Contribution of macroeconomic factors to the prediction of small bank failures

Citation for published version:
Mare, D 2015, 'Contribution of macroeconomic factors to the prediction of small bank failures', *Journal of International Financial Markets, Institutions and Money*, vol. 39, pp. 25-39.
https://doi.org/10.1016/j.intfin.2015.05.005

Digital Object Identifier (DOI):
10.1016/j.intfin.2015.05.005

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
Journal of International Financial Markets, Institutions and Money

Contribution of macroeconomic factors to the prediction of small bank failures

Davide Salvatore Mare[a]

[a] Credit Research Centre, Business School, The University of Edinburgh, U.K.

Abstract

Microprudential regulation is an integral part of any banking supervisory framework. By analysing the link between economic conditions and the survival of small co-operative banks, this study sheds light on the importance of the economic environment after assessing individual bank stability over time. The results show that bank failure is better captured when we account for the state of the economy both at the national and the regional level. Moreover, voluntary closures and acquisitions across provinces appear to be related with bank distress. Our findings have important policy implications. First, using a wider spectrum of information increases the accuracy of default prediction models, improving the supervisory toolbox used to monitor the health of small banks. Second, economic downturns increase a co-operative bank's default risk, supporting the introduction of countercyclical capital buffers to lessen the negative effects associated to bank instability.

JEL-Classification: C23, C41, G21, G28, G33

Keywords: bank failure, probability of default, survival model, macroeconomic factors, Italian co-operative banks

* *Corresponding author: Credit Research Centre, University of Edinburgh Business School, 29Buccleuch Place, EH89JU, Edinburgh, UK. Phone: +44 (0)1316515077, Fax: +44 (0)1316513197, E-mail: davide.mare@ed.ac.uk*

1 Introduction

The regulatory reforms enacted in several countries following the 2007–2009 financial turmoil have attempted to correct major systemic weaknesses that caused the crisis. Policy makers and commentators have advocated the need to develop frameworks able to address the financial stability of the banking sector and increase the resilience of individual banking institutions during periods of stress. Despite this call, few studies have analysed the financial stability of small banks. Microprudential regulation can help reduce the risk of system-wide shocks. Consequently, it is paramount to further explore the causes of bank distress with a particular focus on local and regional retail banks.

This paper analyses the determinants of failure among small banks, which are driving forces of the economic development in rural areas. In several countries, small banks are characterised by the mutual form of ownership. In particular, co-operative banks are mutual banks owned by their members that tend to have strong local roots. A change in economic conditions can have a profound impact on bank performance and profitability, especially when clients are members/owners of the same financial institution. For these banks, the incentive to keep lending during periods of financial distress is high, triggering self-fulfilling crises for both banks and clients. Moreover, geographic concentration exposes small credit institutions to local economic downturns.

We investigate the relationship between the environmental economic conditions and the probability of small bank failure using a sample of all Italian co-operative banks over the period 1993–2011. The analysis is of particular relevance for the socioeconomic role of these credit institutions and for potential local-level output losses.[1] Moreover, recent regulations designed to increase financial stability have established capital buffers to lessen the procyclical behaviour in bank lending. We investigate whether this regulation is well-rooted under the hypothesis that overall solvency risk for small banks is lower during periods of economic downturn.

There are numerous reasons for analysing the solvency of co-operative banks. First, few studies have provided a comprehensive picture of the main determinants of risk among small banks. Recent research has examined the determinants of bankruptcy in commercial banking (Altunbas et al., 2011; Cole and White, 2012; DeYoung and Torna, 2013) and the systemic risk arising from global financial institutions (Huang et al., 2009; Chan-Lau, 2010), but none has covered co-operative banks. In most cases, scant market data is available (e.g., audited financial statements), and much relevant information is not disclosed (Fonteyne, 2007), making a thorough empirical analysis of the determinants of failure among these credit institutions important. Second, co-operative banks contribute to the diversity within the banking industry and to the stability of the financial system (Cihák and Hesse, 2007). Third, savings and co-operative institutions are often the local engine of economic development (Hakenes et al., 2014) and smooth out the effects of tight monetary policy (Ferri et al., 2014). Finally, bank supervisors may favour mergers and acquisitions among small banks as an option for distressed credit institutions. It is therefore important to understand whether the target bank[2] should be considered distressed or not.

---

[1] See, for instance, Ashcraft (2005) for an analysis of the macroeconomic costs at the local level associated with bank failure.
[2] We use the term "target bank" to refer to a credit institution acquired or the "passive" intermediary in a merger.

Is the external environment a significant predictor of small bank failure? Is the banking supervisor likely to find private solutions when small banks are financially strained? We address these questions for Italian co-operative banks,[3] as these credit institutions operate mainly at the local level and are widespread across Italy. In 2014, there were 381 locally operating institutions with more than 4,400 outlets distributed across the 20 Italian regions.

We use a discrete-time survival model to show that co-operative failures are related to macroeconomic variables and to bank-level fundamentals. Our contribution to the literature is three-fold. First, we directly model the risk of distress among small CBs rather than large commercial and global banks, focusing on Italian co-operative banks. Second, we add macroeconomic factors to bank-specific determinants to estimate the risk of default of co-operative banks. By using a wider set of variables, bank supervisors can lessen the dependency of off-site monitoring on accounting data, thus improving the supervisory toolbox used to anticipate banking crises and allowing them to intervene at an early stage of a problem bank. Third, we test whether when co-operative banks are at risk of default, the distress is resolved through mergers, acquisitions, or voluntarily closures. The results of our analysis can help define and identify small bank distress.

The remainder of the paper is organized as follows. Section 2 describes the Italian co-operative banking sector. Section 3 discusses the relevant literature and reports the research hypotheses. Section 4 describes the data and the variables used in the analysis.

---

[3] For expositional convenience, the terms "Italian co-operative banks", "co-operatives", or "CBs" stand for:
1. Banche di credito cooperativo;
2. Casse rurali;
3. Casse Raiffeisen.
Note that Italian banche popolari are not covered in the present analysis since, in terms of governance, they more closely resemble joint-stock companies (Fonteyne, 2007). Also, cooperative networks, such as Rabobank Group in the Netherlands and Crédit Agricole in France, are different from Italian cooperative banking.

Section 5 details the econometric modelling. Section 6 summarises the results of the analysis, and Section 7 describes our robustness checks. Section 8 concludes.

2 The Italian co-operative banking sector

Co-operative banks (CBs) are widespread across Italy and make up a large segment of the Italian banking system, operating primarily at the local level. Of Italy's 110 provinces, CBs operate in 101, and they are located in 2,700 of 8,057 municipalities. As of June 2014, Italy had 381 co-operative banks (56% of the 678 total banks in the country), with 4,449 branches (14% of the total - 31,234), around 1.2 million members, and 37,000 employees (out of approximately 300,000 employees in the whole Italian banking sector).[4] At that time, the CB sector granted credit totalling approximately 136 billion Euro (market share is 7.3%).[5] Moreover, these credit institutions are key players in granting credit to specific customer segments and to micro, small, and medium-sized enterprises (MSME). For instance, according to Federcasse, the market share of loans granted to the MSMEs in June 2014 was 22.5%, to artisan firms was 22.6%, to consumer households was 8.7%, to producer households was 17.9%, to nonfinancial firms was 8.7%, and to non-profit institutions was 12.5%.

The Italian CBs also contribute to the diversity of the Italian banking system. The majority are small, rural credit institutions that specialize in relationship lending. As mutual banks, their mission involves providing members with high-quality products and services, along with adequate profitability. Decision making is based on the one-person,

---

[4] Source of data: Bank of Italy and Federcasse.

[5] To avoid potential double counting due to credit extended to individual co-operative banks, the figure does not include funding granted by second-tier institutions.

one-vote principle,[6] which leads to conservative risk management and a feeling of trust between the local CB and its members and customers. Owners and customers often share a long-term perspective towards generating value.

The Italian Banking Law influences the structure and organization of CBs.[7] Shares are nontradable since they do not reflect the value of the firm; instead, profits are mostly devoted to a reserve fund.[8] This feature is particularly important as it limits the ability of CBs to raise capital on the market. The banks are linked to the local economy through a defined geographic area of competence. Customers and members must be either residents of, headquartered in, or have an economic interest in the bank's geographic area. However, since 1993, co-operative banks have been allowed to offer the same range of products and services to all types of customers as all the other types of banks (e.g., commercial banks).

