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Estimating bank default with generalised extreme value models

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Abstract

This paper considers the joint role of macroeconomic and bank-specific factors in explaining the occurrence of bank failures. As bank failures are, fortunately, rare, we apply a regression model, based on extreme value theory, that turns out to be more effective than classical logistic regression models. The application of this model to the occurrence of bank defaults in Italy shows that, while capital ratios considered by the regulatory requirements of Basel III are extremely significant to explain proper failures, macroeconomic conditions are relevant only when failures are defined also in terms of merger and acquisition.

We also apply the joint beta regression model, in order to estimate the factors that most contribute to the bank capital ratios monitored by Basel III. Our results show that the Tier 1 capital ratio and the Total capital ratio are affected by similar variables, at the micro and macroeconomic level. An important outcome of this part of the analysis is that capital ratio variables can be taken as reasonable proxies of distress, at least as far as the effect sign of the determinants of failure risk is being considered.

1 Introduction and literature review

The study of bank failures is important for two reasons. First, an understanding of the factors related to bank failure enable regulatory authorities to supervise banks more efficiently. Second, the ability to differentiate between sound banks and troubled ones will reduce the expected costs of bank failure. In other words, if supervisors can detect problems early enough, regulatory actions can be taken, to prevent a bank from failing and to minimize social costs, for the stakeholders as well as for the taxpayers.

During the latest financial crisis, started in 2007, the core capital of banks has proved to be insufficient to cover impairment losses potentially arising from both loan and security portfolios. Consequently, several banks have strengthened their capital base and reduced their exposures. In order to reduce the risk of similar crises in the future and to enhance the resilience of the banking sector, a new regulatory framework, the so-called Basel III package, has been proposed, implying more stringent capital requirements for financial institutions (Basel Committee on Banking Supervision, 2011). In this framework, banks are required to operate above minimum capital ratios with an additional time-varying capital buffer (European Central Bank, 2007), which, together with the regulatory capital, forms banks internal target capital ratio. The monitoring and supervision of the new regulatory framework increases the importance of having robust and reliable methods to compute appropriate measutres of distress of banks, such as default probabilities. Indeed, when Lehman Brothers filed for bankruptcy in September 2008 some analysts were almost caught by surprise: two weeks prior to bankruptcy, the official Moodys KMV one-year Estimated Default Frequency (EDF) for Lehman Brothers was only at 0.62% (Fantazzini and Maggi, 2013).

The main objective of this study is thus to identify appropriate measures of distress, that can be used to distinguish between healthy and financially unsound banks. The construction of reliable and consistent measures of distress would allow for the identification of distressed financial institutions before they become insolvent (for example, via the implementation of early warning systems in advance). In this analysis we consider two groups of measures of distress: measures based on bank accounting data and measures based on macroeconomic indicators. There are several studies (e.g. Arena, 2008; Bongini et al., 2001; Gonzalez-Hermosillo, 1999; Mannasooa and Mayes, 2009) that use as indicators a set of bank-specific factors, which can be addressed directly by appropriate banking regulation and supervision authorities under the CAMELS[1] framework, which is applied in the US and has been adapted elsewhere. On the other hand, some studies (Arena, 2008) show that economic conditions in the markets where a bank op-

[1] Capital adequacy, Asset quality, Management soundness, Earnings and profitability, Liquidity, Sensitivity to market risk (CAMELS)

erates also appear to affect the probability of bank failure. Banking crises tend to erupt when the macroeconomic environment is weak, particularly when growth is low and inflation is high. Also, high real interest rates are clearly associated systemic banking sector problems. For this reason, we introduce macroeconomic variables, together with bank-specific ones, in the regression models that we shall develop.

