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Probability of Default and Efficiency in Cooperative Banking

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Abstract

Cooperative banks are small credit institutions, and they are more likely than commercial banks to default in periods of financial stability. Focusing on Italy (one of the largest cooperative banking markets), we analyse the contribution of efficiency to the estimation of the probability of default of cooperative banks. We estimate several measures of bank efficiency, and we run a discrete-time survival model to determine whether different managerial abilities play different roles in predicting bank failures. We show that higher efficiency levels (both in cost minimization and revenue and profit maximization) have a positive and statistically significant link with the probability of survival of cooperative banks. We also find that capital adequacy reduces the probability of default, supporting the view that higher capital buffers provide additional loss absorbency and reduce moral hazard problems.

JEL-Classification: C23, G21, G28

Keywords: Bank failure, Small banks, Efficiency measures, Hazard model.

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1 Introduction

Cooperative banks play a key role in the European banking industry. In 2010, cooperative banks were a driving force for socially committed business at the local level through their 3,900 member banks, 65,000 branches, more than 770,000 employees, 50 million members, and 180 million clients (European Association of Co-operative Banks, 2011). Overall, cooperative banks account for approximately one fifth of the European banking system (market shares of deposits and credits are 21% and 19%, respectively). Various studies (Groeneveld and de Vries, 2009; Cihák and Hesse, 2007; Groeneveld, 2012) suggest that cooperative banks are, on average, more stable than commercial banks because they have a great deal of soft information (which is hard to collect) on the creditworthiness of members/customers, and therefore they are much less likely to make lending mistakes. However, in times of financial stability, regulators are more prone to let a distressed bank go into default if it is a small cooperative bank. This outcome is consistent with the Too-Big-To-Fail policy (i.e., regulators avoid letting the largest and most powerful banks go out of business in order to prevent panic in financial markets) and the Too-Important-To-Fail argument (i.e., regulators avoid letting the most well-known and systematically important banks go out of business in order to prevent the risk that many banks fail together). For instance, the default rate of Italian cooperative banks was almost four times higher than that of commercial banks in the period before the financial crisis (1997–2006). Specifically, there were 44 default cases among cooperative banks (default rate 1.04%) and 8 among commercial banks (default rate 0.28%).

Our paper analyses the determinants of the probability of survival of cooperative banks. What drives the default of banks? Is efficiency a determinant in the default of banks? Does managerial skill play a role in the financial distress of small credit institutions? The purpose of this paper is to empirically address these questions in regard to cooperative banks. Because there is evidence that higher efficiency reduces bank risk-taking (e.g., Berger and DeYoung, 1997; Fiordelisi et al., 2011; Cihák and Schaeck, 2013), we posit that a lower exposure to risky assets increases the survival time of a bank. Consequently, we argue that higher efficiency favours bank soundness. Surprisingly, there is limited available empirical evidence supporting this expectation. As such, we posit that bank survival is related to the managerial ability to save costs (cost efficiency), maximize revenues (revenue efficiency), and maximize profits (operating and interest efficiency).

We have three main results. First, we show that more efficient banks (efficient either in cost saving or in revenue maximization) have a higher probability of survival. Second, we find that when a bank's managerial ability to minimize costs and maximize revenues are jointly considered (e.g., efficiency in generating interest income), more skilful management increases the bank's survival time. Third, we find evidence to support the view that traditional financial ratios are consistent predictors of bank distress. In this regard, we show that capital is a key determinant of bank soundness.

We analyse a large sample with more than 4,200 observations - all the Italian cooperative banks between 1997 and 2009. We estimate the probability of default by running a discrete-time survival model that relates a change in the hazard rate to an absolute change in a given covariate, all else being equal. We focus on Italy because this case is particularly interesting for various reasons. First, cooperative banks play a crucial role in the Italian banking market -

Italian cooperative banks[1] have approximately 36,000 employees, 6.7 million clients, 1.1 million members[2], and 7.3% of the market share of deposits[3]. Second, the Italian cooperative banking sector is the fourth largest in Europe after Germany, France, and Austria (in 2010, 6.7%[4] of the total assets under management in the EU 27 cooperative banking sector). Finally, Italy presents a useful laboratory setting to analyse the impact of the economic, social, and demographic conditions of local areas on bank efficiency. The Italian regions display very different conditions that must be considered to accurately estimate the probability of failure.

The remainder of the paper is organized as follows: Section 2 briefly reviews the relevant literature. In Section 3, we formulate our research hypotheses and describe the data employed in the empirical analysis. Section 4 summarizes the methodology. Section 5 reports the results of the analysis. Section 6 addresses the predictive accuracy of the model, and Section 7 concludes and offers final remarks.

2 Literature review

Our paper joins two separate streams of the economic literature. The first stream concerns efficiency estimation with the aim of comparing cooperative and commercial banks. One group of studies compares cooperative and commercial banks by estimating, first, a specific efficiency frontier for each type of bank and, second, a common frontier that pools together cooperative and commercial banks. These papers provide mixed evidence about the

[1] Note that Italian Banche Popolari are not covered in the present analysis because, in terms of governance, they more closely resemble joint-stock companies (Fonteyne, 2007).
[2] Source of data: Italian Federation of Cooperative Banks (Federcasse), estimated data at 31/12/2011.
[3] Source of data: European Association of Co-operative Banks (2011).
[4] Source of data: own calculation using data from the European Association of Cooperative Banks (2011). Cooperative networks, such as the Dutch Rabobank and the French Crédit Agricole, are not considered in the calculation.

cost and profit efficiency of such banks. Battaglia et al. (2010) show that sample heterogeneity also occurs when estimates are obtained from a single efficient frontier estimated for cooperative banks only. Cooperative banks have a strong link with the geographical area in which they operate; therefore, the levels of efficiency are influenced by the social, demographic, and economic conditions of that specific area.