The Italian CBs are fully autonomous but cooperate closely through network institutions using a two-tiered system. The individual banks are associated with 15 local federations that, in turn, are members of the national association (Federcasse). Federcasse offers member banks legal, fiscal, and organizational support, along with training programs. The regional federations provide technical assistance and internal auditing to their members. A "safety net" of three institutional funds guarantees the liabilities of the individual banks: deposits are guaranteed through the Depositors' Guarantee Fund (Fondo di Garanzia dei Depositanti del Credito Cooperativo); credit rights of bondholders are guaranteed by the Bondholders' Guarantee Fund (Fondo di Garanzia degli Obbligazionisti del Credito Cooperativo); and the Institutional Guarantee

[6] Art. 34, Italian Banking Law.
[7] Italian Banking Law (Legislative Decree no. 385 of 1st September 1993).
[8] At least 70% of the annual net profits must be allocated to the legal reserve fund (Art. 37, Italian Banking Law).

Fund (Fondo di Garanzia Istituzionale del Credito Cooperativo) assures the liquidity and solvency of the member banks through crisis prevention and financial support. In addition, three central institutions (Iccrea Group, Cassa Centrale Banca and Cassa Centrale Raiffeisen dell'Alto Adige) owned by co-operative banks provide specialised products and services to CBs.

3 Selected literature and research hypotheses

Our study contributes to the empirical literature that investigates bank stability from a micro perspective. A long line of literature has employed a similar approach, using individual banks' balance sheet data, sometimes along with market data, to predict bank failure. Prior studies have quantified bank default in two primary ways. First, several authors model default by directly estimating overall bank risk (see, among many others, Meyer and Pifer, 1970; Sinkey, 1975; Santomero and Visno, 1977; West, 1985; Cole and Gunther, 1998; Estrella et al., 2000). Second, others quantify risk via specific measures of bank risk. For instance, many recent works have used the Z-Score[9] (Cihák and Hesse, 2007; Mercieca et al., 2007), the ratio of total nonperforming loans to total loans (Fiordelisi et al., 2011), or the loan-loss reserves to total assets (Altunbas et al., 2007) as proxies for bank soundness. Various covariates are then used to explain bank default, such as bank-specific variables, market information, or macroeconomic data.

Gonzalez-Hermosillo (1999) analyses the role of both micro and macro factors in the occurrence of banking system distress in the United States, Mexico, and Colombia in the 1980s and 1990s. Using panel data and duration models, the author argues that bank-

[9] The Z-Score is computed as the ratio between the sum of the equity ratio (equity to total assets) plus the return on asset indicator (net operating profit after taxes as percent of total assets) divided by the return volatility, often proxied by the standard deviation of the return on asset indicator or stock price data (for listed banks only).

specific variables seem to capture the fundamental sources of ex-ante risk. The introduction of macroeconomic or regional variables enhances the predictive power of the models based on bank-specific data only. Männasooa and Mayes (2009) test a theoretical framework that uses a combination of macroeconomic, structural, and bank-specific factors to predict bank distress in European transition economies. Arena (2008) suggests that systemic macroeconomic and liquidity shocks not only destabilize the banks that were already weak before the crises, but also the relatively stronger banks ex-ante. This result implies that even strong banks can be affected by negative spill-over effects brought by systemic crises.

A few studies have investigated bank failure in the Italian banking sector and specifically among Italian co-operative banks. Fiordelisi and Mare (2013) analyse whether efficiency measures are important in explaining the default of Italian CBs. The authors use a selective definition of bank failure (e.g., distressed mergers are not analysed) and do not examine the macroeconomic environment as a determinant of small bank failure. Other works focus on de novo banks and factors that can influence their survival. Maggiolini and Mistrulli (2005) analyse a sample of recently established CBs and find that they survive longer when there is less local competition. Moreover, they conclude that local real per capita gross domestic product is significantly related to CBs' probability of survival. Libertucci and Piersante (2012) use both survival-time and binary choice models to investigate whether capital is an important determinant of the survival of Italian start-up banks over the period 1994–2006. The authors show that capital is significantly related to both the time to default and the likelihood of default. Moreover, market and management variables appear to be less relevant in explaining bank survival.

To our knowledge, however, no papers to date have assessed whether the local economic environment and macroeconomic developments are significant covariates in predicting individual distress among Italian CBs. Moreover, no studies have explicitly looked into the alternative resolution of individual bank distress by estimating the probability of default associated with distressed mergers and acquisitions. This paper fills these gaps in the literature and provides insights into the role of the economic environment in the failure of individual Italian banks.

Other studies have attempted to include macroeconomic indicators as *ex-ante* determinants of potential banking problems (Quagliariello, 2008). From a theoretical point of view, banks are exposed to the cyclical development of the economy; thus, including macroeconomic variables in predictive models for bank failure should lead to better forecasting performance (Gonzalez-Hermosillo, 1999; Ioannidis et al., 2010). Gonzalez-Hermosillo et al. (1997) include macroeconomic determinants when analysing bank soundness during the Mexican financial crisis and find that banking sector variables significantly explain bank failure, whereas macroeconomic variables largely determine the time to default. Betz et al. (2014) develop an early-warning model for predicting the distress of European banks and show that out-of-sample predictions improve significantly when bank-level characteristics are complemented by macro-financial imbalances and banking sector explanatory variables. Nevertheless, it is important to accurately define the economic area where a bank does its business. Specifically, Italian CBs tend to operate mainly locally. Moreover, the co-operative model clearly places clients at the centre of the business, increasing banks' exposure to the cyclical fluctuations of the local economy because their performance is closely tied to the financial condition of their customers.

A few loosely related studies look at the performance of US regional and community banks, explicitly investigating the role of macroeconomic determinants differentiated at the macro and local levels. Meyer and Yeager (2001) and Daly et al. (2004) find that a variety of measures of state-level economic factors have economically and statistically significant effects on measures of bank performance. Meyer and Yeager (2011) also find that county-level economic data is both statistically and economically insignificant. Yeager (2004) relates measures of performance - the ratio of nonperforming loans to total loans, net charge offs to total loans, and return on assets - to large shocks in regional unemployment rates and finds that local market risk has a non-significant economic effect on community bank performance. Aubuchon and Wheelock (2010) compare the characteristics of failed and healthy US banks during 2007–2010 and show that bank failures are concentrated in regions with the highest degree of distress in real estate markets and the largest declines in economic activity. These studies do not test whether banks' overall risk of solvency is related to macroeconomic dynamics. We fill this void by testing whether the default of Italian co-operative banks depends on aggregate factors (e.g., short-term interest rate) and regional-level drivers (e.g., unemployment rate).

Hypothesis I (H_1): The state of the economy, both at the national and the regional level, affects the survival of co-operative banks ("economic vulnerability" hypothesis).

Alternative Hypothesis I (H_1^A): The state of the economy, both at the national and the regional level, does not affect the survival of co-operative banks ("economic immunity" hypothesis).

To avoid classification problems,[10] some banking studies consider distressed mergers as a failure event (Curry et al., 2007; Kick and Koetter, 2007; Betz et al., 2014). The Italian Banking Law allows mergers as an option for distressed CBs.[11] Because of the small size of these local credit institutions, governments and regulators do not take over the troubled banks but rather favour alternative solutions.

In line with this argument and because the literature on Italian bank failures does not explore this alternative, we test the hypothesis that the Italian bank supervisor (Bank of Italy) favours a change in bank status through acquisition, voluntary closure, or sale to other banks in the case of bank failures. We explore whether the Italian banking supervisor follows a policy of forbearance or a policy of quickly closing co-operative banks. Moreover, from a modelling perspective, it is fundamental to define in broader terms the distress of co-operative banks.

Hypothesis II (H_2): When banks are at risk of default, bank supervisors favour private solutions ("private resolution" hypothesis).

Alternative Hypothesis II (H_2^A): When banks are at risk of default, bank supervisors do not favour private solutions ("market discipline" hypothesis).

4 Sample and variables

We use data from annual financial statements as well as macroeconomic information to investigate the degree of solvency of Italian co-operative banks over the period 1993–

[10] In order to obtain higher model performance, healthy banks should be as diverse as possible from distressed banks in terms of their default determinants.
[11] Article 36, Italian Banking Law.

2011.[12] Financial statements are obtained from Federcasse, and macroeconomic information comes from the Italian National Institute of Statistics (Istat), the Bank of Italy, and Datastream (Thomson Reuters). In 2006, CBs adopted the International Accounting Standards (IAS), causing the dataset before and after 2006 to differ. Therefore, we divide the sample in two, using 1993–2005 data in our main models and 2006–2011 data for out-of-sample robustness checks. Moreover, because no default events occurred during 2007–2008, hold-out data is restricted to years 2008–2011.[13]

After cleaning and organizing the data, we are left with a sample of 4,635 observations from 434 unique banks distributed across the 20 Italian regions. The number of observations per group ranges from 1 to 13. Table 1 shows the participation patterns of the cross-sectional time-series data and indicates that data for each individual bank in the sample is not available for all the years.