We apply these considerations to a dataset of 783 Italian banks, observed over the period 1996-2011 on an annual basis. To model bank distress, at first a definition of bank failure needs to be identified. A strategic decision often needs to be taken by the troubled banks government in order to resolve such distress. Financial distress will, for example, often be resolved via bankruptcy, liquidation, closure or merger and acquisition. However, mergers and acquisitions might have been carried out for strategic reasons, rather than for insolvency ones. For this reason, some authors exclude mergers from bank failure (Arena, 2008). Other authors include them (Bongini et al., 2001; Gonzalez-Hermosillo, 1999). This contradictory indications imply that it is necessary to check the robustness of our results to the inclusion or exclusion of mergers and acquisitions from the definition of bank failure (default). In Section 3 we shall obtain, for the Italian banking sector, that the two definitions lead to different determinants of default. By excluding bank mergers and acquisitions, accounting variables are pivotal to explain bank distress. On the contrary, by including them, only macroeconomic variables become relevant.

Within the Basel III framework, regulators have proposed raising minimum capital requirements and limiting leverage for financial institutions in response to the 2007-2009 banking crisis. While increased capital ratios are widely believed to provide an additional margin of safety to the banking system (as they provide a larger capital cushion to absorb potential losses), some observers have noted that requiring higher capital ratios is likely to have second-order negative consequences, ranging from higher borrowing costs for end users of credit, to reduced rates of return on equity for banks and, to some extent, to a reduction in investor appetite as suppliers of that equity. In addition, while regulators and policymakers have been united in their desire to increase capital requirements, it is unclear what these capital ratios represent.

In this paper, we bring new evidence and data on Tier 1 capital ratio and Total capital ratio to understand whether their deficit can be used as and appropriate "early warning" proxy of bank distress.

By applying a regression model for constrained dependent variables, we show that both these capital ratios are determined by similar characteristics of banks and of the economic cycle and, therefore, can be used interchangeably. In addition, we find that the determinants of bank failure found using an event type distress variable as response are almost the same as those obtained using capital ratio variables as response, with concordant effect signs. This finding, albeit preliminary, seem to indicate that capital ratio variables may indeed be used as early warning indicators of distress. This finding, if confirmed, would be of relevant importance in a context, such as the European one, where bank failures are rare event, and where Merton models, based on market data, do not adequately discriminate between "good" and "bad" banks.

The rest of the paper is organised as follows. The academic literature related to bank distress and target capital ratios is reviewed in Section 2. The regression models used in this work are presented in Section 3. The dataset is presented in Section 4 together with the estimation results.

2 Methodology

2.1 Definition of bank failure

A bank is defined as being in distress when at least one of the following criteria is met, according to the information avaiable from the BankScope database, that we have used in this analysis:

1. bankruptcy
2. dissolved
3. in liquidation

In this analysis, a bank is considered to have failed if it fits into any of the above categories. The Italian insolvency regime establishes that banks experiencing financial distress might be subject to the liquidation procedure, a gone-concern action in which the insolvent bank has to be shut down.

In some literature (Bongini et al., 2001; Gonzalez-Hermosillo, 1999), banks that were merged or acquired by another banks are also included in the definition of failure. However, mergers and acquisition might have been carried out for strategic ends rather than for insolvency reasons (Arena, 2008). For this reason, we will consider two alternative definitions of bank failure: one that includes only the above criteria and one that adds to them mergers and acquisition events.

2.2 GEV model

The event default or non-default of a bank, as defined above, can be represented by a Bernoulli random variable Y_i with parameter π_i that indicates the probability of default of a given bank, for $i = 1, 2, ..., n$ set of banks. The most widely used models to estimate the probability of default of a bank are the probit and the logistic regression models (Arena, 2008; Bongini et al., 2001; Mannasooa and Mayes, 2009). Calabrese and Osmetti (2011) show that the probit and the logistic models could underestimate the probability of default of rare events since the link function is a symmetric function.

To overcome this drawback, Calabrese and Osmetti (2011) suggested a regression model based on extreme value theory. Embrechts et al. (1997) and Dowd (2002) give an extensive overview of extreme value theory for risk management. The Generalized Extreme Value (GEV) is very flexible and its cumulative distribution function is given by

$$F_X(x) = \exp\left\{-\left[1 + \tau\left(\frac{x-\mu}{\sigma}\right)\right]^{-\frac{1}{\tau}}\right\} \tag{2.1}$$

defined on $S_X = \{x : 1+\tau(x-\mu)/\sigma > 0\}$. In this definition, there are three parameters: τ is the tail parameter, μ the location parameter and $\sigma(> 0)$ is the scale parameter, respectively. Some well-known distributions are obtained for different values of the tail parameter τ: for $\tau > 0$ the Fréchet distribution, for $\tau < 0$ the Weibull distribution and for $\tau \to 0$ the Gumbel distribution.

