specifically, the low interest rate policies of the Federal Reserve are considered by some analysts to be responsible for producing the housing bubble. It is argued that banks’ difficulty to obtain profits through margins made many of them start a race for loan allocation. Many loans were too risky. Greenspan [18] replied that it was indeed lower interest rates that spawned the speculative euphoria. But every crisis has its own opportunity and Moshirian [19] argues that this financial crisis has the potential to improve both national and international financial systems, and to manage financial risk more effectively.

Figure 1 shows the path analysis model. Strategies followed by banks are responsible for its bankruptcy, survival or success. Loan growth and bank specialization influence financial ratios such as margin, turnover and risk. Increases in income are an opportunity to obtain higher returns. But, by growing, the bank can give riskier loans: this will be reflected in risk ratios. If a crisis arrives, some
loans cannot be repaid, and so, profitability drops. If the bank has grown, but it has not strengthened its capital at the same time, solvency ratios deteriorate. If a crisis hits the housing market, and the bank is specialized in real estate, the probability of bankruptcy rises. This is the path to failure.

*** Figure 1 ***

The methodology used in this paper is new in bankruptcy studies. Most studies take a set of financial ratios and apply a statistical technique. This has allowed for identifying which variables better predict failure, which are the best techniques to deal with accounting information, and the building of decision models to predict bankruptcy. Beaver [1] used univariate analysis, Altman [20] used linear discriminant analysis, Ohlson [21] used logistic regression, Mar Molinero and Ezzamel [22] used multidimensional scaling, Tam [23] used neural networks, and Premachandra et al [24] used Data Envelopment Analysis, among others. See Demyanyk and Hasan [4] or Ioannidis et al [25] for a revision of other recent techniques. This paper focuses on the causes of failure. This is not an easy task, because statistical methods cannot really prove causality, only correlation. The Greek philosopher Democritus said that he would rather discover a causal relationship than being King of Persia. The paper uses PLS-Path Modeling, an approach where the concept of causality is formulated in terms of linear conditional expectation [26]. The model has been tested with SmartPLS software [27], based on multivariate linear regression. The results provided are R-squares and beta coefficients, commonly used in Social Sciences.

**H.1 Symptoms preceding failure**

This hypothesis establishes that there are symptoms preceding failure. This hypothesis is at the fundamentals of studies predicting bankruptcy from financial ratios ([1], [20], [21] and [23]). It is considered that this crisis is not different to previous ones, and that financial symptoms will also predict firm failures. In the banking industry, symptoms are a lack of profits, translated into low returns. Another expected symptom is low solvency, defined as core capital to risk-weighted assets. Drops in efficiency, understood as the relationship between non interest expenses divided by total income are also expected.

Beaver [1] showed that, five years before failure, financial ratios already had predictive power. The same is expected: some years before the crisis financial ratios allow for distinguishing between failed and non-failed banks.

Stability is a key issue for any bank. Dambolena and Khoury [28] analyzed the stability of financial ratios and its relationship with corporate failure. Instability showed a significant increase over time as the corporation approached failure. A possible way of analyzing stability is to examine if
ratio values have not changed much over time. It is expected that the ratio that better predicts a given ratio value will be the value of the same ratio one year before. Sudden changes in ratio values along time will happen in banks with a high probability of failure. So, financial ratios are expected to be more autoregressive in non-failed banks than in failed banks.

H.2 Specialization

The second hypothesis studies the role of specialization. To be specialized is not bad in itself, because the firm is focused on doing something that it does well. Berger et al [29], in their study on the effects of focus versus diversification on Chinese bank performance, find that more focused banks are associated with higher profits, lower costs, higher profit efficiency, and higher cost efficiency. In the case of USA banks, the most visible concentration is on real estate. If real estate loans are considered good, the risk is maintained at low levels. These kinds of loans can be assigned with a lower risk level than other exposures due to the collateral, according to the rules by the Bank for International Settlements [12] and Federal Register [13]. But if real estate loans are considered bad, risk ratio values will be high. Specialization entails an additional problem: to put all your eggs in one basket, Winton [30]. On the risk of concentration, much can be learnt from the history of bankers. Patrick [31] refers to the failure of Fugger Bankers, the first German bankers. They funded the expeditions to America by Phillip II of Spain. As sole lenders of the kingdom, they received argent from Colonies as interest payments. But the kingdom stopped payments and caused Fugger Bank’s collapse. The Bank of England identified 22 banks that failed or encountered severe difficulties, among them 10 due to over-specialization, Latter [10].