<Insert here Table 1>

Table 2 shows the geographic distribution of the banks in our sample. Almost half are located in one geographic area (North-East, 42%), and almost a quarter in one region (Trentino Alto-Adige, 25%). At the end of 2005, the median asset size of the sample banks was €185.1 million, and the median number of branches per bank was 6.0. The biggest banks in terms of the average number of branches per bank and of the average asset size are located in the North West. Banks located in the South and the Islands are smaller, in terms of both average total assets and average number of branches.

<Insert here Table 2>

[12] As in Poghosyan and Čihak (2011), the data set on default events begins and ends one year later than the bank-level and economic data sets (i.e., 1994-2012) to account for the relationship between bank distress and lagged covariates.
[13] See Section 5 for a detailed explanation of the difference between the observation period (1994–2012) and the data used to estimate the model (1993–2005) and those used to run the out-of-sample test (2006–2011).

Previous studies have found that bank failure is associated with public intervention (Arena, 2008; Männasooa and Mayes, 2009; Fiordelisi and Mare, 2013). The Italian insolvency regime rules that major companies (groups) experiencing financial distress can be subject to either special administration or liquidation procedures. Special administration is a "going-concern" intervention that aims at restructuring and reorganizing the enterprise while protecting the company from creditor action. Liquidation is a "gone-concern" action in which the license is revoked by the regulator. Moreover, the Italian insolvency regime rules that in case of distress, troubled CBs may be merged with healthy banks. This resolution is optional and does not necessarily mean that mergers follow distress. Consequently, we do not include this possibility in our definition of "failure." Instead, we limit our classification of a bank in default as one entering into special administration (i.e., conservatorship) or compulsory liquidation between January 1, 1994 and December 31, 2006. This definition indicates either temporary instability or a bank's inability to continue its operations. Moreover, defining default in this manner leaves us with an adequate number of cases (i.e., 59) to draw statistical inference from the data. The explained variable is computed as a dummy that takes a value of 1 if the bank is subject to one of the aforementioned procedures in a specific year, and 0 otherwise.

<Insert here Table 3>

Tables 3 and 4 provide descriptive statistics for our sample of Italian CBs. Table 3 shows that the number of CBs decreased between 1993 and 2012, primarily due to acquisitions and mergers. According to Table 4, of the total number of banks cancelled from the Bank of Italy's register during the 1993–2011 period (444), 86% merged with or were acquired by other banks (380). Moreover, of the 100 cases of default, 61 ended with a merger or acquisition favoured by the bank regulator (Bank of Italy).

<Insert here Table 4>

The data set for the explanatory variables combines accounting and macroeconomic data. We do not consider market information because CBs are not listed on a stock exchange, and very little other market information is available.[14] We draw a set of potential explanatory variables from the extant literature and also take into account specific CB characteristics. The covariates are divided into two broad categories: macroeconomic factors - both at the national and regional levels - and bank-level fundamentals.

Macroeconomic variables

The first category of regressors seeks to gauge the impact of the economic environment on bank risk. Our underlying assumption is that economic variables proxy risk within the environment in which CBs operate. Since diversification is not an option due to specific restrictions on CBs' business activities, adverse local economic conditions increase the vulnerability of these banks to local exogenous financial shocks. We compute macroeconomic factors at both the regional and national levels to capture the heterogeneity of Italian regions and to control for systemic risk.

Following earlier studies, we examine a broad set of indicators to capture the risk of banking crises (Borio and Lowe, 2002, 2009; Davis and Karim, 2008; Demirguc-Kunt and Detragiache, 2005). After performing univariate tests and employing a stepwise procedure, we select three macroeconomic variables to include in the model: the

[14] A few CBs are provided with credit ratings by External Credit Assessment Institutions.

interstate deposit rate, the unemployment rate, and an indicator of industry concentration.

Our first variable of macroeconomic risk, the three-month average interbank deposit rate, gives an indication of the liquidity of the Italian banking market. In recent years, when the value of this indicator has been high, there has been higher distress on the wholesale banking market, leading banks to rely more heavily on core liabilities (i.e., deposits) or on liquidity lines from the central banks. The second variable, the regional unemployment rate, helps determine environmental risk. The majority of CB customers/members are households and small and medium-sized firms with a local business. A high unemployment rate could affect both the consumption and credit worthiness of customers, which translates into high environmental risk. Our third macro-level variable is the concentration of regional outlets, which indicates regional competition in the banking industry. A higher value indicates that CBs account for a higher percentage of the total number of regional outlets and consequently face less competitive pressure from other types of banks (e.g., commercial banks).

Bank-level variables

We are also interested in capturing individual banks' idiosyncratic risk. To ensure coverage of the most important aspects of bank vulnerability, we follow the extant literature and the CAMEL framework[15] to devise a set of bank-level variables to help us estimate the financial distress of individual banks (Männasooa and Mayes, 2009; Fiordelisi and Mare, 2013; Betz et al., 2014). We use bank-level accounting data to

---

[15] CAMEL refers to the following five factors traditionally examined by US banking regulators: "C" stands for capital adequacy, "A" for asset quality, "M" for management quality, "E" for earnings, and "L" for liquidity. A more recent framework (CAMELS), take into consideration an additional factor: "S" for sensitivity to market risk. However, CBs do very little market activity, meaning that market risk is a residual determinant of the overall risk of failure.

control for the effects of other elements that provide early warning of distress. These ratios provide information about the symptoms rather than the causes of financial difficulty (Arena, 2008).

We again employ univariate analyses and a stepwise methodology to select the most relevant variables. Specifically, we measure capital adequacy using the Basel III leverage ratio (i.e., equity to total assets). We estimate a bank's asset quality using the ratio of loan-loss provisions to total loans. We proxy management quality using staff costs divided by the sum of interest and fee income. We account for earnings using the adjusted return on asset indicator (sum of net profit after taxes and loan-loss provisions divided by total assets), and we measure the liquidity risk as loans to deposits. In addition, we control for the bank's idiosyncratic risk (Emmons et al., 2004) using total assets. Table 5, Panel A defines our analytic variables and lists prior studies that have used them. Panel B reports descriptive statistics for failed and healthy banks in the training set.[16]

<Insert here Table 5>

5 Modelling bank default

In this study, we examine the relevance of macroeconomic determinants in estimating the probability of CB default. We expect that small bank distress stems from both internal determinants (i.e., managerial risk) and external conditions (i.e., economic

[16] The training set is the data used to estimate the model.

environment). Following Quagliariello (2008), we model the probability of default of Italian CBs using the following specification:

Prob(Failure)=f(Bank Specific, Macroeconomic Variables) (1)

We estimate the probability of failure at each point in time using a discrete-time survival model, which includes macroeconomic variables that are the same for all banks at given points in time (Shumway, 2001; Leow and Crook, 2014). Moreover, this methodology allows us to capture the change in a bank's risk of bankruptcy over time and to account for censoring.[17] We estimate the following complementary log-log model (cloglog), which is consistent with interval-censored survival time:

$$h(j, \mathbf{X}_{i,j-1}, \mathbf{M}_{j-1}) = 1 - \exp\left[-\exp\left(\beta^I \mathbf{X}_{i,j-1} + \delta^I \mathbf{M}_{j-1} + \gamma_{j-1}\right)\right], \tag{2}$$

where $h(j, \mathbf{X}_{i,j-1}, \mathbf{M}_{j-1})$ is the hazard rate or the probability that a bank fails in a given time interval. *j* and *i* denote, respectively, a time interval and a specific bank; $\mathbf{X}_{i,j-1}$ is the vector of the time-varying, bank-specific covariates, lagged one year; $\mathbf{M}_{j-1}$ is the vector of the time-varying, bank-independent covariates (i.e. macroeconomic variables), lagged one year; and γ_{j-1} is the parametric baseline estimated as the log of time. β^I and δ^I are vectors of parameters to be estimated. The discrete hazard rate expresses the probability of exit in a specific interval *j*, conditional on survival until interval *j*. See Appendix A for further details.

[17] In the empirical literature, many other studies employ hazard models in analyzing bank failures such as Lane et al. (1986), Whalen (1991), Männasooa and Mayes, (2009), Brown and Dinç (2011), and Fiordelisi and Mare (2013).

Following the ex-post empirical approach used in previous bank failure studies,[18] the explanatory variables ($X_{i,j}$, M_j) are drawn from data for a time period prior to failure. We compare the characteristics of two groups of banks - sound and default - using a time lag to examine dynamic behaviour. The explanatory variables are one-year lagged ($X_{i,j-1}$, M_{j-1}) such that the hazard rate expresses the probability of default in period *j* in relation to the control variables of period *j-1*. The econometric model then predicts the likelihood that a bank, currently considered safe and sound, fails within a period of 0–12 months.

We run a three-stage analysis. First, we estimate a complementary log-log model (cloglog) using macroeconomic factors and firm-specific CAMEL ratios, separately and then jointly, as explanatory variables. We exclude from the estimation banks that have merged, been acquired, or closed by owners. The observation period is 1994–2006, and the model is estimated using data from 1993 to 2005, allowing us to investigate whether macroeconomic variables are significantly related to small bank failure.