Since bank defaults are, fortunateley, rare, the characteristics of bank defaults are more informative than those of non-defaults. For this reason, to focus the attention on the tail of the response curve for values close to one, that represent the characteristics of bank failures, Calabrese and Osmetti (2010) suggest the GEV cumulative distribution function as the response curve in a Generalized Linear Model

$$\pi(\boldsymbol{x}_i) = \exp\{-[1 + \tau(\boldsymbol{\beta}'\boldsymbol{x}_i)]^{-1/\tau}\}. \tag{2.2}$$

with

$$\boldsymbol{\beta}' = [\beta_0, \beta_1, ..., \beta_k] \qquad \boldsymbol{x}' = [1, x_1, ..., x_k].$$

Note that, for $\tau \to 0$ the previous model (2.2) becomes the response curve of the log-log generalised linear model.

For the interpretation of the parameters $\boldsymbol{\beta}$, if the parameter β_j (with $j = 1, 2, ..k$) is positive and all the other parameters are fixed, by increasing the j-th regressor the estimate $\pi(\mathbf{x})$ decreases. For all fixed values of τ and for a null independent variable, β_0 has a positive monotonic relationship with the estimate of $\pi(\mathbf{x})$. Finally, variations of the parameter τ do not affect $\pi(\mathbf{x})$ variations. The parameters of the GEV model can be estimated by means of (approximate) maximum likelihood method.

2.3 Joint beta regression model

We now consider modelling the regulatory capital quantities (Tier 1 or Total Capital Ratio) as response variables, functions of the available explanatory variable. A suitable distributional function for such responses, that are ratio variables, is the Beta. Since the beta density function is flexible, Calabrese (2012), within a context of recovery rate modelling, proposes a regression model under the assumption that the dependent variable is beta distributed. The following parametrization is considered

$$E(Y) = \mu \qquad\qquad var(Y) = \frac{\mu(1-\mu)}{\phi + 1}, \tag{2.3}$$

This means that the random variable Y has the following density function

$$f(y; \mu, \phi) = \frac{y^{\mu\phi - 1}(1-y)^{\phi - \mu\phi - 1}}{B(\mu\phi, \phi - \mu\phi)} \qquad 0 < y < 1 \tag{2.4}$$

with $0 < \mu < 1$ and $\phi > 0$ and where $B(\cdot, \cdot)$ denotes the beta function. Generalized Linear Models (McCullagh and Nelder, 1989) model only the mean μ and they consider the precision parameter $\phi = p + q$ as a nuisance parameter. On the other hand, Calabrese (2012) models, jointly, the mean μ and the precision parameter ϕ of the response beta random variable Y. By choosing the logit and the log functions as link functions, it follows that

$$\mu_i = \frac{1}{1 + e^{-\boldsymbol{v}_i' \boldsymbol{\eta}}} \qquad\qquad \phi_i = e^{-\boldsymbol{w}_i' \boldsymbol{\theta}},$$

with $i = 1, 2, ..., m$, where $\boldsymbol{\eta}$ and $\boldsymbol{\theta}$ are vectors of respectively k and l unknown regression parameters, $\boldsymbol{v}_i$ and $\boldsymbol{w}_i$ are the two vectors of observations on respectively k and l covariates ($k + l < m$), which are assumed fixed and known.

3 Italian empirical evidence

3.1 Data and explanatory variables

Financial statements for Italian banks and other financial institutions have been obtained from Bankscope, a comprehensive database of balance sheet and income statement data for individual banks across the world. The information covers the period 1996-2011, with observations on an annual basis.

The early warning indicators of bank failure present in Bankscope can be divided into two sets: those that are bank specific and macroeconomic or external factors that affect all banks. Overall there is no universal set of indicators used across previous studies, although there is more commonality over broad-based macrovariables, such as GDP and inflation indexes (e.g. Mannasoo and Mayes, 2009). By contrast the set of bank-specific variables is less uniform across studies.