The problem with over-specialization in real estate sector arises when a collapse happens, as has occurred in the USA housing market. It is expected that failed banks will have a higher percentage of real estate loans than non-failed banks. In the case of failed banks, and given the low quality of their real estate loans, a positive relationship is also expected between the percentage of real estate loans and risk. In the case of non-failed banks, this relationship is not expected.

H.3 Risky growth

The third hypothesis analyses the role of loan growth. To raise the revenues level is good in any kind of business. Growing is better than stagnating. Rising revenue goes usually jointly with rising future profits, and this improves financial ratio values. This is valid for most companies, but the banking business is different. If in every company to achieve a sale is a reason for satisfaction, for a bank it is only the starting point for a customer relationship. If this loan is a good business it will be
known later on. The key issue is not only to give loans, but to give loans to creditworthy borrowers. If there is a rash of troubled loans, this growth can lead to bankruptcy, as shown by the history of bankers. De Roover [11] studies the failure of powerful Florentine Banks of the fourteenth century concluding that their crash was probably caused by overextension of credit.

Loan growth can imply risky growth, because the last loans allocated have higher probability of default. Risk weights for retail exposures are based on separate assessments of probability of default, according to aspects such as credit scores, loan terms and structure, geographical location of the borrower, or collateral type ([12] and [13]). Empirical studies provide some support for the view that faster loan growth leads to higher loan losses. Keeton [32] points out that an increase in loan growth can lead to higher loan losses only if the source of the faster loan growth is a shift in the supply of bank credit. The consequences of unusually rapid loan growth will arise in the balance sheet some years later, when large increases in delinquencies appear. Foos et al [33] investigate whether loan growth affects the riskiness of individual banks in 16 major countries. Their results suggest that loan growth represents an important driver of the banks’ riskiness.

For these previous reasons, it is expected that failed banks had a higher loan growth than non-failed banks. A positive relationship between loan growth and risk is also expected. This effect is expected to be more acute in failed banks.

But rises in risk levels do not necessary imply lower solvency levels. Tier1 solvency ratio is defined as core capital divided by risk-weighted assets, Bank for International Settlements [12]. If rises in the denominator (risks) are accompanied by stronger capital levels, the Tier1 ratio can remain stable. It is expected that non-failed banks will compensate for higher risk levels by strengthening their capital levels. Contrarily, in failed banks, it is expected that risk will negatively affect their solvency.

**H.4 Turnover vs margin strategy**

Companies can follow two different strategies: trying to sell more or trying to get more margins in each sale. Sometimes it is not possible to be successful in both strategies. The study of firms’ strategy, based on the disaggregation of profitability ratios into their components is known as “DuPont Analysis”. This kind of analysis has been widely studied. Out-of-sample forecasting results confirm that the disaggregation can be used to improve profitability forecasts, Fairfield and Yohn [34].

Lower levels of market interest rates have led many banks to reduce their margins. Turnover strategies are the way to compensate reductions in margin, Beitel [35]. This is not the only possible
option, because there are other ways to keep the margin stable, such as cuts in costs or a more efficient technology use. The risks of higher turnover have already been mentioned, because the bank is allocating low quality loans and capturing deposits at high interest rates. We consider that the correct strategy for a bank is to get stable margin, instead of increases in turnover. It is expected that failed banks will have higher turnover and lower margins than non-failed banks. This relationship is expected to be statistically significant.