We next explore whether some of the excluded credit institutions (e.g., merged banks) were distressed before the change of status. We compute the hazard rate for each bank using the estimated coefficients of the discrete-time survival model for the period 1994 to 2006 and then rank all banks from the least risky (1st decile of the hazard rate distribution) to the riskiest (10th decile of the hazard rate distribution). We expect the banks with the highest hazard rate to be the most likely to fail. We then calculate the percentage of banks subject to merger, acquisition, or voluntary closure that are assigned to each decile of the hazard rate distribution.

---

[18] Among others, Martin (1977), Espahbodi (1991), Männasooa and Mayes (2009), and Fiordelisi and Mare (2013).

As a further test, we analyse whether a subsample of merged/acquired institutions is more significant in terms of level of distress. We control for whether the banks that were acquired by/merged with an intermediary located in a different province[19] were more or less risky compared to the full sample. This analysis allows us to test H_2, the private resolution hypothesis, because it involves the combination of institutions with different "local" roots. In addition, we investigate whether there is a statistically significant difference between the mean hazard rate of defaulted banks and that of banks subject to merger, acquisition, or closure.

Finally, to determine whether the inclusion of macroeconomic determinants improves out-of-sample predictions, we calculate out-of-sample forecasts of the hazard rate. We use the estimated coefficients in conjunction with data for the period 2008–2011 to test the model performance over the period 2009–2012.

6 Results

The discrete time survival model relates the hazard rate to internal and external conditions that trigger default. The regression coefficients summarise the effect on the hazard of absolute changes in the corresponding covariates. Positive values are associated with bank failure, and non-positive values indicate survival. We run the model using a one-year lag in the explanatory variables and three different specifications. We are interested in whether the relation between the macroeconomic variables and small bank default is statistically significant. Table 6 shows the results.

<Insert here Table 6>

[19] Note that the Constitution of the Italian Republic (Article 114) states that the main territorial subdivisions in ascending order are the municipalities, the provinces, the metropolitan cities, the regions, and the state.

The interbank deposit rate is negatively related to the probability of financial distress within a year. Although at first surprising, this result might be explained in two ways. First, CBs are net contributors to the Italian interbank market; therefore, a higher ratio value indicates an increase in CB revenues. Second, CBs do not rely heavily on borrowing; hence, the increase in the pressure is mainly born by commercial banks, giving a further competitive advantage to CBs. If costs inflate faster than revenues for borrowers and for banks, then funding via deposits would be more attractive than other revenue streams. Because deposits are the main source of CB funding, commercial banks are at a disadvantage when the interbank deposit rate is high.

Table 6 also indicates that the regional unemployment rate is highly statistically significant and is positively correlated with the hazard rate. When regional economic conditions worsen, CBs face a decrease in survival probability. Moreover, in a univariate context, this variable shows high discriminatory power, meaning that local economic downturns weaken small bank performance.[20] The concentration of regional outlets is negatively associated with the hazard rate, implying that local competitors may have a negative effect on CB performance due to "unhealthy" competition. Co-operative banks are prepared to support the local communities, but perhaps higher competition leads to more risk-taking behaviour, which CBs are not equipped to deal with (Mercieca et al., 2007). These findings support the economic vulnerability hypothesis.

Turning to the CAMEL-type variables, a high percentage of capital is associated with low risk. This relative measure indicates that the larger the capital holdings, the lower the probability of distress. The ratio of loan-loss provisions to total loans is a proxy for

[20] Results of the univariate analysis are available from the author upon request.

credit risk. The positive sign indicates that higher risk decreases CBs' survival. The ratio of personnel expenses to interest and fee income gives a relative measure of labour productivity. The negative sign implies that higher values for this ratio are associated with lower risk of failure. If we assume that highly skilled personnel earn higher salaries, a better qualified work force (e.g., management) has a positive impact on CB survival. The adjusted return on assets is negatively related to distress; hence, earnings are an important source of stability for CBs. The liquidity ratio is positively and statistically significantly related to the hazard rate. Liquidity is critical for CBs, as they rely mainly on deposits; therefore, the comparison with loans gives an indication of potential future problems. The negative sign of the size coefficient supports the traditional view that bigger institutions are less likely to fail. For instance, bigger banks are better able to diversify their business.

Crisis management is one of the key functions of bank supervisors. Distress may be resolved through a private solution (i.e., merger and acquisition), take over, bail out, or closure of the failing bank. Not only is a bank more likely to be acquired when it is weak, but also the regulators' decision to approve or reject an acquisition may be related to individual bank health and to the overall weakness of the banking sector.

Using the estimated model coefficients, we compute the hazard rate for the banks subject to merger, acquisition, and voluntary closure. Table 7 reports the results. As already noted in other studies (e.g., Betz et al., 2014), in some countries episodes of acquisition by other banks may be associated with financial distress. We do not find a similar indication for the Italian CBs in our sample that merged or were acquired, suggesting that episodes of mergers and acquisitions could be related to the consolidation trend that occurred in the European banking market during the 1990s.

However, for the subset of mergers and acquisitions for which the active intermediary[21] was located in a different province, the estimated mean hazard rate (Table 7, Panel B, 2.2%, 31.5%, and 29.5% for the specification with macroeconomic variables only, accounting ratios only, and with all the explanatory variables, respectively) is higher, meaning that there could be a regulatory intervention favouring the resolution of the crisis. Surprisingly, we do not find a similar result in regard to mergers, despite the Italian banking law explicitly mentioning mergers as a way to resolve distress.

We also find a high estimated hazard rate (Table 7, Panel A, 4.2%, 49%, and 56% for the specification with macroeconomic variables only, accounting ratios only, and with all the explanatory variables, respectively) among voluntary closures, suggesting that banks may have been forced to close by the bank supervisor. The results from the mean-comparison tests show no clear pattern in the episodes of merger and acquisitions, but voluntary closures are indeed associated with bank distress. However, the descriptive evidence does not allow us to either reject or to fail to reject the private resolution hypothesis.

<Insert here Table 7>

7 Robustness tests

We test the predictive ability of our model both in- and out-of-sample to assess how well the econometric model fits the observed data. Overall the model shows good predictive power both in-sample and in the hold-out sample.

[21] We define the term “active intermediary” as the bank acquiring the passive credit institution.

Table 8 shows the in-sample check of the model's performance. In Panel A, we report six predictive accuracy indicators: sensitivity, specificity, classification accuracy, ROC area, accuracy ratio, and Brier score. Throughout these robustness checks, we classify a bank as "failed" if its posterior probability of failure is greater than an optimum cut-off point, the level of the sample's prior probability of failure (see Table 3, sample default rate column).

Panel B presents the accuracy of the estimated hazard rate distribution on actual bankruptcies, giving further evidence of the model's predictive ability (Cole and Gunther, 1998). The results are in line with previous studies (e.g., Poghosyan and Čihak, 2011; Fiordelisi and Mare, 2013) and show that the model does a fairly good job of predicting and classifying the occurrence of CB failures in-sample. Moreover, the specification that combines macroeconomic information with bank-level fundamentals performs the best.

<Insert here Table 8>

We repeat the same analyses out-of-sample because within-sample predictive performance is a blurred estimate of population performance. One might argue that since we are analysing a period overlapping with the financial crisis, risk drivers may be different. Nevertheless, the recent literature focussing on the United States proves that not much has changed (e.g., Cole and White, 2012). The accuracy of the performances is mixed. Sensitivity, specificity, and overall predictive accuracy rely on the choice of the optimal threshold. The default sample average is quite low (0.7%), indicating that the model tends to misclassify healthy institutions (i.e., Type 2 error). Looking at the other performance measures, the model places actual failures in the highest percentiles of the estimated hazard rate distribution. Moreover, the specification that considers all the available information outperforms the other specifications.

<Insert here Table 9>

8 Conclusions

Accurately assessing bank solvency is a crucial element for increasing the resilience of banking sectors. Small mutual banks play a key role in the banking systems of many countries, and they often drive economic development in rural areas. Weakness among these institutions can have long-range repercussions for the wider economy. Two key features set co-operative banks apart from larger commercial institutions. On the one hand, co-operative banks are less driven by profit maximization and the bonus culture than other types of financial institutions. On the other hand, CBs are strongly linked to the real economy, and their unique stakeholder structure may occasionally weaken bank soundness. When the economy experiences a downturn, CBs are slow to recover due to structural features that affect their ability to cope with crisis situations.