Various papers also compare commercial and cooperative banks by focusing on issues other than efficiency. Cihák and Hesse (2007) use individual bank data to test whether cooperative banks reduce the stability of other banks and respond slowly to financial distress. Contrary to the findings of previous studies (Brunner et al., 2004; Goodhart, 2004; Fonteyne, 2007), Cihák and Hesse find cooperative banks to be more stable than commercial banks: the lower volatility of the cooperative banks' returns more than offsets their lower profitability and capitalization. Groeneveld (2012) compares commercial and cooperative banks, focusing on the mean values of some indicators (return on equity, Tier 1 capital, and Z-score). Overall, the author concludes that in Europe cooperative banks are less profitable and more stable than commercial banks.

The second stream of literature addresses the estimation of bank failures and is characterized by two approaches: micro- and macro-approaches. The "micro" strand focuses on individual banks' balance sheet data, possibly integrated with financial market data, to predict bank failures. This approach stems from the seminal papers of Altman (1968) and Beaver (1966), who use accounting data to discriminate between sound and troubled firms. Since then, many studies have assessed the ability of financial ratios to predict the financial health of bank operations (see, among many others, Meyer and Pifer, 1970; Sinkey, 1975; Santomero and Visno, 1977; West, 1985; Estrella et al., 2000). Various papers have also tested the superiority of one specific assessment technique over another (Martin, 1977; Espahbodi, 1991; Shumway, 2001; Glennon et al., 2002; Boyacioglu et al., 2009). Recently, Demyanyk and Hasan (2010) reviewed this extensive literature and showed that the combination of operational research techniques with statistical methods substantially improves the prediction of bank failures. Other recent works have focused on the subprime mortgage crisis and the subsequent banking failures (Davis and Karim, 2008a; Jin et al., 2011; Cole and White, 2012).

The “macro” approach investigates banking crises by focusing on macroeconomic determinants (Demirguc-Kunt and Detragiache, 1998; González-Hermosillo, 1999; Davis and Karim, 2008b). These studies typically analyse a large sample of countries to determine which macroeconomic factors signal a banking crisis in advance. For instance, Demirguc-Kunt and Detragiache (1998) argue that GDP growth, excessively high real interest rates, and high inflation significantly increase the likelihood of systemic banking crises. Other recent studies (DeYoung, 2003; Arena, 2008; Männasoo and Mayes, 2009; Mare, 2012) have used both the micro and macro perspectives, highlighting that combining different sources of information increases the accuracy of predictions of bank financial distress.

Various papers have estimated the probability of bank failure or survival. Lane et al. (1986) pioneered the field by using duration analysis. The authors were the first to use the Cox proportional hazards model to predict US commercial bank failures. Estrella et al. (2000) estimate the likelihood of failure using cross-sectional logit regressions and then analyse time-dependency in the conditional probability of failure through a proportional hazards model. Wheelock and Wilson (2000) use a competing-risks hazard model to identify characteristics leading to either failure or acquisition. The authors demonstrate that US banks that have low capitalization, high leverage, low liquidity, poor-quality loan portfolios and low earnings are more prone to failure. Moreover, the authors suggest that inefficiency, measured through management quality, increases the likelihood of bank failure.

Shumway (2001) develops a discrete-time hazard model to determine probability estimates for corporations at each point in time. The author argues that hazard models are theoretically preferable to single-period classification models (static models) because hazard models consider that firms change over and through time. Hence, the resultant probabilities of default consistently approximate the true probabilities of failure. Arena (2008) performs both cross-sectional logit estimation and survival time analysis to prove that bank-level fundamentals, the banking system, and macroeconomic variables significantly affect the likelihood of bank failures in the case of banking crises in East Asia and Latin America. In addition, the author suggests that systemic macroeconomic and liquidity shocks destabilized not only the banks that were already weak before the crises, but also those banks that were relatively stronger ex-ante. This result suggests that negative effects triggered by systemic crises can also affect sound banks. Männasoo and Mayes (2009) use a discrete complementary log-log model to link banks' hazard rates to macroeconomic, structural, and bank-specific factors. The study suggests that changes in bank earnings, efficiency (measured by the cost-income ratio), and the relative size of the credit portfolio are not early warning indicators.

Although various studies (e.g., Berger and DeYoung, 1997; Fiordelisi et al., 2011; Cihák and Schaeck, 2013) have analysed the relationship between bank efficiency and risk-taking, no studies have directly related different managerial skills to the occurrence of bank failure. This is surprising because efficiency is one of the key factors behind bank performance (Fiordelisi, 2007; Fiordelisi and Molyneux, 2010) and it guarantees bank survival over time.

The recent crises of credit institutions have shown the importance of assessing how well management contributes to bank survival (in terms of minimizing costs, maximizing revenues, or maximizing various measures of profits). The accurate prediction of bank survival is fundamental for practitioners, investors, academics, and regulators. Whilst this is true for all banks, it is critical for cooperative banks because their failure has been historically more likely than that of commercial banks and might generate higher social costs at the local level.

3 Research hypotheses and data

In this section, we formulate our research hypotheses, and then we outline the data used for the estimation. The key question addressed in the paper is to verify whether the managerial ability of a bank to reduce costs and/or increase revenues plays a role in avoiding bank default. Our approach entails an empirical analysis of the link between various efficiency measures and the probability of default of cooperative banks. Moreover, we estimate four different efficiency measures using stochastic frontier analysis and test our results using a balance-sheet measure of operating efficiency (i.e., cost-income ratio, as in Männasoo and Mayes, 2009). We specify three hypotheses that focus on various efficiency concepts.

