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CREDIT RISK AND BUSINESS CYCLE OVER DIFFERENT REGIMES

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ABSTRACT

In the recent banking literature on the relationship between credit risk and business cycle, the presence of asymmetric effects both across credit risk regimes and through the business cycle has been generally neglected. Employing threshold regression models both at the aggregate and the bank level and exploiting a unique dataset on Italian bank borrowers' default rates, this paper analyzes whether this relationship is characterized by regime switches and thus by asymmetries, determining endogenously the thresholds. Our results show that not only are the effects of business cycle on credit risk more pronounced during downturns but also when credit risk conditions are worse.

JEL Classification: C22, C23, G21, G28

Keywords: Credit Risk, Panel Threshold Regression Models, Regime Switching, Default Rate, Business Cycle

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I. Introduction

In the recent banking literature, the relationship between credit risk and business cycle has been analyzed for both (macro) financial stability and (micro) risk management purposes. Indeed, the potential impact of economic developments on banks' portfolios is relevant for both policy makers, interested in forecasting and preventing banks' instability due to unfavorable economic conditions, and risk managers, who pay attention to the robustness of their capital allocation plans under different scenarios. These different perspectives are not mutually exclusive. In fact, the reform of the Basel Accord on banks' capital requirements made it clear the need to match both the micro and macro dimensions.

From a macro prudential point of view, many analyses have quantified the effects of macroeconomic conditions on asset quality (for a survey, see Quagliariello, 2007). As an example, Pesola (2001) shows that shortfalls of GDP growth below forecast contributed to the banking crises in the Nordic countries, while Salas and Saurina (2002) document that macroeconomic shocks are quickly transmitted to Spanish banks' portfolio riskiness. Similarly, using Italian data, Marcucci and Quagliariello (2007) find that bank borrowers' default rates increase in downturns. Meyer and Yeager (2001) and Gambera (2000) document that a small number of macroeconomic variables are good predictors for the share of non-performing loans in the US. Similarly, Hoggarth *et al.* (2005) provide evidence of a direct link between the state of the UK business cycle and banks' write-offs. Analogous evidence is provided in cross-country comparisons by Bikker and Hu (2002), Laeven and Majoni (2003) and Valckx (2003).

However, the vast majority of these studies generally neglect asymmetric effects, i.e., the possibility that the impact of macroeconomic conditions on banks' portfolio riskiness is dissimilar in different phases of the business cycle.[1]

By contrast, these asymmetries are somewhat taken into account in a number of studies on credit risk management. In particular, some studies on the properties of credit rating transition matrices (i.e., of the probability of borrowers to migrate from a rating class to another) over the cycle have analyzed whether transition probabilities are affected to a larger (smaller) extent by recessionary (expansionary) conditions. Regime switching models are commonly used for this kind of investigations. On the basis of GDP growth, Nickell *et al.* (2000) divide the business cycle into three categories (peaks, normal times and troughs) finding that in peaks low-rated bonds are less prone to downgrades. The impact of macroeconomic conditions appears therefore to be asymmetric and dependent on the starting creditworthiness of each borrower.

In their analysis of the linkage between macroeconomic conditions and migration matrices Bangia *et al.* (2002) distinguish two states of the economy, expansion and recession, and condition the transition matrix to these states. Their findings suggest that downgrading probabilities, particularly in the extreme classes, increase significantly in recessions. Pederzoli and Torricelli (2005) adopt a similar framework in order to assess the impact of the business cycle on capital requirements under Basel 2. This approach requires the identification of expansions/recessions based on some external sources.[2] In our view, a further shortcoming of this literature is that

[1] To the best of our knowledge, the only exception is the paper by Gasha and Morales (2004) who apply a SETAR model to country-level data showing that GDP growth affects non-performing loans only below a certain threshold.

[2] Most studies in this field employ the NBER business cycle classifications. Lucas and Klaassen (2005) cast serious doubts on their use.

the hypothesis that asymmetries depend on the severity of the recession rather than on the dichotomy expansion/recession is completely ignored.