3. EMPIRICAL STUDY

3.1 Sample and data

We will study the case of USA bank failure in 2009 and 2010. The database comes from the Federal Deposit Insurance Corporation (FDIC). It contains data on 9,966 banks from year 2003. For each bank we have selected 9 financial ratios, whose definition can be found in Table 1.

***Table 1***

Financial symptoms are the 3 following ratios: Return on Equity (ROE), solvency ratio (TIER1) and efficiency ratio (EFFICIENCY). The higher the value of EFFICIENCY, the lower the efficiency of the bank. Ratios that come from the disaggregation of the profitability ratio are MARGIN and TURNOVER. The ratio that measures increases in loans is expressed as INC-LOANS. The specialization in real estate loans is measured with the ratio: all real estate loans divided by net loans and leases (REALESTATE). The ratio %RISK is calculated as risk-weighted assets divided by the average of the total assets. SALARY is calculated as salaries and employee benefits divided by the number of employees.

3.2 Statistical methodology

First, the sample was split into failed and non-failed banks in order to analyze the temporal evolution of financial ratios in both subgroup and the differences between them. Both parametric and non-parametric differences tests were performed. The results were very similar. As expected, most financial ratios were non-normally distributed [36]. The sample had outliers and several observations were off the scale. In that case, the median test is recommended, Siegel and Castellan [37].

We considered it interesting to analyze the financial ratios of best banks, to extract their key patterns and compare them with failed banks. With this aim, we obtained a sub-sample of best banks. This was done through logistic regression. The dependent variable of this regression is a dummy variable taking the 0 value if the FDIC has classified it as failed in 2009, and the 1 value if has been classified as non-failed. We took the 140 failed banks in 2009 and the same number of non-failed banks, building this way a paired sample matched by size, measured by the number of employees.
The rest of the banks constitute the holdout sample. A first regression was built using as independent variables ROE, EFFICIENCY and SOLVENCY. This way, for each bank in the original sample, the estimated probability of failure was obtained. Also, for each bank in the holdout sample, the predicted probability of failure was obtained.

Three more regression models using different sets of variables were built, and the procedure was repeated. Having obtained four different probabilities of failure for each bank, we decided to perform a principal components analysis, a data reduction technique. The factor loading of each bank on the first principal component can be interpreted as a ranking of failure/excellence. The banks with higher factor loadings are those with lower probability of failure, that means: excellent banks. We selected 140 of them, once again, matched by size. The average and median values of the 9 financial ratios for the 140 excellent banks were calculated. A differences test between failed and excellent banks was performed.

Finally, a PLS-PM model was estimated. This technique suffers from the same problems as any multivariate linear regression. For example, it is very sensitive to outliers. The regression studies were performed in four different ways: (1) using all the original data, (2) removing the outliers, (3) winsorizing the data, and (4) using robust regression. Results were very similar in all the four procedures, but we decided to take the winsorized sample because the estimators are robust and it allows for working with all the data from the sample.

3.3 Hypotheses tests results

Table 2 displays the results of the explanatory data analysis. For each subgroup, average and median values of the 9 given ratios in the period 2003-2009 are shown. It also shows the p-values of a differences test. Figure 2 shows the evolution of the financial ratios median.

The first hypothesis deals with the usefulness of financial ratios to predict bank failure. The first graph in Figure 2 shows the REAL ESTATE ratio. According to Table 2, in average, 78% of the loans in failed banks were real estate, 68% in non-failed banks, and 56% in excellent banks. The values for the median are 82% in failed banks, 70% in non-failed banks and 58% in excellent banks. The differences are statistically significant throughout the period. The exposure to the housing market is clearly higher in banks that finally went bankruptcy.

The following graph shows the loan growth ratio (INC-LOANS). Remarkable loan growth ratios, followed by a sharp decrease, can be appreciated in failed banks. Hasty climbers have sudden falls. Notice that excellent banks had a sustainable growth rate of around 5% yearly, facing a 20%
growth rate of finally failed banks. Table 2 displays the average and median values. Differences are statistically significant between failed and non-failed banks, and between failed and excellent banks. This is coherent with the study by Ivashina and Scharfstein [38] on bank lending during the financial crisis of 2008, who found that banks experiencing problems reduced their lending more than other banks.