First, we posit that if a bank is more cost efficient than its competitors, it is less likely to default. The underlying assumption is that if bank managers have superior skills in managing costs and inducing higher cost efficiency, this will help the bank survive during individual or sector distress. We call this assumption “cost-management excellence”. A competing hypothesis is “cost-skimping” (originally posited by Berger and DeYoung, 1997, and recently tested by Fiordelisi et al., 2011): if a bank is more cost efficient than its competitors, there is a higher likelihood of default. The underlying idea is that cost-efficient banks probably devote fewer resources to credit screening and monitoring, which implies a trade-off between short-term cost efficiency and future risk-taking.

Hypothesis I (H_1): if a bank is more cost efficient than its competitors, it has a lower probability of default ("cost-management excellence" hypothesis).
Alternative Hypothesis I (H_1^A): if a bank is more cost efficient than its competitors, it has an increased probability of default ("cost-skimping" hypothesis).

Second, we argue that if a bank is more revenue efficient than its competitors, it has a lower likelihood of default. The underlying assumption is that if bank managers have superior skills in managing revenue and stimulating higher revenue efficiency, this will help the bank survive in cases of individual or sector distress. We name this assumption "revenue-management excellence". A competing hypothesis is "short-term revenue": if a bank is more revenue efficient than its competitors, it has a higher likelihood of default. The underlying idea is that revenue-efficient banks probably have a lower quality loan portfolio, and customers are therefore willing to pay higher interest rates. This implies a trade-off between short-term revenue efficiency and future bank-soundness.

Hypothesis II (H_2): if a bank is more revenue efficient than its competitors, it has a lower probability of default ("revenue-management excellence" hypothesis).
Alternative Hypothesis II (H_2^A): if a bank is more revenue efficient than its competitors, it has an increased probability of default ("short-term revenue" hypothesis).

Third, we assume that the probability of default is not only related to the bank's ability to manage either its costs or revenues, but also to its ability to concurrently manage costs and revenues to achieve higher profits. Specifically, a cost-efficient bank could be disastrous at managing revenue or the reverse. We posit that if a bank is more profit efficient than its competitors, it has a lower likelihood of default. The underlying assumption is that higher profit efficiency implies that bank managers have superior skills in managing both costs and revenues, which will help the bank survive in times of individual or sector distress. We call this assumption "management excellence". Similar to hypothesis H_2^A, an alternative and competing hypothesis is that of "short-term profits": if a bank is more profit efficient than its competitors, it will have a higher likelihood of default (due to a lower quality loan portfolio), implying a trade-off between short-term profits and the future soundness of the bank. We test these two competing assumptions using two different profit measures: operating profits (which includes all operating costs and revenues) and the interest margin (which includes only interest costs and revenues).

Hypothesis III (H_3): if a bank is more profit efficient than its competitors, it has a lower probability of default ("management-excellence" hypothesis).

Alternative Hypothesis III (H_3^A): if a bank is more profit efficient than its competitors, it has an increased probability of default ("short-term profits" hypothesis).

Our sample comprises more than 4,200 observations and includes the financial statements of almost all the Italian cooperative banks. The data cover the period between

1997 and 2009, although we do not include the years 2007 and 2008 because they contain no default events. Each bank contributes T_t rows of data, corresponding to the number of time periods *t* in which it was at risk of failure.

The data set for the explanatory variables is comprehensive, combining bank-level data, geographical information, and efficiency measures. Market information is not considered because cooperative banks are not publicly traded and have very little market activity.

We collect data from various sources. Data on distressed banks are retrieved from the Italian Central Bank (Bank of Italy); accounting data are obtained from the Italian Association of Cooperative Banks (Federcasse); and we garner local geographical information from the Italian National Institute of Statistics (ISTAT). The bank-level data, a potential leading indicator of failure, are drawn from the banks' financial statements. Data are publicly available for most key items - liquidity, balance sheets, profits and losses, off-balance sheet items, large depositors, and large exposures. The major constraints are information on the sector pattern of lending (including exposure to the property sector) and the interest rates on liabilities and assets.

4. Methodology

Following Männasoo and Mayes (2009), we estimate a discrete-time survival model to determine the probability of failure at each point in time. We run a two-stage analysis. First, a complementary log-log model (cloglog) is estimated using various efficiency measures, macroeconomic information, and bank risk-taking variables. Second, we test out-of-sample the accuracy of the prediction of the model and the robustness of the results.

4.1 The hazard model

We estimate the survival model in discrete time because our data set only provides observations discretely. We focus on a single-state model, and we assume that we have single-spell data for each bank. Our model implicitly assumes that all relevant differences between banks can be summarized by the observed explanatory variables. We also assume that bankruptcy only occurs at discrete points in time (t= 1, 2, 3,..., n). Moreover, each bank either fails during the sample period or survives. If banks merge or are liquidated or if the identification variable (Abi) is not available for the whole observation window, they are omitted from the sample. 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* the realization thereof. The discrete-time duration model implies that we observe the probability of survival of cooperative banks at distinct points in time. Because the sample data refer to an observation window of ten years, the survival time data set is right-censored, meaning that we observe the start date of the spell (year 1996) but not the total length of transition out of the current state (from soundness to failure). It is also assumed that the process that gives rise to censoring is independent from the survival-time process. The probability of exit within the j_{th} interval is expressed as follows:

$$\Pr(a_{j-1} < T < a_j) = F(a_j) - F(a_{j-1}) = S(a_{j-1}) - S(a_j) \qquad (1)$$

where $a_1, a_2, \ldots, a_k$ are the interval boundary dates (years); $F(a_j)$ is the cumulative distribution function of T at duration time *j* (failure function); 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:

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

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. Written in terms of interval hazard rates, it corresponds to:

$$S(j) = (1-h_1)*(1-h_2)*.....*(1-h_{j-1})*(1-h_j) = \prod_{k=1}^{j}(1-h_k) \tag{3}$$

We allow the hazard rate to vary between banks depending on their characteristics, and 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 hazard rate and the selected characteristics are linked through an index function. Following Männasoo and Mayes (2009), we employ a complementary log-log model (cloglog):

$$h(j,\mathbf{X}_j) = 1-\exp[-\exp(\beta'\mathbf{EF}_j + \delta'\mathbf{CAL}_j + \omega'\mathbf{ENV}_j + \gamma_j)] \tag{4}$$

where $\mathbf{X}_j$ contains time-varying covariates; β', δ', and ω' are the vectors of coefficients; $\mathbf{EF}_j$ denotes efficiency measures; $\mathbf{CAL}_j$ captures bank-level fundamentals; $\mathbf{ENV}_j$ represents environmental variables; and γ_j is the log of the difference between the integrated baseline hazard evaluated at the end of the interval and at the beginning of the interval (a_{j-1}; a_j]. Each regression coefficient summarizes the effect on the hazard of absolute changes in the corresponding covariates. The coefficients do not vary with survival time.