In this paper, we develop a model to predict default among Italian co-operative banks. We use a survival model, estimated using data on bank defaults observed over 13 years, that examines how macroeconomic factors help predict small bank failure. We test two hypotheses. First, we posit that the state of the economy, both at the national and regional level, affects the survival of co-operative banks (economic vulnerability hypothesis). Second, we expect that when co-operative banks are at risk of default, bank supervisors may favour banks' change of status through mergers, acquisitions, or voluntarily closures (private resolution hypothesis).

We find evidence supporting the economic vulnerability hypothesis since macroeconomic factors, both at the regional and the national level, are significantly related to the risk of failure among co-operative banks. Also, using the estimated model coefficients, we document that voluntary closures and acquisitions across provinces often mask distress. Nonetheless, we do not find enough conclusive evidence to either support or dismiss the private resolution hypothesis, although the bank regulator seems to favour voluntary closures and acquisitions of failing banks across provinces.

Our results have important policy implications. First, models that attempt to estimate small bank risk of failure should include macroeconomic factors. Doing so also has the advantage of creating a simple framework for stress testing.

Second, bank supervisors should closely monitor the state of the economy, particularly at the local level, to anticipate small bank distress. The Italian economy contracted between 2012 and 2014, increasing vulnerability of the country's banking sector. The response of credit institutions has been uneven. For instance, according to the Bank of Italy's 2014 annual report, in 2013 total lending declined by 3.7%, but small banks reduced the credit provided by only 0.7%. This discrepancy shows that not only may small credit co-operatives be more exposed to the cyclical fluctuations of the local economy, but also that they play a positive role in smoothing out the negative effects of the ongoing economic crisis. Co-operative banks' capital buffers are higher than the national average (as of June 2014, the common equity tier1 ratio stands at 15.6% vs. 12%), but the Italian banking supervisor should carefully consider whether this is enough to weather a prolonged crisis period.

Third, countercyclical capital buffers for small banks should account not only for lending behaviour (i.e., boom-bust dynamics in lending behaviour) but also for the overall solvency risk. The stress test jointly carried out in 2014 by the European Central Bank and the European Banking Authority found a capital shortfall of 9.4 billion euro under an adverse scenario for the Italian banks included in the analysis. The only co-operative bank included in the stress test analysis - Iccrea Holding S.p.A. - was not found lacking, indicating high resilience under adverse market conditions. Nevertheless, as confirmed by our results, a prolonged period of economic contraction poses severe risks for Italian co-operative banks; hence, policy makers and relevant authorities should carefully design adequate responses to limit the impact of the potential disruption. Recent evidence supports this conclusion: the total number of conservatorships of co-operative banks over the period 2013–2014 (15) increased significantly compared to the period 2011–2012 (5).

In conclusion, our results show that macroeconomic time series data help to explain small bank default. Capital requirements might take into account the impact of the state of the economy on the overall solvency risk of small banks. Policy makers should carefully monitor local economic conditions for a parallel increase in the tendency for inadequate risk-taking or an increase in the overall risk of the co-operative banking sector.

Acknowledgements

I am thankful to Franco Fiordelisi, Jonathan Crook, Thomas Archibald, Roberto Rossi, Aristotelis Boukouras, Daniele Previati, David Pelilli and Maria Paula Gerardino who kindly gave their comments on earlier versions of this paper. I am also very grateful to Federcasse for providing the data necessary for the estimation of the model and for the helpful collaboration, especially to Alessandra Appennini, Juan Lopez and Roberto Di Salvo. I thank the editors, Jonathan Batten and Geoffrey Booth, and an anonymous referee for valuable comments and suggestions that led to a significant improvement of the manuscript, as well as the conference participants at the IFABS 2012 and at the 26th

Euro Conference. I am also grateful to Karen DeVivo for professional proofreading. All errors and omissions are mine.

Appendix A

A.1. Discrete-time survival model

We estimate the survival model in discrete time since our data set provides observations only annually. We focus on a single state model and assume we have single spell data for each bank. Also, we assume that bankruptcy only occurs at discrete points in time (t= 1, 2, 3,..., n). Moreover, each bank either fails during the follow-up period or survives. We eliminate from the sample banks that merge or are liquidated or for which the identification variable (Abi) is not available for the study period. To summarize, the following entry and exit events are adopted for the study: bank *i* enters the analysis in year *t*, which is the later occurrence of a) the start of the study period (1994), or b) the beginning of banking operations. Bank *i* exits the analysis if a) it fails, or b) it survives until 31 December 2006. Thus, we consider exits from a single state (soundness) to a single destination (failure).

The random variable T denotes the time to exit from the sample (failure), and t is a realization thereof. The discrete time duration model implies that we observe the probability of survival of cooperative banks at distinct points in time. Since the sample data refers to an observation window of 13 years (1994–2006), the survival time data set is right-censored, meaning that we observe the start date of the spell (year 1994 or later) but not the total length of transition out of the current state (from soundness to failure). We also assume that the process that gives rise to censoring is independent of the survival time process. Moreover, the risk of failure is observable only after the bank enters the sample (Lane et al., 1986). The probability of exit within the j_{th} interval is

$$\Pr\left(a_{j-1} < T < a_j\right) = F(a_j) - F(a_{j-1}) = S(a_{j-1}) - S(a_j)\ , \tag{A.1}$$

where $a_1, a_2, \ldots\ldots, a_k$ are the interval boundary dates (years); $F(a_j)$ is the cumulative distribution function of T (failure function) at time *j*; and $S(a_j)$ is the survival function at time *j*. The discrete hazard rate is the conditional probability of exit in the interval $(a_{j-1}, a_j]$, defined as

$$\Pr\left(a_{j-1} < T \le a_j \mid T > a_{j-1}\right) = 1 - \frac{S(a_j)}{S(a_{j-1})}. \tag{A.2}$$

The discrete time survivor function is the product of probabilities of not experiencing the event in each of the intervals up to and including the current one. We write it in terms of interval hazard rates as follows:

$$S(j) = (1-h_1)\times(1-h_2)\times\ldots\ldots\times(1-h_{h-1})\times(1-h_h) = \prod_{k=1}^{j}(1-h_k) \tag{A.3}$$

If we allow the hazard rate to vary between banks depending on their characteristics, we summarize this information in a vector of variables. Time-varying covariates offer an opportunity to dynamically examine the relationship between the distress probability and the changing conditions under which the distress takes place. The relationship between the hazard rate and the selected characteristics are linked by an index function. Following Männasoo and Mayes (2009) and Fiordelisi and Mare (2013), we use a complementary log-log model (cloglog) that includes macroeconomic determinants of the banks' conditional failure rate:

$$h(j, \mathbf{X}_{i,j-1}, \mathbf{M}_{j-1}) = 1 - \exp\left[-\exp\left(\beta^{I}\mathbf{X}_{i,j-1} + \delta^{I}\mathbf{M}_{j-1} + \gamma_{j-1}\right)\right]. \quad \text{(A.4)}$$

where $h(j, \mathbf{X}_{i,j-1}, \mathbf{M}_{j-1})$ is the hazard rate or the probability that a bank fails in a given time interval; *j* and *i* denote, respectively, a time interval and a specific bank; and $\mathbf{X}_{i,j-1}$ is the vector of the time-varying, bank-specific covariates, lagged one year. $\mathbf{M}_{j-1}$ is the vector of the time-varying, bank-independent covariates, i.e. macroeconomic variables, lagged one year; γ_{j-1} is the parametric baseline estimated as the log of time; and β^{I} and δ^{I} are vectors of parameters to be estimated.

References

Altunbas, Y., Carbo, S., Gardener, E.P.M., Molyneux, P., 2007. Examining the relationships between capital, risk and efficiency in European banking. *European Financial Management 13*, 49–70.

Altunbas, Y., Manganelli, S., Marques-Ibanez, D., 2011. Bank risk during the Great Recession: do business models matter? *ECB Working Paper Series 1394*, European Central Bank, Frankfurt.

Arena, M., 2008. Bank failures and bank fundamentals: a comparative analysis of Latin America and East Asia during the nineties using bank-level data. *Journal of Banking & Finance 32 (2)*, 299-310.

Ashcraft, A.B., 2005. Are banks really special? New evidence from the FDIC-induced failure of healthy banks. *American Economic Review 95 (5)*, 1712–1730

Aubuchon, C. P., Wheelock, D. C. (2010). The geographic distribution and characteristics of US bank failures, 2007-2010: do bank failures still reflect local economic conditions?. *Federal Reserve Bank of St. Louis Review 92(5),* 395-415 .

Betz, F., Opricǎ, S., Peltonen, T. A., Sarlin, P., 2014. Predicting distress in European banks. *Journal of Banking & Finance 45*, 225-241.

Borio, C., Lowe, P., 2002. Assessing the risk of banking crises. *BIS Quarterly Review*, December 2002, 43–54.

Borio, C., Lowe, P., 2009. Assessing the risk of banking crises - revisited. *BIS Quarterly Review*, March 2009, 29–46.