High correlation among variables is a drawback since it leads to multicollinearity in the regression models. In order to measure the severity of multicollinearity we have computed the Variance Inflation Factor (VIF) for each explanatory variable. Firstly, we consider 14 independent variables and we remove those with a VIF higher than 5, so we obtain 11 covariates.

Finally, with regard to observations, all Italian banks with a Bankscope account are 1,053, of these only for 783 banks all data are available.

3.2 Determinants bank failure

Financial ratios associated with the CAMELS rating system will be used to measure bank-level fundamentals related to asset risk and leverage, assuming that these ratios capture the market, credit, operational, and liquidity risk faced by banks. These ratios are used as explanatory variables of bank failure in our proposed model and, therefore, whether significant, can be interpreted as determinants of such failure. Moreover, capital ratios monitored by Basel III and macroeconomic variables are also included in the model. In compliance with Basel III, our model attempts to predict bank failure one year in advance. Therefore, all explanatory variables are evaluated one year in advance, with respect to the time in which a bank response variable (default or non-default) is evaluated. We apply the logistic model and the GEV model described in Section 2.2 to both the definitions of bank failure. Since the percentage of defaults for the "restricted definition" is 4.469%, the logistic regression model is unsuitable to correctly classify "good" and "bad" banks (Calabrese and Osmetti, 2010). Hence, we report only the estimation results of the GEV model.

Table 1 shows our obtained estimates, when the definition of bank failure includes only banks bankrupted, dissolved or in liquidation. Conversely, Tables 2 shows the obtained results by including mergers and acquisitions in the definition of bank failure. Comparing the results in Table 1 with those in Table 2, the first relevant finding is that financial and capital ratios are significant to explain the first definition of default but not for the second definition. This outcome confirms that mergers and acquisitions might have been carried for strategic rather than for distress reasons. They seem indeed to be strongly influenced by the economic cycle, since Table 2 shows that most macroeconomic variables (with the exclusion of the interest rate) are important for the second definition of bank failure. To complete the picture, note that Tier 1 capital ratio is the only financial and/or capital ratio that is significant (at 5%) for the "enriched" definition of default that includes mergers and acquisitions. On the other hand, the inflation rate is the only macroeconomic variable that is significant (at 5%) for the "restricted" definition of default.

To understand how the explanatory variables affect bank distress, we highlight that, when the parameter estimate is positive, by increasing the corresponding variable and fixing all the others, the estimate of the probability of bank default decreases (Calabrese and Osmetti, 2011) and, conversely, when the estimate is negative.

For financial and capital variables, the signs and the magnitude of the estimates can be read off Table 1. Regarding asset quality, the amount of loss reserves is significant and is expected to be negatively related to the risk of bank failure: the higher the coverage, the lower the risk, as expected; the loans to assets ratio, instead, is positively related, in accordance with what expected, analougosly to Arena (2008), Ashcraft (2008) and Boyd et al. (2009). The ROA variable is, on the other hand, negatively correlated with the probability of failure. The signs of the estimates in Table 1 coincide with what expected also for the solvency ratio, equity to total assets, as in Arena (2008): higher

Variable	Estimate	Std. Error	z value	Pr$(>\lvert z\rvert)$
τ	-1.42	0.673		
Intercept	5.908e+01	3.457e+01	1.709	0.08743 .
	Asset quality			
Loan loss Reserve Gross	2.640e-01	8.513e-02	3.101	0.00193 **
Loans to assets	-3.119e-06	1.494e-06	-2.088	0.03678 *
	Return on assets			
ROA	7.260e-02	2.868e-02	-2.531	0.01137 *
	Solvency			
Equity/Total Assets	3.898e-01	1.419e-01	2.748	0.00600 **
	Liquidity			
Liquid Assets/Tot Dep Bor	-6.450e-02	2.748e-02	-2.347	0.01890 *
	Capital ratios			
Tier 1 capital ratio	8.104e-01	2.747e-01	-2.950	0.00318 **
Total capital ratio	4.132e-01	2.116e-01	1.953	0.05084 .
	Macroeconomic variables			
Growth rate GDP	3.729e+01	3.896e+01	-0.957	0.33851
Inflation rate	-5.809e-01	3.054e-01	-1.902	0.05713 .
Unemployment rate	-1.591e+00	1.008e+00	-1.579	0.11438
Interest rate	-7.374e-01	6.957e-01	1.060	0.28919