4.2 Variables

4.2.1 Event of failure

Following previous studies (Arena, 2008; Männasoo and Mayes, 2009, among others), bank default is defined as the occurrence of public intervention to solve a critical distress situation. We model bank failures using a categorical variable that equals 1 if bank *i* failed at time *t* and equals 0 otherwise. Following Italian law, we define a bank as being in default if it underwent either of the two following events between January 1, 1997 and December 31, 2006: a) it entered extraordinary administration (e.g., conservatorship), or b) it entered liquidation. Each of these government interventions objectively shows that a bank is unable to continue its operations.

We collect data on distressed banks from the Bank of Italy. Overall, there were 44 cases of government intervention (either extraordinary administrations or liquidations) in the period analysed, as shown in Table 1. Accounting data for all cooperative banks are obtained from the Italian Federation of Cooperative Banks (Federcasse).

< Insert here Table 1 >

4.2.2 Explanatory variables

The set of potential explanatory variables is chosen in order to explain the probability of failure as a consequence of the better management of bank operations quantified by the efficiency measures.

First, we estimate cost efficiency by using Battese and Coelli's (1995) stochastic frontier model, as detailed in Appendix 1. We also compute the cost-to-income ratio as a direct test to measure efficiency in generating operating income. We then include other variables that are likely to contribute to the survival of a cooperative bank. We take into consideration the economic conditions of the local area environment (measured by the annual growth rate in Italian GDP per capita and the employment growth in the regional workforce) because these are likely to affect the survival of cooperative banks (Mare, 2012). A second group of variables focuses on bank-specific factors. We select the indicators following the well-known CAMEL framework[5]: specifically, we measure Capital Adequacy as the ratio between the capital in excess of regulatory requirements and the minimum capital requirement; we estimate bank Asset Quality using the ratio of annual loan loss provisions to total loans and we quantify the Liquidity Risk as the ratio of bank deposits to customer deposits. The two remaining CAMEL categories (i.e., Management Quality and Earnings) are explicitly included in the estimation of the efficiency measures. We also control for a bank's asset size and for a bank's credit orientation. Table 2 describes the variables employed in the analysis and reports the expected signs of the estimated parameters.

< Insert here Table 2 >

The descriptive statistics for the explanatory variables are reported in Table 3. We separate all banks into two categories: failed and non-failed banks. T-tests are computed to detect statistically significant differences in univariate comparisons.

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[5] CAMEL is the acronym referring to the following five factors introduced by US regulators in November 1979: "C" stands for Capital Adequacy, "A" for Asset Quality, "M" for Management Quality, "E" for Earnings, and "L" for Liquidity. In 1996, CAMEL evolved into CAMELS, where "S" is the Sensitivity to Market Risk. Cooperative banks engage in very little market activity; thus, the CAMEL framework is more appropriate to analyze their bank soundness.

< Insert here Table 3 >

5. Results

We report the results from the hazard function in Table 4. Following Männasoo and Mayes (2009), the explanatory variables are lagged by one year. The discrete-time survival model relates a change in the hazard rate due to an absolute change in a given regressor, *ceteris paribus*. The characteristics of the economic environment (at both the local and national level) and bank-specific indicators are introduced to the analysis to control for factors that could influence the link between bank efficiency and the probability of default. The control variables are standardized to make it easier to compare the individual contributions of the different factors to the survival of cooperative banks.

< Insert here Table 4 >

To test our research hypotheses, we run our cloglog model (Equation 4) using five different specifications to link efficiency and bank failure (respectively, one for each efficiency measure and one using the cost-to-income ratio).

Our results support the cost-management hypothesis (H_1): we find that higher cost efficiency engenders a higher probability of survival. The estimated cost-efficiency coefficient (in Estimation 1 of Table 4) is negative and statistically significant at the 1% confidence level. As a result, we can reject the cost-skimping hypothesis (H_1^A).

In regard to a bank's ability to maximize its revenues, our results support the revenue-management hypothesis (H_2), suggesting that banks that are able to extract more revenues from services provided to customers and achieve higher returns from their investments have a higher probability of survival. The estimated revenue-efficiency coefficient (in Estimation 2 of Table 4) is negative and statistically significant at the 10% confidence level. Consequently, we can reject the short-term revenue hypothesis (H_2^A).

Turning to profits, our findings support the management-excellence hypothesis (H_3) because more profit–efficient banks are found to have a higher probability of survival. We use two measures of profitability: operating income and interest margin. In both cases, the coefficient (in Estimations 3 and 4 of Table 4) is negative and statistically significant at the 1% confidence level. Consequently, we can also reject the short-term profits hypothesis (H_3^A). In Estimation 5 in Table 4, the cost-to-income ratio is positively related to a bank's risk of failure, as banks that are less able to contain their operating costs are more likely to be poorly managed and show a higher hazard rate.