Brown, C.O., Dinç, I.S., 2011. Too many to fail? Evidence of private resolution when the banking sector is weak. *Review of Financial Studies 24 (4)*, 1378-1405.

Chan-Lau, J. A., 2010. Regulatory capital charges for too-connected-to-fail institutions: a practical proposal. *Financial Markets, Institutions & Instruments 19(5)*, 355-379.

Cihák, M., Hesse, H., 2007. Co-operative Banks and Financial Stability. *IMF Working Papers 2*, International Monetary Fund, Washington D.C.

Cole, R. A., Gunther, J. W., 1998. Predicting bank failures: A comparison of on-and off-site monitoring systems. *Journal of Financial Services Research 13(2)*, 103-117.

Cole, R., White, L., 2012. Déjà vu all over again: the causes of U.S. commercial bank failures this time around. *Journal of Financial Services Research 42(1-2)*, 5-29.

Curry, T. J., Elmer, P. J., Fissel, G. S., 2007. Equity market data, bank failures and market efficiency. *Journal of Economics and Business 59(6)*, 536-559.

Daly, M., Krainer, J., Lopez, J. A., 2004. Does regional economic performance affect bank conditions? New analysis of an old question. *Federal Reserve Bank of San Francisco Working Paper 4*.

Davis, E. P., Karim, D., 2008. Comparing early warning systems for banking crises. *Journal of Financial Stability 4 (2)*, 89–120.

Demirguc-Kunt, A., Detragiache, E., 2005. Cross-country empirical studies of systemic bank distress: a survey. *IMF Working Paper 5*, International Monetary Fund, Washington. D.C.

DeYoung, R., Torna, G., 2013. Nontraditional banking activities and bank failures during the financial crisis. *Forthcoming Journal of Financial Intermediation*.

Emmons, W. R., Gilbert, R. A., Yeager, T. J., 2004. Reducing the risk at small community banks: is it size or geographic diversification that matters?. *Journal of Financial Services Research 25(2-3)*, 259-281.

Espahbodi, P., 1991. Identification of problem banks and binary choice models. *Journal of Banking & Finance 15 (1)*, 53-71.

Estrella, A., Sangkyun, P., Stavros, P., 2000. Capital ratios as predictors of bank failure. *Economic Policy Review 6 (2)*, 33-52.

Ferri, G., Kalmi, P., Kerola, E., 2014. Does bank ownership affect lending behavior? Evidence from the Euro area. *Journal of Banking & Finance 48*, 194-209.

Fiordelisi, F., Mare, D.S., 2013. Probability of default and efficiency in Co-operative banking. *Journal of International Financial Markets, Institutions and Money 26*, 30-45.

Fiordelisi, F., Marques-Ibanez, D., Molyneux, P., 2011. Efficiency and risk in European banking. *Journal of Banking & Finance 35 (5)*, 1315-1326.

Fonteyne, W, 2007. Co-operative banks in Europe: policy issues. *IMF Working Paper (159)*, International Monetary Fund, Washington. D.C.

Gonzalez-Hermosillo, B., 1999. Determinants of Ex-Ante Banking System Distress: A Macro-Micro Empirical Exploration of Some Recent Episodes. *IMF Working Paper No 337* .

Gonzalez-Hermosillo, B., Pazarbaşioğlu, C., Billings, R., 1997. Determinants of banking system fragility: A case study of Mexico. *IMF Staff Papers 44(3)*, 295-314.

Hakenes, H., Hasan, I., Molyneux, P., Xie, R., 2014. Small banks and local economic development. *Forthcoming Review of Finance*

Huang, X., Zhou, H., Zhu, H., 2009. A framework for assessing the systemic risk of major financial institutions. *Journal of Banking & Finance 33 (11)*, 2036-2049

Ioannidis, C., Pasiouras, F., Zopounidis, C., 2010. Assessing bank soundness with classification techniques. *Omega 38(5)*, 345-357.

Lane, W.R., Looney, S.W., Wansley, J.W., 1986. An application of the Cox proportional hazards model to bank failure. *Journal of Banking and Finance 10 (4)*, 511 - 531

Leow, M., Crook, J., 2014. The stability of survival model parameter estimates for predicting the probability of default: Empirical evidence over the credit crisis. *Forthcoming European Journal of Operational Research*.

Libertucci, M., Piersante, F., 2012. Start-up banks' default and the role of capital. *Bank of Italy Working Papers 890*.

Kick, T., Koetter, M., 2007. Slippery slopes of stress: ordered failure events in German banking. *Journal of Financial Stability 3(2)*, 132-148.

Maggiolini, P., Mistrulli, P. E., 2005. A survival analysis of de novo co-operative credit banks. *Empirical Economics 30(2)*, 359-378.

Männasooa, K., Mayes, D.G., 2009. Explaining bank distress in Eastern European transition economies. *Journal of Banking & Finance 33 (2)*, 244-253.

Martin, D., 1977. Early warning of bank failure. *Journal of Banking & Finance* 1 *(3)*, 249-276.

Mercieca, S., Schaeck, K., Wolfe, S., 2007. Small European banks: benefits from diversification?. *Journal of Banking & Finance 31(7)*, 1975-1998.

Meyer, P.A., Pifer, H. W., 1970. Prediction of bank failures. *Journal of Finance 25 (4)*, 853-868.

Meyer, A. P., Yeager, T. J., 2001. Are small rural banks vulnerable to local economic downturns?. *Federal Reserve Bank of St. Louis Review*, 25-38.

Nuxoll, D.A., 2003. The contribution of economic data to bank-failures models. *Federal Deposit Insurance Corporation Working Paper No 3*

Poghosyan, T., Čihak, M., 2011. Determinants of bank distress in Europe: evidence from a new data set. *Journal of Financial Services Research 40(3)*, 163-184.

Quagliariello, M., 2008. Does macroeconomy affect bank stability? A review of the empirical evidence. *Journal of Banking Regulation 9(2)*, 102-115.

Santomero, A. V., Vinso, J.D., 1977. Estimating the probability of failure for commercial banks and the banking system. *Journal of Banking & Finance 1* (2), 185-205.

Shumway, T., 2001. Forecasting bankruptcy more accurately: A simple hazard model. The Journal of Business 74(1), 101-124.

Sinkey, J. F., 1975. A Multivariate Statistical Analysis of the Characteristics of Problem Banks. *Journal of Finance 30* (1), 21-36.

Sundararajan, V., Enoch, C., San Jose, A., Hilbers, P., Krueger, R., Moretti, M., Slack, G., 2002. Financial Soundness Indicators: Analytical Aspects and Country Practices. *IMF Occasional Paper 212*, International Monetary Fund, Washington. D.C.

West, R.C., 1985. A factor-analytic approach to bank condition. *Journal of Banking & Finance 9 (2)*, 253-266.

Whalen, G., 1991. A proportional hazards model of bank failure: an examination of its usefulness as an early warning tool. *Economic Review*, 21-31

Yeager, T. J., 2004. The demise of community banks? Local economic shocks aren't to blame. *Journal of Banking & Finance 28 (9)*, 2135-2153.

Tables

Table 1

Participation pattern

The table presents the duration pattern of the banks in the sample during the period 1993–2005. Under the column “pattern,” 1 indicates the availability of financial statements for a bank in a specific year such that a “frequency” of 160 means that the financial statements of 160 individual banks are available for the whole sample period (13 years). For each cross-sectional unit *i* (banks), we have a different time span, meaning that the sample contains unbalanced panel data. This fact is mainly due to a) data availability, b) default (as per model definition), c) mergers, d) acquisitions, e) voluntary closures, and f) the date in which a bank starts its operations. The sample duration pattern derives from data cleaning and organization following the single state approach assumed in the model.

Frequency	%	Cumul. %	Pattern
163	37.56	37.56	.111111111111
160	36.87	74.42	1111111111111
15	3.46	77.88	111111
7	1.61	79.49	1111111
7	1.61	81.11	..11111111111
6	1.38	82.49	1111
6	1.38	83.87	11111
4	0.92	84.79	11
4	0.92	85.71	.1111........
62	14.29	100.00	(other patterns)
434	100%	-	-

Table 2

Distribution of banks, branches, and assets by year and geographical area

Panel A reports the data on the distribution of banks by year and geographic region. According to the Italian statistics institute (Istat), Centre includes Abruzzi, Lazio, Marches, Tuscany, and Umbria; North-East comprises Emilia-Romagna, Friuli-Venezia Giulia, Trentino-Alto Adige, and Veneto; North-West includes Liguria, Lombardy, Piedmont, and Aosta Valley; finally, South includes Basilicata, Calabria, Campania, Molise, Apulia, Sardinia, and Sicily.