The next 3 graphs display turnover, margin and ROE. Graphs clearly show how failed banks have, since 2003, higher turnover than non-failed banks. By contrast, margins are higher in excellent banks than in failed banks. Table 2 shows that these differences are statistically significant. It can be concluded that there are different strategies in both groups of banks: failed banks get profits by rising turnover, with a high number of operations with low margin. By analyzing the database we have found, already in 2003, banks with margins close to 0 that only got profits by multiplying the number of operations.

Next ratio is ROE. Until 2006, this ratio did not show differences between failed and non-failed banks. Not even excellent banks were different. Low margin levels were compensated with high turnover and thus, profitability remained without significant differences among the three groups of banks. A fall in profitability (ROE) is a symptom that only appears two years before the crisis.

A possible way of keeping a high margin in a low interest rates environment is to maintain a low costs level. This can be obtained through low operating expenses, tight wages policy, high productivity, or better technology, among others. The SALARY ratio is higher in failed banks than in solvent banks. Excellent banks had the lowest SALARY ratio levels. These differences are statistically significant throughout the years analyzed.

Efficiency is considered as one of the ratios that better synthetize the bank’s performance, however in the present study it is not really a good failure predictor. From year 2003 to 2006 no great differences can be appreciated among failed and non-failed banks in terms of efficiency. When the crisis arose, differences in efficiency become evident.

The %RISK is higher in failed banks than in non-failed banks. It could be associated to higher numbers of bad loans in failed banks. The following analyzed ratio is solvency ratio TIER1. Figure 2 shows that this ratio, already in 2003, discriminated between failed and non-failed banks. The value of this ratio is, for failed banks, much lower if compared to non-failed banks and half, if compared to excellent banks. According to Table 2 there are statistically significant differences between failed and non-failed banks, and between failed and excellent banks. The worsening of solvency is noticeable, especially since 2006, facing the excellent banks’ tendency to strengthen their solvency.

Table 3 shows the results of the different logistic regression models. It has to be remembered
that the models were estimated with the 140 failed banks in 2009 and with a paired sample of 140 solvent banks. After having estimated the logistic function, its predictive power was assessed through a holdout sample. This holdout sample includes 127 banks failed in 2010 and 7,112 non-failed banks. The mathematical model obtained will be accurate if is able to predict with a high percentage of correctly classified failed and non-failed banks. It should be noticed that the paper was written when the banking crisis was still not over, and the accuracy percentage could be different in the future. There will be banks classified by the model as doomed to failure, that had not failed in 2010, but due to the crisis, they could fail from 2011 on.

***Table 3***

The first model (M1) includes 2008 symptoms (ROE, TIER1 and EFFICIENCY). 90.6% of the banks in the original sample were correctly classified (90.1% failed and 91.6% non-failed). Predicting in the holdout sample, the model has a global accuracy ratio of 94.8%, but it only correctly classified a 57.6% of the failed banks.

The M2 model only includes ratios from year 2003. It correctly classified a 70.7% of the original simple and a 68.8% of the holdout sample. Considering that the model only takes data 5 years from before bankruptcy, the percentage is acceptable. M3 model includes 2008 symptoms (ROE, TIER1 and EFFICIENCY), jointly with the 2003 percentage of real estate loans and 2003 loans growth. The accuracy ratio in the holdout sample is 94.8%, but it is rather unbalanced because it only correctly classified a 63% of the failed banks. The last model, M4, also combines 2003 and 2008 financial ratios, with fairly acceptable accuracy rate. Table 3 expands the results of this last model. From the 127 failed banks in 2010, the model has correctly classified 93 (73.2% accuracy rate). From the 7,113 non-failed banks, the model has correctly classified 6,485 (91.2% accuracy rate). These accuracy rates are in line with previously published distress prediction models. Lau [39] revises the percentages of correctly classified firms in several studies. They are close to 90% in the original sample and 80% in the holdout sample. However, in several published papers, holdout samples were drawn from the same time period as the original samples, which is not an intertemporal validation. In summary, results in Table 3 and Figure 2 met the hypothesis (H1a to H1c) on the usefulness of financial ratios to predict bank failure.