We find that the CAMEL indicators are statistically significant (at the 10% level or less) and strongly related to the hazard rate. Specifically, higher capital levels reduce the probability of default. This supports the view that higher capitalization provides additional loss absorbency and reduces a bank's moral hazard (Lane et al., 1986; Fiordelisi et al., 2011; Haq and Heaney, 2012, among many others). As such, strengthening the capital requirement in the cooperative banking sector, as proposed in the Basel III agreement[6], may help to prevent bank distress.

[6] The Basel III framework comprehends a set of documents issued by The Basel Committee on Banking Supervision (first publication in December 2010). The aim is to reduce the impact of banking crises in the future. The Basel III agreement follows

We also note that asset quality (measured by the loan loss provision ratio) is positively related (at the 1% level) to the probability of default. As such, in the case of a decrease in asset quality (i.e., the loan loss provision ratio increases), the probability of default for cooperative banks increases. In line with Männasoo and Mayes (2009), we find that the liquidity ratio is positively and statistically significantly related to the probability of default. This result suggests that when cooperative banks rely too heavily on the interbank market, they are exposed to the sudden freezing of funds. This can lead banks to default, especially during periods of systemic financial distress when funding is critical. Size is negatively related to bank failure, as larger cooperative banks have less concentrated portfolios and can diversify lending towards different industrial sectors.

6. Testing the Model's Predictive Ability

We test the predictive accuracy of our model both in-sample and by using holdout data. The analysis of the goodness-of-fit enables us to determine how well the econometric model fits the observed phenomena[7]. We again run the five models in Table 4 using only the variables that were statistically significant at the 10% level; therefore, we do not consider employment growth in our computations. In Model 5 of Table 4, we include the cost-to-

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the publication of the first accord on capital measurement and capital standards (Basel I, July 1988) and a second, more comprehensive framework (Basel II, June 2004).

[7] As a further test, we run a robustness check by comparing the impact of efficiency on the probability of bank default in cooperative and commercial banking. We retrieve accounting data on Italian commercial banks from the Bankscope database. Because data on defaults for commercial banks are insufficient to estimate a model (8 defaults over the period 1997–2006), we focus on 2009 (6 defaults). All estimated coefficients for efficiency measures in both commercial and cooperative banks have signs that are consistent with those estimated in Column 5 of Table 4. However, the overall statistical power of the estimation is poor, mainly due to the low number of defaults. Results from this test are available upon request.

income ratio because it is statistically significant at the 10% level after removing the liquidity variable, employment growth, and GDP growth.

Table 5 reports the in-sample check of the accuracy of the predictions. In Panel A of Table 5, we report six indicators: Sensitivity, Specificity, Overall Predictive Power, ROC Area, Accuracy Ratio, and Brier Score. Efficiency measures, estimated through the stochastic frontier analysis, increase the predictive accuracy of the model when compared with Model 5, in which the cost-to-income ratio proxies for managerial ability to reduce costs (inputs) and to produce revenues (output).

Sensitivity quantifies the proportion of banks in default that are correctly identified as such; *Specificity* measures the proportion of safe banks (e.g., sound) that are correctly identified. These two indicators are closely related to the concepts of Type I and Type II errors: all estimated models have an in-sample Sensitivity higher than 54% (70%, if we do not consider Estimation 5, which has the lowest performance) and Specificity higher than 75% (80%, if we omit Estimation 5, which has the lowest performance), values that are largely superior to those of a naïve model (i.e., 50%). The *Overall Predictive Power* is the ratio between the sum of all safe and defaulted banks accurately classified and the total number of banks. All estimations have in-sample Overall Predictive Power higher than 74% (80%, if we omit Specification 5, which has the lowest performance, and 83% in the best specification, which includes operating cost efficiency), a figure that is largely superior to that of a naïve model (i.e., 50%).

We compute the *ROC Curve*, which measures the impact of changes in the probability threshold, i.e., the decision point used by the model for classification. The area under the ROC Curve measures the discriminating ability of a binary classification model: the larger this area, the higher the likelihood that an actual default case will be assigned a higher probability of being in default than an actual sound case. All estimations have an in-sample Overall Predictive Power higher than 76% (83% if we omit Specification 5, which has the lowest performance, and 88% in the best specification, which includes operating cost efficiency), which is largely superior to that of a naïve model (i.e., 50%).

We also compute the *Brier Score*, which evaluates the quality of the forecasts as follows:

$$B = \frac{1}{n}\sum_{i=1}^{n}(p_i - \theta_i) \tag{5}$$

where p_i is the estimated default probability of the banks (from 1 to *n*), and θ_i is the actual outcome of the event of default (equal to 1 if obligor *i* defaults and 0 otherwise). The Brier Score must therefore always be between zero and one. The closer the Brier Score is to zero, the better the forecast of default probabilities. All estimated models have an in-sample Brier Score close to zero.

Overall, the specifications (especially Specification 1, which includes cost efficiency) provide sound estimates in line with (or better than) the overall performance of previous studies (Shumway, 2001; Männasoo and Mayes, 2009; Arena, 2008).

< Insert here Table 5 >

We also run an out-of-sample test by estimating hazard rates using the estimated coefficients and data from 2009. This enables us to validate our results by tackling the problem of sample-specific estimation. The meaning of the goodness-of-fit test is limited, as we observe only six default cases in 2009 (and no defaults in 2007 and 2008). Not surprisingly, we find that the predictive accuracy of the model (Table 6) is lower than that obtained in-sample (Table 5), but the predictive power of our model is still high. The overall predictive power is higher than 74% for all the models, and the Brier Score continues to be very low (lowest value 0.014).

< Insert here Table 6 >

7. Conclusions

Our paper analyses the contribution of efficiency to the probability of bank failure among cooperative banks. Cooperative banks play a key role in the European banking industry. Despite their importance, these banks experience financial distress more frequently than commercial banks during periods of financial stability. The default rate of Italian cooperative banks was almost four times that of commercial banks in the period before the recent financial crisis (1997–2006). Specifically, there were 44 default cases among cooperative banks (default rate 1.04%) and 8 among commercial banks (default rate 0.28%).