Table 1: Signif. codes: 0 “***” 0.001 “**” 0.01 “*” 0.05 “.” 0.1 “ ” 1 Parameter estimates on 783 Italian banks from 1996 to 2011. The definition of failure includes bankruptcy (no bank), dissolved (16 banks) and in liquidation (19 banks).

solvency implies lower risk of failure.

Concerning liquidity risk, we consider a deposit run off ratio and look at what percentage of deposit and borrowings could be met if they were withdrawn suddenly. In contrast with what expected expectations (Arena, 2008), this ratio turns out to be positively related

Variable	**Estimate**	**Std. Error**	**z value**	**Pr**$(>\|z\|)$
τ	-0.148	0.189		
Intercept	5.471e+01	1.132e+01	4.832	1.35e-06 ***
	Asset quality			
Loan loss Reserve Gross	6.760e-02	4.567e-02	1.480	0.13885
Loans to assets	-1.269e-09	7.568e-09	-0.168	0.86681
	Return on assets			
ROA	1.946e-01	2.281e-01	-0.853	0.393595
	Solvency			
Equity/Total Assets	-4.298e-02	5.718e-02	-0.752	0.45224
	Liquidity			
Liquid Assets/Tot Dep Bor	-2.006e-03	1.160e-02	-0.173	0.86271
	Capital ratios			
Tier 1 capital ratio	1.840e-01	9.570e-02	-1.923	0.05454 .
Total capital ratio	1.526e-01	9.449e-02	1.615	0.10624
	Macroeconomic variables			
Growth rate GDP	1.660e+01	5.561e+00	-2.985	0.00284 **
Inflation rate	-4.938e-01	8.319e-02	-5.935	2.93e-09 ***
Unemployment rate	-1.133e+00	3.536e-01	-3.204	0.00135 **
Interest rate	-2.590e-01	3.547e-01	0.730	0.46522

Table 2: Signif. codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1 Parameter estimates on 783 Italian banks from 1996 to 2011. The definition of failure includes bankruptcy (no bank), dissolved (16 banks), in liquidation (19 banks), merged or acquired (306 banks).

to the risk of bank failure. Wolf (2006) explains that event though higher asset liquidity directly benefits stability by encouraging banks to reduce the risks on their balance sheets and facilitating the liquidation of assets in a crisis, it also makes crisis less costly for banks. As a result, banks have an incentive to take on an amount of new risk that more than offsets the positive direct impact on stability. Finally, as expected, the capital ratio parameters are both negatively correlated with the risk of bank failures. Between the two, the most significant is the Tier1 capital ratio.

Concerning macroeconomic variables, their effects should be read from Table 2. The estimates in Table 2 show that, while an increase in the GDP growth rate has a negative effect on the risk of bank distress (it decreases the risk), an increase in the inflation rate or in the unemployment rate has a positive effect (they increase the risk). Macroeconomic effects, therefore, are in line with the expectations and this seems to be a valid conclusion especially as merger and acquisition events do prevail in the data behind Table 2. Note finally that, among the macroconomic variables, the macroeconomic interest rate does not seem to have a significant effect on bank failure.

3.3 Model comparison

The main aim of this subsection is to show that the GEV model overcomes the drawback of the logistic regression in the PD underestimation. The performance of models can be highly sensitive to the data sample used for validation. To avoid embedding unwanted sample dependency, models should be validated on observations that are not included in the sample used to estimate the model. Hence, we run out-of-sample validation to compare the GEV and the logistic regression models. For this aim we consider the confusion matrix (Figini and Giudici, 2009), the Area Under the Curve (AUC) index (Hand, 2001), the H measure (Hand, 2009 and 2010), the MAE and MSE so defined

$$MAE = \frac{\sum_{i=1}^{n} |y_i - \hat{y_i}|}{n} \qquad MSE = \frac{\sum_{i=1}^{n} (y_i - \hat{y_i}^2}{n}.$$

We consider the H measure since it overcomes the drawbacks of the AUC when the class sizes and the classification error costs are extremely unbalanced (Hand, 2009 and 2010); both these characteristics are satisfied by credit scoring models.