Table 4 shows the betas and r-square values of PLS-PM estimation by the winsorized sample. The last two columns of this table show the results of a Smith-Satterthwaite t-test for the difference in betas coefficients among groups: failed vs. non-failed banks and failed vs. excellent banks.

***Table 4***

First of all, it can be noticed that the autoregressivity hypothesis of financial ratios is met (H1d
to H1). That is, a given ratio in a given year is mostly explained by the value of the same ratio the previous year. This is corroborated by failed, non-failed and excellent banks. But the beta and t-statistic values are higher in the case of excellent banks. The Smith-Satterthwaite test finds significant differences among groups, in several relationships. A visual analysis of Figure 2 reveals that excellent banks show a stable evolution of the ratios. By contrast, failed banks show breaks in their trend lines. This is confirmed by the statistical tests in Table 4.

Hypothesis 2 states that one of the drivers of bank failure is specialization, because it increases risk. Table 4 shows that failed banks present a statistically significant relationship between the percentage of real estate loans and risk (H2a: $\beta=0.39$, $t=3.93$). By contrast, excellent banks follow a different pattern: the relationship is negative (H2a: $\beta=-0.27$, $t=2.38$). The multigroup analysis confirm the differences in behavior between failed and non-failed banks ($p=0.000$). Data analyzed confirm that excellent banks have allocated less real estate loans with higher quality compared to failed banks.

Table 4 shows that the higher the growth, the higher the risk. This relationship is stronger in failed banks (H3a: $\beta=0.48$, $t=6.89$) than in excellent banks (H3a: $\beta=0.31$, $t=2.46$), but the test does not detect statistically significant differences among groups. No significant relationship is found between growth and return or margin, among any of the groups.

Table 4 also shows the different behavior in the relationship risk-solvency. In failed banks, the higher the risk, the lower the solvency (H4a: $\beta=-0.36$, $t=2.97$). In non-failed and excellent banks the relationship is not significant (H4a: $\beta=-0.04$, $t=0.51$). Risk increases are compensated by capital increases. The differences between failed and excellent banks are statistically significant.

Finally, the relationship between margin and efficiency is significant in all the cases (H4b), as well as between margin and ROE (H4c). But the relationship between turnover and ROE is significant only in failed banks (H4d).

To sum up, based on the analyzed data, the empirical tests confirms the hypotheses. R-square values are fairly high. But other variables and relationships could be included in the model. For example, lack of liquidity can trigger bankruptcy. It would be interesting to study the role of personnel productivity or delinquency ratios. Also, some blame the role of financial engineering for the current banking crisis, International Monetary Fund [17]. But the model has chosen to be parsimonious. This model can explain most of the banking failures: putting all the eggs in one basket, giving loans to uncreditworthy borrowers, exaggerating loan growth and spoiling the margin.
5. CONCLUSIONS

The wrong strategy followed by a bank explains its failure. Long before bankruptcy happens its signs can be identified by analyzing balances and profit and loss accounts. This paper goes into the causes that originated the symptoms of failure, by analyzing the USA banking crisis started in 2008. Three of the causes were analyzed: risky loan growth, specialization in real estate and high turnover strategies facing margin stability.

Three groups of banks have been analyzed: failed, non-failed and excellent. Results show that the exposure to the housing market was clearly higher in failed banks, compared to the rest of the groups. Remarkable loan growth ratios can be appreciated in failed banks, close to 20%, followed by a sharp fall. Excellent banks enjoyed a sustained loan growth around 5% yearly. Excellent banks also had, since 2003, higher margins than failed banks. By contrast, the turnover is higher in failed banks than in non-failed banks. It can be concluded that there were differences in the strategies followed by each group of banks. Failed banks strategy was based on increasing the number of their operations with lower margins. The profitability ratios remained stable until 2006. No differences in ROE were found among excellent, failed and non-failed banks. By contrast, statistically significant differences were found in the solvency ratio, among all the groups, all the years.