Our paper analyses the determinants of the probability of survival of cooperative banks by focusing on the role of efficiency. Our results indicate that lower risk is related to a higher survival time for cooperative banks. These findings contribute to the existing literature that investigates the direct link between efficiency and risk-taking (Chortareas et al., 2011; Chronopoulos et al., 2011; Fiordelisi et al., 2011) by showing that prudent and skilful managerial abilities increase the survival time of cooperative banks. To support our view, we test three research hypotheses that focus on the contribution of efficiency to the probability of bank failure. Namely, we posit that bank survival is related to the managerial ability to save costs (H_1), maximize revenues (H_2), and maximize profits (H_3).

We study a large sample of Italian cooperative banks. We show that all efficiency measures have lower hazard rates, meaning that an increase in these variables increases the survival time of banks. Specifically, we find that more efficient banks (either in terms of cost saving or revenue and profit maximization) show a higher probability of survival, supporting the cost, revenue, and excellent-management hypotheses.

Our findings are of interest for policy makers and supervisors. Recent developments in banking regulations stem from the idea that efficiency is a key element in assessing the relationship between bank risk and capital levels. There is a parallel between Basel II prescriptions regarding internal control processes and higher efficiency gains because both contribute to an increase in the resilience of banks. Similarly, the new corporate governance directives for banks support the cost, revenue, and excellent-management hypotheses, in line with the results of the paper. Moreover, we show that higher capital levels reduce the probability of default: this supports the view that higher capital levels provide additional loss absorbency and reduce a bank's moral hazard. As such, in the cooperative banking sector, strengthening the capital requirement as proposed in the Basel III agreement may help to prevent bank distress.

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Appendix 1

Efficiency measures estimation

The set of potential explanatory variables is chosen in order to explain the probability of failure as a consequence of the better management of bank operations quantified by the efficiency measures. Cost efficiency is measured using stochastic frontier analysis and the Battese and Coelli (1995) stochastic frontier model. We use the following translog functional form:

$$LnTC = a_0 + \sum_{i=1}^{4} b_i \ln Y_i + \sum_{j=1}^{3} c_j \ln P_j + e_1 \ln E + t_1 T + \frac{1}{2}\left[\sum_{i=1}^{4}\sum_{j=1}^{4}\delta_{ij} \ln Y_{ij} + \sum_{i=1}^{3}\sum_{j=1}^{3}\gamma_{ij} \ln P_{ij} + e_{11} \ln E \ln E + t_{11} T^2\right] + \tag{6}$$
$$+ \sum_{i=1}^{4}\sum_{j=1}^{3}\varphi_{ij} \ln Y_i \ln P_j + \sum_{i=1}^{4}\phi_i \ln Y_i \ln E + \sum_{i=1}^{4}\psi_i \ln Y_i T + \sum_{j=1}^{3}\theta_j \ln P_j \ln E + \sum_{j=1}^{3}\lambda_j \ln P_j T + \omega T \ln E$$

where TC is the logarithm of the total production cost; y_i (i=1, 2, 3, 4) are output quantities; P_j (j=1, 2, 3) are input prices; ln E is the natural logarithm of total equity capital; and T is the time trend to account for possible changes in technology during the observed period. In order to guarantee linear homogeneity in factor prices, it is necessary (and sufficient) to apply the following restrictions: 1) the standard symmetry and 2) linear restriction of the cost function. Following previous studies (Vander Vennet, 2002; Girardone et al., 2004), we include equity as a netput, specifying interaction terms with both output quantities and input prices.

Italian cooperative banks constitute a heterogeneous dataset. To overcome this problem and take into consideration local market conditions, we adopt the technical inefficiency effects model proposed by Battese and Coelli (1995). Following Battaglia et al., (2010), we include a large set of environmental variables (Table 7) that are estimated at the regional level[8].

< Insert here Table 7>

To obtain a complete view of the performance of cooperative banks, we also estimate revenue- and profit-efficiency measures, which specify various measures of profits (respectively, total revenue, and operating income and interest margin) given the level of outputs rather than the output prices. The frontier definition is the same as in the cost case, except for the dependent variable: total cost is replaced by the previously mentioned profit measure.

[8] Our frontier model includes environmental variables that are estimated at the regional level (for each of the 20 Italian country regions), but we only report summary statistics at the macro-geographical-area level. Statistics at the more detailed regional level are available upon request.

Tables

Table 1. Number of banks and historical default rates: cooperative vs. commercial banks

	Cooperative Banks					Commercial Banks				
Year	**Number of Banks (A)**	**Liquidation (B)**	**Administration (C)**	**Total Number of Banks in Default (D=A+B)**	**Default Rate (E=D/A)**	**Number of Banks (A)**	**Liquidation (B)**	**Administration (C)**	**Total Number of Banks in Default (D=A+B)**	**Default Rate (E=D/A)**
1997	405	1	3	4	0.99%	291	-	2	2	0.69%
1998	404	1	5	6	1.49%	299	-	-	-	0.00%
1999	414	-	4	4	0.97%	288	1	1	2	0.69%
2000	432	-	5	5	1.16%	284	-	1	1	0.35%
2001	436	-	5	5	1.15%	296	-	-	-	0.00%
2002	436	-	6	6	1.38%	293	-	1	1	0.34%
2003	430	1	6	7	1.63%	282	-	1	1	0.35%
2004	434	-	2	2	0.46%	279	-	1	1	0.36%
2005	424	-	4	4	0.94%	279	-	-	-	0.00%
2006	432	-	1	1	0.23%	283	-	-	-	0.00%
Pre-Crisis Period (1997-2006)	4,247	3	41	44	1.04%	2,874	1	7	8	0.28%
2007	431	-	-	0	0.00%	234	-	-	-	0.00%
2008	431	-	-	0	0.00%	255	-	1	1	0.39%
2009	421	1	5	6	1.43%	285	-	6	6	1.75%
Crisis Period (2007-2009)	1,283	1	5	6	0.47%	774	0	7	7	0.90%
Overall Period (1997-2009)	5,530	4	46	50	0.90%	3,648	1	14	15	0.41%