To assess the predictive performance of the GEV model and the logistic model for the two definitions of bank failure mentioned above, we implement a cross-validation procedure. We use 70% of the observations as training set and 30% as validation set. For simplicity, we report the false positive rate (the number of predicted defaults that do not occur over the number of non-defaults) and the false negative rate (the number of predicted non-defaults that actually default over the number of defaults) predictions of the two models only for a control sample in Table 3.

It is much more costly to classify a bank as good-performing when it is in bankruptcy than to classify a bank as in bankruptcy when it is safe. In particular, when a bankrupted bank is classified as good-performing by the scoring model, the economic system keeps on lending to the bank. If the bank becomes in bankruptcy, the lenders can loose their loans, with strong consequence on the stability of the economic system. On the contrary, when a good-performing bank is classified as in bankruptcy, the Bank of Italy could give state aid, which will give back when the good performance of the bank is verified. For this reason, the identification of bank failures is a pivotal aim for central banks. For all these reasons, false negative errors are more important than false positive errors. Table 3 shows that false negative errors for the logistic model are much higher than the ones for the GEv model.

Model	False positive rate	False negative rate
Logistic regression on failures	0.0172	0.6225
GEV regression on failures	0.0732	0
Logistic regression on failures & mergers	0.0287	0.1538
GEV regression on failures & mergers	0.1724	0.0153

Table 3: Prediction errors of the logistic and the GEV regression models on the control sample.

Table 4 and Table 5 report the means of [2]the H measure, AUC, MAE and MSE. Our proposal shows the means of MAE lower than the respective errors of the logistic regression model for both the definitions of bankruptcy. The mean of MSE is lower for the GEV model if defaults are defined as failures and mergers, but it is slightly higher than the logistic one for the first definition of default. From Table 4, the average H measure for the GEV model is always higher than the same measure for the logistic regression model. On the contrary, this

[2]To compute the H measure and AUC, we use the H measure package of R-program. For the H measure we consider a severity ratio of 0.01 for true defaults and 0.001 for all defaults.

Definition of default	*Error*	*Models*	
		GEV regression	*Logistic regression*
Failures	MAE	0.0231	0.0321
	MSE	0.0220	0.0219
	AUC	0.7134	0.7889
	H	0.5779	0.5295
Failures & Mergers	MAE	0.0742	0.0758
	MSE	0.0357	0.0378
	AUC	0.8846	0.9380
	H	0.7511	0.7437

Table 4: Average forecasting accuracy measures for different PDs on the control sample.

relationship is inverted if we consider the AUC. To understand this result we should consider that the H measure is equivalent to averaging the misclassification loss over a cost ratio distribution which enables us to represent the highly unbalanced misclassification costs. Instead, this weight function in the AUC depends on the score distributions (Hand, 2009), so different classifiers are incoherently evaluated using different metrics.

3.4 Capital requirements under Basel III

To better understand the minimum capital requirements of Basel III, in this section we estimate the factors contributing to banks' target capital ratios. The Tier 1 Capital ratio and Total Capital ratio share the same denominator, which is a risk-weighted sum of banks on-balance sheet and off-balance sheet activities. However, the tier 1 capital ratio and total capital ratio differ with respect to their numerator: while the former consists of only tier 1 capital, the latter consists of both tier 1 and tier 2 capitals. Tier 1 capital, also called core capital, consists mainly of stockholder equity capital and disclosed reserves, whereas tier 2 capital or 'supplementary capital' includes elements like undisclosed reserves and subordinated debts (provided that their maturity do not exceed five years). The difference between tier 1 and tier 2 capital thus emphasizes the extent to which capital of a bank is permanent or not.