The stability of financial ratios has been analyzed. In excellent banks solvency, profitability and efficiency remained stable, facing the stumbling behavior of failed banks’ ratios.

The path to solvency and the path to failure have been established through a structural equations model. The proposed model relates symptoms to causes through a series of hypotheses. This model has been tested by Partial Least Squares Path Modeling (PLS-PM). In failed banks, a statistically significant relationship is found between real estate loans percentage and risk. By contrast, this relationship is negative in excellent banks. These banks have less real estate loans with better quality.

For all the banks, the higher the growth, the higher the risk. But for failed banks, the higher the risk, the lower the solvency. For non-failed and excellent banks this relationship is not significant, because risk growth is compensated by strengthening the core capital.

The study reveals patterns of adequate and inadequate banking management. The latter are associated to put all the eggs in one basket, to give loans to uncreditworthy borrowers, to exaggerate loan growth and to ruin the margin. This explains most of the banking failures.
REFERENCES


Figure 1. The structural model.
<table>
<thead>
<tr>
<th>REALSTATE</th>
<th>INC-LOAN</th>
<th>TURNOVER</th>
</tr>
</thead>
</table>

17
Figure 2. Median time evolution for failed, non-failed and excellent banks.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>REALSTATE</td>
<td>Concentration in real estate loans (lnre/lnlsnet). All real estate loans divided by net loans and leases</td>
</tr>
<tr>
<td>INC-LOANS</td>
<td>Net loans and leases growth (increase in lnlsnet / lnlsnet * 100).</td>
</tr>
<tr>
<td>TURNOVER</td>
<td>Yield on earning assets (intincy). Total interest income as a percentage of average earning assets.</td>
</tr>
<tr>
<td>MARGIN</td>
<td>Net operating income to average earning assets (noij/ernast5). Net income excluding discretionary transactions such as gains (losses) on the sale of investment securities and extraordinary items divided by the average of all loans and other investments that earn interest or dividends.</td>
</tr>
<tr>
<td>ROE</td>
<td>Return on equity (roe). Annualized net income as a percentage of average equity on a consolidated basis.</td>
</tr>
<tr>
<td>SALARY</td>
<td>Salaries (esal/numemp). Salaries and employee benefits divided by total employees (full-time equivalent)</td>
</tr>
<tr>
<td>EFFICIENCY</td>
<td>Efficiency ratio (eeffr). Noninterest expense, less the amortization expense of intangible assets, as a percent of the sum of net interest income and noninterest income.</td>
</tr>
<tr>
<td>%RISK</td>
<td>Risk ratio (rwaj/asset5). Risk-weighted assets as defined by the federal regulator for prompt corrective action divided by the average of the total assets represented on the balance sheet</td>
</tr>
<tr>
<td>TIER1</td>
<td>Tier 1 risk-based capital ratio (rbc1rwaj). Tier 1 (core) capital as a percentage of risk-weighted assets.</td>
</tr>
</tbody>
</table>

Table 1. Variables employed and their definition. In parentheses, the terms used by the Federal Deposit Insurance Corporation (FDIC).
<table>
<thead>
<tr>
<th>Year</th>
<th>Nonfail Mean</th>
<th>Fail Mean</th>
<th>Excellent Mean</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>5.78 6.18 5.66</td>
<td>6.01 6.63 5.76</td>
<td>6.74 7.63 6.38</td>
<td>(0.000)</td>
</tr>
<tr>
<td>2004</td>
<td>5.80 6.17 5.28</td>
<td>6.02 6.75 5.43</td>
<td>6.73 7.81 6.16</td>
<td>(0.000)</td>
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<td>2005</td>
<td>9.01 21.35 5.12</td>
<td>8.34 24.36 6.05</td>
<td>7.00 15.86 4.16</td>
<td>(0.000)</td>
</tr>
<tr>
<td>2006</td>
<td>8891 252 140</td>
<td>8677 264 140</td>
<td>8525 273 140</td>
<td>(0.000)</td>
</tr>
<tr>
<td>2007</td>
<td>8891 252 140</td>
<td>8677 264 140</td>
<td>8525 273 140</td>
<td>(0.000)</td>
</tr>
<tr>
<td>2008</td>
<td>8891 252 140</td>
<td>8677 264 140</td>
<td>8525 273 140</td>
<td>(0.000)</td>
</tr>
<tr>
<td>2009</td>
<td>8891 252 140</td>
<td>8677 264 140</td>
<td>8525 273 140</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