Source: own calculations using data from Federcasse. For commercial banks, data were obtained from the Supervision Bulletin of the Bank of Italy. Data were not available for all the active banks in the period.
Notes: This table presents the historical time series of Italian banks, subject to temporary conservatorship (Administration) or closed (Liquidation) by the Italian banking supervisor (Bank of Italy). Data are presented separately for cooperative and commercial banks. Cooperative banks' default rate is more than twice the figure for commercial banks during the overall period (1997–2009) and almost four times higher during the pre-crisis period (1997–2006). During the 2007–2009 financial turmoil, this tendency was reversed, with the commercial default rate rising to almost twice as high as the failure rate for cooperative banks.

Table 2. Variable definitions

Variable	Definition	Representative studies
Cost	This is the cost efficiency, estimated using the method illustrated in Appendix 1.	Various studies, see a review in Hughes and Mester (2010)
Revenue	This is the revenue efficiency, estimated using the method illustrated in Appendix 1.	Fiordelisi and Molyneux (2010)
Operating	This is the profit efficiency, estimated using the method illustrated in Appendix 1.	Various studies, see a review in Hughes and Mester (2010)
Interest	This is the interest margin efficiency, estimated using the method illustrated in Appendix 1.	
Cost- Income	This is the ratio between operating expenses and operating income.	Lane et al. (1986); Männasoo and Mayes (2009)
Capital Adequacy	This is the ratio between capital in excess of regulatory requirements over the minimum capital requirements.	Regulatory requirements
Credit Orientation	This is the ratio between total loans and total assets.	Lane et al. (1986); Männasoo and Mayes (2009)
Asset Quality	This is the ratio between loan loss provisions and total loans.	Männasoo and Mayes (2009); Arena (2008)
Liquidity	This is the ratio between bank deposits and customer deposits.	Männasoo and Mayes (2009)
Size	This is the natural logarithm of total assets.	Cole and White (2012); Arena (2008)
Employment Growth	This is the regional workforce employment growth over a two-year period.	DeYoung (2003)
GDP Growth	This is the annual growth rate in the Italian GDP per capita (at current prices).	Arena (2008); Sundararajan et al. (2002)

Notes: This table reports the names and definitions of the variables employed in the estimation. The column "representative studies" lists some studies that have used the explanatory variables.

Table 3. Descriptive statistics

Variables	All		Non-Failed		Failed		T-test for Means	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	Difference	t-statistic
Cost Efficiency	0.630	0.269	0.632	0.269	0.487	0.210	0.144	3.543***
Revenue Efficiency	0.630	0.263	0.629	0.263	0.702	0.268	-0.073	-1.843*
Operating Efficiency	0.611	0.271	0.614	0.269	0.329	0.231	0.284	6.978***
Interest Efficiency	0.729	0.242	0.731	0.241	0.542	0.230	0.189	5.172***
Cost-Income	0.780	0.127	0.779	0.123	0.900	0.310	-0.122	-6.380***
Capital Adequacy	2.631	2.230	2.629	2.223	2.768	2.851	-0.139	-0.4107
Credit Orientation	0.642	0.122	0.641	0.122	0.716	0.128	-0.075	-4.038***
Asset Quality	0.003	0.005	0.003	0.005	0.010	0.011	-0.007	-9.083***
Liquidity	0.026	0.045	0.026	0.044	0.031	0.059	-0.005	-0.779
Size	11.663	0.983	11.675	0.971	10.490	1.324	1.185	8.016***
Employment Growth	0.021	0.020	-	-	-	-	-	-
GDP Growth	3.877	1.248	-	-	-	-	-	-

Notes: This table reports the descriptive statistics for the variables employed to explain bank failures over the period from 1997–2006. Data are presented for all banks and separately for surviving banks and defaulted banks. In the last two columns, we present the difference in means between the two groups (Non-Failed and Failed) and the t-statistic under the hypothesis of equality of variances for the two populations. The t-statistic is computed as the ratio of the difference in means to the difference in standard errors.

Table 4. Estimation results of the discrete-time hazard regression model in cooperative banking between 1997 and 2006

	Models				
Variables	(1)	(2)	(3)	(4)	(5)
Cost	-4.34***				
	(1.017)				
Revenue		-1.643*			
		(0.927)			
Operating			-3.559***		
			(0.962)		
Interest				-1.959***	
				(0.662)	
Cost-Income					0.060
					(0.051)
Capital Adequacy	-0.752***	-0.548***	-0.493**	-0.524***	-0.653***
	(0.202)	(0.203)	(0.195)	(0.191)	(0.225)
Credit Orientation	0.896***	0.472**	0.425**	0.501***	0.623***
	(0.164)	(0.207)	(0.178)	(0.178)	(0.166)
Asset Quality	0.453***	0.583***	0.489***	0.497***	0.544***
	(0.076)	(0.08)	(0.077)	(0.077)	(0.073)
Liquidity	0.322***	0.254**	0.357***	0.323***	0.249**
	(0.102)	(0.105)	(0.095)	(0.099)	(0.106)
Size	-0.678***	-1.082***	-0.728***	-0.85***	-0.949***
	(0.208)	(0.17)	(0.167)	(0.164)	(0.183)
Employment Growth	-0.311	9.325	2.743	4.064	6.631
	(8.224)	(8.59)	(7.78)	(7.913)	(8.398)
GDP Growth	-0.484***	-0.531***	-0.451***	-0.534***	-0.738***
	(0.098)	(0.164)	(0.094)	(0.103)	(0.08)
Observations	4215	4215	4215	4215	4215
Number of Failures	44	44	44	44	44
Number of Banks	476	476	476	476	476

Notes: This table presents the results of the survival model estimated in discrete time. The five models include the same set of variables apart from the efficiency measure. In Model (1), we include cost efficiency; in Model (2) we consider revenue efficiency; Model (3) comprises operating income efficiency; in Model (4) we evaluate the contribution of interest margin efficiency; and in Model (5) we consider the cost-to-income ratio. Standard errors are in parenthesis. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors.