Variable	Estimate	Std. Error	t value	Pr$(>\|t\|)$
Intercept	-5.552	0.858	-6.470	1.717e-10 ***
	Asset quality			
Loan loss Reserve Gross	0.018	0.003	5.804	9.407e-09 ***
Loans to assets	-1.514	0.113	-13.369	6.916e-37 ***
	Return on assets			
ROA	0.033	0.016	1.990	0.004 *
	Solvency			
Equity/Total Assets	0.080	0.002	32.391	5.401e-147 ***
	Liquidity			
Liquid Assets/Tot Dep Bor	-0.007	0.001	-6.568	9.253e-11 ***
	Macroeconomic variables			
Growth rate GDP	0.618	0.609	1.014	0.311
Inflation rate	-0.018	0.006	3.058	2.300e-03 ***
Unemployment rate	-0.090	0.025	3.485	5.187e-04 ***
Interest rate	0.041	0.027	1.522	0.128

Table 5: Signif. codes: 0 “***” 0.001 “**” 0.01 “*” 0.05 “.” 0.1 “ ” 1 Parameter estimates on 783 Italian banks from 1996 to 2011. The dependent variable is the Tier 1 Capital Ratio.

Basel I and Basel II, which are the relevant regulation for our dataset, stipulate that the Tier 1 ratio should exceed 4 % (Basel Committee on Banking Supervision, 1988, 2004). This minimum increases to 6% by Basel III, plus a conservation buffer of 2,5%. Instead, the lower limit for the Total capital ratio is 8%, plus a conservation buffer.

In this analysis we would like to understand whether capital ratios (and which of them) can be assumed as early warning indicators for banking distress. For this reason, they will be taken as response variables, playing the same role as the failure event in the previous subsection. As explanatory variables, all previously considered variables will be taken, both at the micro and at the macroeconomic level. As before, in compliance with the regulations, the explanatory vari-

Variable	**Estimate**	**Std. Error**	**t value**	**Pr**$(>\|t\|)$
Intercept	-5.298	0.703	-7.533	1.346e-13 ***
		Asset quality		
Loan loss Reserve Gross	0.014	0.003	4.871	1.340e-06 ***
Loans to assets	-1.439	0.106	-13.457	2.364e-37 ***
		Return on assets		
ROA	0.019	0.015	1.211	0.226
		Solvency		
Equity/Total Assets	0.070	0.002	29.390	3.057e-129 ***
		Liquidity		
Liquid Assets/Tot Dep Bor	-0.006	0.001	-5.993	3.112e-09 ***
		Macroeconomic variables		
Growth rate GDP	0.663	0.575	1.153	0.249
Inflation rate	-0.019	0.005	3.748	1.910e-04 ***
Unemployment rate	-0.090	0.022	4.085	4.859e-05 ***
Interest rate	0.046	0.020	2.294	0.002 ***

Table 6: Signif. codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1
Parameter estimates on 783 Italian banks from 1996 to 2011. The dependent variable is the Total Capital Ratio.

ables have been evaluated one year in advance with respect with the corresponsding response variable. In order to obtain a variable constrained to the unit interval, Tier 1 Capital ratio and Total Capital ratio are standardized. To these values we apply the joint beta regression model, examined in Section 3.3. The estimate results are reported in Table 3 and Table 4.

By comparing the results in Table 3 and Table 4, note that the determinants of Tier 1 Capital ratio and Total Capital ratio are very similar, both in terms of sign and magnitude of their effects. The only differences are that Return On Assets is a significant determinant for the Tier 1 Capital ratio but not for the Total Capital ratio and the interest rate is relevant to explain the Total Capital ratio but not the Tier 1 Capital ratio.

Comparing either Table 3 or 4 with Tables 1 and 2, note that the signs of the coefficients of the explanatory variables are rather concordant: a higher coverage, a higher ROA and a higher solvency ratio lead to a lower risk of bank failure; while a higher Loan to Assets ratio, a higher liquidity ratio, a higher inflation rate and a higher unemployment rate all lead to a higher risk of bank failure. The only difference is the GDP growth rate which does not seem to have a significant effect, when a capital ratio is used as a "failure indicator", differently from what happens when the actual failure event variable is being used.

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