Table 2. Exploratory analysis. In parentheses, the p-values of the median test.
### Panel A)

<table>
<thead>
<tr>
<th>Models</th>
<th>Original sample</th>
<th></th>
<th></th>
<th></th>
<th>Holdout sample</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Failed</td>
<td>Non-failed</td>
<td>Overall</td>
<td>Failed</td>
<td>Non-failed</td>
<td>Overall</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M1</td>
<td>TIER1(<em>{2008}) + ROE(</em>{2008}) + EFFICIENCY(_{2008})</td>
<td>90.1</td>
<td>91.2</td>
<td>90.6</td>
<td>57.6</td>
<td>95.5</td>
<td>94.8</td>
<td></td>
</tr>
<tr>
<td>M2</td>
<td>REALSTATE(<em>{2003}) + INC-LOANS(</em>{03-04}) + RISK(<em>{2003}) + MARGIN(</em>{2003}) + TURNOVER(_{2003})</td>
<td>72.8</td>
<td>68.4</td>
<td>70.7</td>
<td>72.4</td>
<td>68.7</td>
<td>68.8</td>
<td></td>
</tr>
<tr>
<td>M3</td>
<td>TIER1(<em>{2008}) + ROE(</em>{2008}) + EFFICIENCY(<em>{2008}) + REALSTATE(</em>{2003}) + INC-LOANS(_{03-04})</td>
<td>92.0</td>
<td>92.3</td>
<td>92.1</td>
<td>63.0</td>
<td>95.3</td>
<td>94.8</td>
<td></td>
</tr>
<tr>
<td>M4</td>
<td>MARGIN(<em>{2008}) + TURNOVER(</em>{2008}) + EFFICIENCY(<em>{2008}) + REALSTATE(</em>{2008}) + INC-LOANS(_{2003})</td>
<td>80.0</td>
<td>91.5</td>
<td>85.5</td>
<td>73.2</td>
<td>91.2</td>
<td>90.9</td>
<td></td>
</tr>
</tbody>
</table>

### Panel B)

<table>
<thead>
<tr>
<th>Predicted by model M4</th>
<th>Selected Cases</th>
<th></th>
<th></th>
<th></th>
<th>Unselected Cases</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed</td>
<td>Failed</td>
<td>Non-failed</td>
<td>% Correct</td>
<td>Failed</td>
<td>Non-failed</td>
<td>% Correct</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Failed</td>
<td>100</td>
<td>25</td>
<td>80.0</td>
<td>93</td>
<td>34</td>
<td>73.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-failed</td>
<td>10</td>
<td>107</td>
<td>91.5</td>
<td>628</td>
<td>6485</td>
<td>91.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall Percentage</td>
<td>85.5</td>
<td></td>
<td></td>
<td></td>
<td>90.9</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 3.** Multivariate Logistic Regression results. Panel A shows the accuracy rates of the four different models. Panel B details results by model M4.
**Hypotheses test results.**