Table 5: Predictive accuracy: in-sample checks

Panel A: Goodness-of-fit indicators

Measure	**Models**				
	1	**2**	**3**	**4**	**5**
Sensitivity	0.795	0.705	0.773	0.750	0.545
Specificity	0.833	0.801	0.814	0.813	0.748
Overall Predictive	0.832	0.800	0.813	0.812	0.745
ROC Area	0.879	0.832	0.866	0.845	0.765
Accuracy Ratio	0.757	0.664	0.733	0.689	0.531
Brier Score*	0.947	0.939	0.908	0.926	1.108

Source: own calculations. * Brier Score is multiplied by 100.
Notes: This table reports the results of the measures of predictive power of the model in-sample.

*Panel B: Probability rankings versus actual bankruptcies; percent**

Measure	**Models**				
	1	2	3	4	5
1-5	0.068	0.136	0.045	0.114	0.091
6	0.023	0.000	0.023	0.000	0.114
7	0.023	0.068	0.023	0.068	0.136
8	0.091	0.091	0.068	0.068	0.159
9	0.114	0.091	0.091	0.182	0.136
10	0.682	0.614	0.750	0.568	0.364

Source: own calculations. * Probability rankings versus actual bankruptcies; percent classified out of 44 possible. ** Deciles of the distribution of the estimated hazard rate.
Notes: This table reports the ranking of the banks using the estimated hazard rate. Notice that the sum is not necessarily equal to one due to rounding.

Table 6: Predictive accuracy: out-of-sample checks

Panel A: Goodness-of-fit indicators

Measure	**Models**				
	1	**2**	**3**	**4**	**5**
Sensitivity	0.500	0.167	0.167	0.167	0.000
Specificity	0.793	0.894	0.878	0.749	0.998
Overall Predictive	0.789	0.884	0.868	0.741	0.984
ROC Area	0.715	0.657	0.680	0.567	0.626
Accuracy Ratio	0.430	0.313	0.359	0.134	0.252
Brier Score	0.016	0.015	0.014	0.015	0.014

Source: own calculations.
Notes: This table reports the results of the measures of the predictive power of the model out-of-sample. The coefficients estimated through the model are multiplied by the values of the explanatory variables in 2008 to obtain the estimated hazard rate for 2009 (see §4 for a detailed explanation of the estimation of the discrete-survival model).

*Panel B: Probability rankings versus actual bankruptcies; percent**

Measure	**Models**				
	1	2	3	4	5
1-5	0.167	0.167	0.333	0.500	0.333
6	0.167	0.333	0.000	0.000	0.000
7	0.000	0.167	0.000	0.333	0.167
8	0.167	0.000	0.000	0.000	0.333
9	0.167	0.167	0.500	0.000	0.000
10	0.333	0.167	0.167	0.167	0.167

Source: own calculations. * Probability rankings versus actual bankruptcies; percent classified out of 6 possible. ** Deciles of the distribution of the estimated hazard rate.
Notes: This table reports the ranking of the banks using the estimated hazard rate. Notice that the sum is not necessarily equal to one due to rounding.

Table 7: Environmental variables included in the efficiency estimation (mean values by macro-geographical area)

	Centre	North East	North West	South	Total
Z_1 Population density (number of inhabitants per square kilometre) [A]	194.00	132.74	337.80	214.53	192.17
Z_2 Index of concentration in the territory, (percentage ratio between people resident in the main city of the region and those resident in the towns) [A]	64.76	33.22	32.24	33.77	39.13
Z_3 Gross domestic product per head [A]	24.75	27.73	28.81	15.18	24.20
Z_4 Entrepreneurial liveliness (ratio of the net number of incorporations in the Registrar of Companies) [A]	2.11	1.77	1.79	2.82	2.10
Z_5 Incidence of nonperforming loans (incidence of precarious loans, overdue bills, groundings, and restructured loans on the total amount of bank assets) [B]	7.90	6.50	5.77	16.43	9.13
Z_6 Number of cash points (ATM and POS) owned by cooperative banks over the total existing in the territory [B]	10.23	19.13	6.52	6.05	12.52
Z_7 Number of bank branches owned by cooperative banks over the total existing in the territory [B]	9.66	37.80	8.58	9.12	21.47
Z_8 Number of ATM and POS (owned by cooperatives and other banks) per 1,000 inhabitants [B]	18.45	25.51	15.50	8.63	18.65
Z_9 Number of branches (owned by cooperatives and other banks) per 1,000 inhabitants [B]	0.58	0.85	0.62	0.32	0.64
Z_{10} Index of firm weakness (number of bankruptcies declared per 1,000 firms) [A]	2.97	1.75	2.53	2.66	2.31
Z_{11} Level of criminality (number of bank robberies per 1,000 branches) [C]	77.06	41.40	93.44	91.45	67.52
Z_{12} Index of solidarity (number of blood donors per 1,000 inhabitants) [D]	0.22	0.35	0.34	0.12	0.27

(A) Source of data: ISTAT (Italian National Institute of Statistics)
(B) Source of data: Statistical Bulletins attached to the magazine *Cooperazione di Credito*
(C) Source of data: *Ministero dell'Interno* (Ministry of Home Affairs)
(D) Source of data: AVIS (Italian Association of Blood Donors)