Panel A: Distribution of banks by year and geographic region

Region	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Centre	52	75	76	76	76	75	75	84	83	83	80	81	78
North-East	58	161	160	160	160	160	162	166	169	170	169	169	168
North-West	49	49	49	49	50	50	50	53	54	53	52	52	52
South	24	75	81	82	78	75	77	76	76	76	75	76	76

Panel B lists the data on the distribution of the average number of branches by year and geographic region. The values are computed by dividing the sum of branches located in a specific region by the total number of banks in the region.

Panel B: Distribution of branches by year and geographic region

Region	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Centre	4.212	4.280	4.276	4.566	4.829	5.427	5.720	5.810	6.518	7.181	7.313	7.914	6.949
North-East	3.931	4.031	4.313	4.663	4.975	5.281	5.667	6.090	6.846	7.347	7.740	7.911	8.458
North-West	5.551	6.184	7.041	7.878	8.280	9.420	9.760	9.604	10.981	11.660	12.404	12.615	13.250
South	2.125	2.573	2.593	2.841	3.026	3.213	3.338	3.395	3.816	3.908	4.187	4.224	4.342

Panel C summarises the data on the distribution of the average total assets by year and geographic region. The values are computed by dividing the sum of total assets of the banks located in a specific geographic region with the total number of banks in that region.

Panel C: Distribution of total assets by year and geographic region (thousands of euros)

Region	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Centre	106,979	103,435	110,330	128,818	139,439	152,440	164,798	175,064	205,564	223,463	254,984	278,679	253,607
North-East	69,971	82,254	91,992	105,531	114,487	122,872	131,569	146,452	176,320	209,560	230,076	259,695	281,241
North-West	170,907	181,858	205,548	237,052	247,469	274,192	283,729	294,494	335,862	373,107	423,671	448,362	486,435
South	39,681	51,685	50,479	57,534	62,910	67,109	69,289	75,208	88,590	95,040	104,483	109,708	119,496

Table 3

Number of banks, number of defaults, and default rates

The table summarizes the number of active banks, the number of defaults under the definition used in the econometric specification, and the default rate both in sample and observed historically. The figures in-sample are computed using data from Federcasse. Historical defaults are calculated using data from the Bank of Italy. Data from 1993–2005 (4,635 observations) is used for the estimation of the discrete time survival model. Data from 2008–2011 (1,658 observations) is used for the out-of-sample test .Source: own calculations using data from Federcasse and Bank of Italy. Note that data cleaning and availability (identification variable is not available for the whole observation window) have restricted the number of banks and defaults in sample.

	SAMPLE			HISTORICAL		
Year	**Number[I]**	**# Default[II]**	**Default rate**	**Number**	**# Default**	**Default rate**
1993	183	-	-	669	6	0.90%
1994	360	3	0.83%	642	10	1.56%
1995	366	6	1.64%	619	8	1.29%
1996	367	3	0.82%	591	5	0.85%
1997	364	7	1.92%	583	8	1.37%
1998	360	6	1.67%	562	8	1.42%
1999	364	4	1.10%	531	8	1.51%
2000	379	5	1.32%	499	6	1.20%
2001	382	5	1.31%	474	5	1.05%
2002	382	6	1.57%	461	6	1.30%
2003	376	7	1.86%	445	7	1.57%
2004	378	2	0.53%	439	2	0.46%
2005	374	4	1.07%	439	4	0.91%
2006	434	1	0.23%	438	2	0.46%
2007	411	-	-	442	-	-
2008	432	-	-	432	-	-
2009	416	6	1.44%	421	6	1.43%
2010	407	7	1.72%	415	7	1.69%
2011	403	2	0.50%	411	2	0.49%
2012	-	3	-	394	3	0.76%
Total	7,138	74	1.04%	9,907	103	1.04%

[I] Banks not yet failed.
[II] Banks failed in that year.

Table 4

Number of mergers, acquisitions, voluntary closures, and cancellations from the supervisory register

The table provides the number of bank mergers, acquisitions, and voluntary closures among Italian cooperative banks between 1993 and 2011. It also reports information on the historical development of the mergers, acquisitions, and cancellations from the supervisor bank register. Note that banks subject to mergers, acquisitions, and closures are not included in the estimation of the hazard rate. Source: own calculations using data from Federcasse and Bank of Italy.

	SAMPLE			HISTORICAL		
Year	**# Mergers[I]**	**# Acquisition[II]**	**# Closures[III]**	**# Mergers[I]**	**# Acquisition[II]**	**# Cancellation[IV]**
1993	-	-	-	22	16	43
1994	1	3	-	11	20	36
1995	5	7	-	22	17	46
1996	6	17	-	11	25	41
1997	9	5	1	10	10	25
1998	5	11	1	5	19	28
1999	10	17	1	13	27	45
2000	16	11	3	20	20	45
2001	12	10	1	12	17	36
2002	5	11	1	6	11	20
2003	6	7	-	6	10	20
2004	-	4	-	-	8	9
2005	-	3	-	-	3	3
2006	2	2	-	2	2	4
2007	-	-	-	-	2	3
2008	-	-	-	6	5	14
2009	-	-	-	2	9	13
2010	-	-	-	2	6	8
2011	-	-	-	-	3	5
Total	77	108	8	150	230	444

[I] Target banks.
[II] Acquired banks.
[III] Voluntary closures.
[IV] Banks cancelled from the public registry held by the Bank of Italy.

Table 5

Variable definitions and summary statistics

Panel A provides the name, definition, and representative studies along and the unit of measure for the variables employed in the analysis.

Panel A: Definitions of the explanatory variables

Variable	Definition	Representative studies	Unit
Dependent variable			
Default	Binary variable taking a value of 1 if a bank entered special administration or liquidation, 0 otherwise. Source: own calculation using data from Bank of Italy.	Mannasoo and Mayes, 2009; Fiordelisi and Mare, 2013; Betz et al., 2014.	-
Macroeconomic factors			
Interbank deposit rate	Average rate on 3-month deposits. High values signal high cost of funding. Source: Datastream (Thomson Reuters).	Gonzalez-Hermosillo, 1999; Sundararajan et al., 2002.	Percentage
Region unemployment rate	Unemployment rates by Italian region. The higher the ratio, the worse is the economic conditions of the related region. Source: Istat - Time Series	Nuxoll (2003); Meyer and Yeager (2001); Yeager (2004).	Percentage
Concentration of regional outlets	Percentage of CB outlets over total outlets in the region. Source: own calculation on data from Bank of Italy.	Maggiolini and Mistrulli (2005)	Percentage
CAMEL variables			
Basel III leverage ratio	Bank capital adequacy in terms of capitalization level. The higher the ratio, the better the bank withstands losses. Source: own calculation using data from Federcasse.	Arena, 2008; Mannasoo and Mayes, 2009; Poghosyan and Čihak, 2011.	-
Loan-loss-provisions / loans	Credit risk measure. Higher values indicate higher risk. Source: own calculation using data from Federcasse.	Mannasoo and Mayes, 2009; Arena, 2008; Fiordelisi and Mare, 2013.	Percentage
Staff costs / Interest and fee income	Employee productivity ratio. Higher values denote higher inefficiency. Source: own calculation using data from Federcasse.	-	-
Adjusted Return on Assets	Sum of profit after taxes and loan-loss provisions, divided by total assets. Relative strenghts in earnings. Source: own calculation using data from Federcasse.	Meyer and Yeager, 2001.	Percentage
Loans / Deposits	Liquidity mismatching. The higher the value of the indicator, the higher the maturity mismatch between assets and liabilities, hence, the higher the liquidity distress. Source: own calculation using data from Federcasse.	Lane et al., 1986.	-
Size	Size effect proxied by total assets (in thousands of euros). Source: own calculation using data from Federcasse.	DeYoung and Torna, 2013.	Standardize d

Panel B reports the descriptive statistics of the variables employed in the analysis for Italian co-operative banks between 1993 and 2005. The total number of observations is 4,635, classified as either healthy or defaulted banks. The column "t-Statistic" reports the value of the mean-comparison tests in which the null hypothesis is that the means of the two groups (sound and default) are equal. The column "AR" summarises the information on the Accuracy Ratio (i.e., individual discriminating ability of the variable).

Panel B: Descriptive statistics of the explanatory variables

	Y = 0			Y = 1			Univar. measures	
Variable	**Obs**	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**	**t-Statistic**	**AR**
Interbank deposit rate	4,576	5.263	2.878	59	5.709	2.753	-	-
Regional unemployment rate	4,576	7.903	5.685	59	13.564	5.668	-7.601***	0.529
Concentration of regional outlets	4,576	22.786	21.085	59	11.428	9.678	4.132***	0.366
Basel III leverage ratio	4,576	0.127	0.037	59	0.113	0.054	2.863**	0.245
Loan-loss provisions / loans	4,576	0.028	0.090	59	0.091	0.208	-5.186***	0.050
Staff costs / Interest and fee income	4,576	0.238	0.066	59	0.234	0.105	0.558	0.149
Adjusted Return on Assets	4,576	1.075	0.716	59	-0.426	1.752	15.522***	0.548
Loans / Deposits	4,576	1.149	0.384	59	1.462	0.608	-6.164***	0.301
Size	4,576	166.243	182.049	59	75.894	121.983	3.801***	0.529

Table 6

Estimation results using one year lag

This table shows the results of a discrete hazard model with one year lagged covariates. A negative sign for the coefficients implies an increase in bank survival. A positive sign suggests an increase in the hazard rate (i.e., probability of default). The errors are corrected for potential heterogeneity (i.e., robust standard errors). *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively.