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Standardized coefficients and bootstrap t values</th>
<th>P-value of differences</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-failed</td>
<td>Failed</td>
</tr>
<tr>
<td></td>
<td>Beta</td>
<td>T-statistic</td>
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<tr>
<td>H1d TIER1_{2005} \rightarrow TIER1_{2006}</td>
<td>0.86</td>
<td>15.93**</td>
</tr>
<tr>
<td>H1e TIER1_{2006} \rightarrow TIER1_{2007}</td>
<td>0.86</td>
<td>14.91**</td>
</tr>
<tr>
<td>H1f TIER1_{2007} \rightarrow TIER1_{2008}</td>
<td>0.88</td>
<td>20.33**</td>
</tr>
<tr>
<td>H1g ROE_{2005} \rightarrow ROE_{2006}</td>
<td>0.77</td>
<td>12.25**</td>
</tr>
<tr>
<td>H1h ROE_{2006} \rightarrow ROE_{2007}</td>
<td>0.77</td>
<td>10.86**</td>
</tr>
<tr>
<td>H1i ROE_{2007} \rightarrow ROE_{2008}</td>
<td>0.67</td>
<td>7.57**</td>
</tr>
<tr>
<td>H1j EFFICIENCY_{2005} \rightarrow EFFICIENCY_{2006}</td>
<td>0.71</td>
<td>6.67**</td>
</tr>
<tr>
<td>H1k EFFICIENCY_{2006} \rightarrow EFFICIENCY_{2007}</td>
<td>0.75</td>
<td>7.10**</td>
</tr>
<tr>
<td>H1l EFFICIENCY_{2007} \rightarrow EFFICIENCY_{2008}</td>
<td>0.78</td>
<td>9.59**</td>
</tr>
<tr>
<td>H2a REALSTATE_{2003} \rightarrow %RISK_{2004}</td>
<td>0.24</td>
<td>1.87</td>
</tr>
<tr>
<td>H2b REALSTATE_{2003} \rightarrow MARGIN_{2004}</td>
<td>-0.05</td>
<td>0.48</td>
</tr>
<tr>
<td>H2c REALSTATE_{2003} \rightarrow TURNOVER_{2004}</td>
<td>0.29</td>
<td>2.56*</td>
</tr>
<tr>
<td>H3a IIN-LOANS_{2004} \rightarrow %RISK_{2004}</td>
<td>0.36</td>
<td>4.66**</td>
</tr>
<tr>
<td>H3b INC-LOANS_{2004} \rightarrow MARGIN_{2004}</td>
<td>-0.01</td>
<td>0.17</td>
</tr>
<tr>
<td>H3c INC-LOANS_{2004} \rightarrow TURNOVER_{2004}</td>
<td>0.04</td>
<td>0.50</td>
</tr>
<tr>
<td>H4a %RISK_{2004} \rightarrow TIER1_{2005}</td>
<td>-0.14</td>
<td>1.65</td>
</tr>
<tr>
<td>H4b MARGIN_{2004} \rightarrow EFFICIENCY_{2005}</td>
<td>-0.46</td>
<td>5.15**</td>
</tr>
<tr>
<td>H4c MARGIN_{2004} \rightarrow ROE_{2005}</td>
<td>0.64</td>
<td>7.53**</td>
</tr>
<tr>
<td>H4d TURNOVER_{2004} \rightarrow ROE_{2005}</td>
<td>0.13</td>
<td>1.56</td>
</tr>
</tbody>
</table>

** Significant at the 0.01 level
* Significant at the 0.05 level

**Non-Failed** N= 9,679; R² for TIER1_{2008}=0.76; R² for EFFICIENCY_{2008}=0.60; R² for ROE_{2008}=0.44; R² for %RISK_{2004}=0.20; R² for MARGIN_{2004}=0.00; R² for TURNOVER_{2004}=0.09

**Failed** N= 140; R² for TIER1_{2008}=0.04; R² for EFFICIENCY_{2008}=0.27; R² for ROE_{2008}=0.05; R² for %RISK_{2004}=0.36; R² for MARGIN_{2004}=0.06; R² for TURNOVER_{2004}=0.15

**Excellents** N= 140; R² for TIER1_{2008}=0.86; R² for EFFICIENCY_{2008}=0.54; R² for ROE_{2008}=0.46; R² for %RISK_{2004}=0.15; R² for MARGIN_{2004}=0.03; R² for TURNOVER_{2004}=0.00

**Table 4.** Hypotheses test results.