Model	**Macro**		**Accounting**		**Overall**	
Dependent variable Default (Y)	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Interbank deposit rate	-0.334***	(0.037)			-0.138***	(0.050)
Region unemployment rate	0.032***	(0.012)			0.047**	(0.023)
Concentration of regional outlets	-0.059**	(0.026)			-0.040**	(0.017)
Basel III leverage ratio			-10.237***	(2.975)	-9.767***	(2.954)
Loan-loss-provisions / loans			2.724***	(0.933)	1.876*	(0.980)
Staff costs / Interest and fee income			-10.633***	(1.951)	-9.737***	(1.970)
Adjusted Return on Assets			-1.157***	(0.102)	-1.103***	(0.116)
Loans / Deposits			1.007***	(0.247)	1.342***	(0.239)
Size			-0.008**	(0.004)	-0.005*	(0.003)
Baseline hazard	-1.397***	(0.121)	-0.323*	(0.183)	-0.404*	(0.228)
No. of banks	434		434		434	
Observations	4,635		4,635		4,635	
No. of defaults	59		59		59	
Default rate	1.27%		1.27%		1.27%	
Log pseudolikelihood	-301.7		-217.6		-202.10	

Table 7

Model goodness-of-fit for mergers, acquisitions, and voluntary closures

Panel A ranks the banks using the estimated hazard rate, from the least risky to the riskiest. The hazard rate is computed using the estimated coefficients for the variables in the model using different specifications (i.e., macro, accounting, and all information) for the banks in sample between 1993 and 2005. This permits us to rank banks subject to mergers, acquisitions, and voluntary closures during the period 1994–2006 (77, 108, and 8, respectively) into the deciles of the hazard rate distribution of the whole sample. We separately report the mean hazard rates for banks subject to merger, acquisition, and closure (row mean hazard). We also report the p-value of the mean-comparison tests (row t-test), in which the null hypothesis is that the mean hazard rate of defaulted banks and the mean hazard rates of banks subject to merger, acquisition, and closure are the same.

Panel A: Estimated hazard rate for banks subject to M&A and voluntary closure

Decile	**Macro**			**Accounting**			**Overall**		
	Merger	Acq.	Closure	Merger	Acq.	Closure	Merger	Acq.	Closure
1-5	0.299	0.509	0.000	0.506	0.176	0.000	0.377	0.519	0.000
6	0.221	0.065	0.000	0.065	0.083	0.125	0.078	0.065	0.000
7	0.156	0.148	0.125	0.078	0.120	0.000	0.156	0.130	0.000
8	0.091	0.102	0.125	0.143	0.139	0.000	0.130	0.117	0.125
9	0.182	0.074	0.375	0.130	0.157	0.000	0.195	0.143	0.000
10	0.052	0.102	0.375	0.078	0.324	0.875	0.065	0.429	0.875
Mean hazard	0.014	0.015	0.042	0.020	0.136	0.490	0.015	0.117	0.560
Mean hazard (default)	0.033	0.033	0.033	0.230	0.230	0.230	0.237	0.237	0.237
t-Statistic	0.000***	0.002***	0.536	0.000***	0.063*	0.051*	0.000***	0.012**	0.016**
#	77	108	8	77	108	8	77	108	8

Panel B ranks the banks using the estimated hazard rate from the least risky to the riskiest. The analysis only includes banks targeted by or acquired from an intermediary located in a different province. The hazard rate is computed using the estimated coefficients for the variables in the model using different specifications (i.e., macro, accounting, and all information) for the banks in the sample between 1993 and 2005. This permits us to rank banks subject to mergers and acquisitions during the period 1994–2006 (8 and 32, respectively) into the deciles of the hazard rate distribution of the whole sample. We separately report the mean hazard rates for banks subject to merger, acquisition, and closure (row mean hazard). We also report the p-value of the mean-comparison tests (row t-test), in which the null hypothesis is that the mean hazard rate of defaulted banks and the mean hazard rates of banks subject to merger, acquisition, and closure are the same.

Panel B: Estimated hazard rate for banks subject to M&A across provinces

Decile	**Macro**		**Accounting**		**Overall**	
	Merger	Acq.	Merger	Acq.	Merger	Acq.
1-5	0.222	0.219	0.222	0.156	0.222	0.094
6	0.444	0.188	0.000	0.031	0.000	0.031
7	0.000	0.219	0.111	0.031	0.111	0.063
8	0.000	0.094	0.333	0.063	0.222	0.125
9	0.222	0.125	0.111	0.125	0.222	0.063
10	0.111	0.156	0.222	0.594	0.222	0.625
Mean hazard	0.015	0.022	0.017	0.315	0.014	0.295
Mean hazard (default)	0.033	0.033	0.230	0.230	0.237	0.237
t-Statistic	0.179	0.178	0.066*	0.291	0.048**	0.455
#	9	32	9	32	9	32

Table 8

Predictive accuracy: *in-sample* performance

Panel A reports the measures of predictive power of the model in-sample. "Sensitivity" measures the proportion of banks in default that are correctly identified as such. "Specificity" quantifies the proportion of safe banks (e.g., healthy) that are correctly identified. These two indicators are closely related to the concepts of type I and type II errors. The "overall predictive" power is the ratio of the sum of all safe and failed banks accurately identified to the total number of banks. The "ROC curve" quantifies the impact of changes in the probability threshold, e.g. the decision point used by the model for classification. The "accuracy ratio" measures the discriminating ability of a binary classification model: the larger its value, the higher the likelihood that an actual default case will be assigned a higher probability of default than an actual non-default case. The "Brier score" ranges between 0 and 1. The closer it is to zero, the better the forecast of default probabilities.

Panel A: goodness-fit indicators

Measure	**Macro**	**Accounting**	**Overall**
Sensitivity	0.559	0.864	0.847
Specificity	0.691	0.820	0.843
Overall predictive	0.690	0.821	0.843
ROC area	0.733	0.904	0.926
Accuracy ratio	0.466	0.809	0.852
Brier score	0.013	0.010	0.010

Panel B ranks the banks using the estimated hazard rate from the least risky (1st decile) to the riskiest (10th decile). The table shows in which decile of the hazard rate distribution the failed banks are ranked.

Panel B: Probability rankings versus actual bankruptcies

Decile	**Macro**	**Accounting**	**Overall**
1-5	0.203	0.051	0.051
6	0.102	0.000	0.000
7	0.136	0.017	0.017
8	0.034	0.068	0.034
9	0.153	0.153	0.102
10	0.373	0.712	0.797
# Default	59	59	59

Table 9

Model goodness-of-fit: *out-of-sample* performance

Panel A reports the measures of predictive power of the model out-of-sample. "Sensitivity" measures the proportion of banks in default that are correctly identified as such. "Specificity" quantifies the proportion of safe banks (e.g., healthy) that are correctly identified. These two indicators are closely related to the concepts of type I and type II errors. The "overall predictive" power is the ratio of the sum of all safe and failed banks accurately identified to the total number of banks. The "ROC curve" quantifies the impact of changes in the probability threshold, e.g. the decision point used by the model for classification. The "accuracy ratio" measures the discriminating ability of a binary classification model: the larger its value, the higher the likelihood that an actual default case will be assigned a higher probability of default than an actual non-default case. The "Brier score" ranges between 0 and 1. The closer it is to zero, the better the forecast of default probabilities.

Panel A: goodness-fit indicators

Measure	Macro	Accounting	Overall
Sensitivity	1.000	0.667	0.778
Specificity	0.232	0.645	0.605
Overall predictive	0.240	0.645	0.607
ROC area	0.606	0.734	0.786
Accuracy ratio	0.211	0.467	0.572
Brier score	0.016	0.031	0.025

Panel B ranks the banks using the estimated hazard rate from the least risky (1st decile) to the riskiest (10th decile). The table shows in which decile of the hazard rate distribution the failed banks are ranked.

Panel B: Probability rankings versus actual bankruptcies

Decile	Macro	Accounting	Overall
1-5	0.389	0.167	0.111
6	0.167	0.111	0.111
7	0.056	0.056	0.111
8	0.111	0.167	0.000
9	0.111	0.111	0.222
10	0.167	0.389	0.444
# Default	18	18	18