In this paper, we analyze the asymmetries in the relationship between credit risk and business cycle using threshold regression models both at the aggregate level and the bank level. We test whether the impact of the business cycle is more pronounced when either credit risk levels are higher or economic conditions are worse, identifying endogenously the threshold over/below which such impact is different. We start with a standard threshold regression approach at the aggregate level and then move ahead, suggesting some panel threshold regression models with one or more threshold variables. These can be interpreted as regime switching panel data models where each regime is determined endogenously through one or more observable threshold variables. Also, we exploit a unique dataset on Italian borrowers' default rates at the bank level. We also suggest an innovative four-regime approach with two different threshold variables which allows us to provide a more comprehensive picture of the behavior of default rates over changing economic and credit risk conditions.

At the aggregate level, we find that banks' portfolio riskiness is mostly affected by the business cycle during downturns and also when portfolio quality is not good. In addition, macroeconomic conditions tend to affect banks' portfolio riskiness mainly during slowdowns.

Similar results are obtained exploiting the cross-sectional dimension of our rich dataset. For those banks with lower asset quality, the increase in default rates due to one percentage point decrease in the output gap (our measure of the business cycle) is almost nine times higher than the effect for those banks with better portfolios. Furthermore, from our results, we notice that the impact of business cycle on credit risk is stronger the lower the banks' asset quality for models with two or more regimes with one threshold variable.

In the four-regime model, where we combine credit risk and business cycle regimes, we find that i) during economic slowdowns, the impact of the business cycle on portfolio riskiness for banks with lower asset quality is three times higher than that for sound banks. Also, ii) the impact of business cycle on credit risk for banks with lower asset quality (the a priori riskier ones) during recessions is almost five times higher than what we have during booms. In addition, iii) during recessions the impact of business cycle on credit risk for banks with better asset quality is almost the double of that during expansions. Finally, iv) the impact of business cycle on banks' riskiness during expansionary phases is substantially the same both for riskier and less risky banks.

In sum, riskier banks' portfolios are more cyclical (i.e., more sensitive to the business cycle) than less risky ones and cyclicality is more pronounced in bad economic times. Several checks strongly support the robustness of our empirical results under different hypotheses and circumstances.

Under the Basel 2 new Capital Accord, which introduces risk sensitive capital requirements, this evidence may provide some guidance to banks and supervisors in the choice of adequate capital buffers over different phases of the business cycle. Furthermore, the methodology we propose may be easily adopted for stress testing purposes.

The paper is organized as follows. Section II describes the data on Italian banks' portfolios. Section III presents the single threshold model at the aggregate level with two regimes and the related empirical results. In section IV we describe the panel data model with single threshold variable and multiple regimes (both credit risk and business cycle regimes) along with the empirical results. Section V delineates the panel data model with two different threshold variables and four regimes and the associated empirical results. Finally, section VI draws some concluding remarks and directions for further research.

II. Data

Our data set comprises both data on Italian banks and macroeconomic time series on a quarterly basis for a period spanning from 1989Q4 to 2005Q2. Accounting ratios for the individual institutions are built up using the statistics that intermediaries are required to report to the Bank of Italy while the macroeconomic variables are drawn from the OECD statistics.

Since we want to analyze the evolution of banks' portfolio riskiness over the business cycle, the starting point for building up our dataset is the choice of an adequate measure of credit risk.

In Italy, banks must value loans in their portfolios at their estimated realizable value. In particular, the exposures to insolvent borrowers are classified as bad loans. Since Italian banks tend to correctly classify their exposures with appropriate timing (Moody's, 2003) and bad loans are a good ex-post indicator of the riskiness of banks' debtors, we compute our riskiness indicator as the ratio of the flow of loans classified as bad debts in the reference quarter to the stock of outstanding performing loans at the end of the previous one. The ratio can be interpreted as the default rate of Italian banks' borrowers. With respect to other riskiness indicators, based on stock measures, such as the non-performing loan ratio, the default rate is a more precise and timely proxy for banks' portfolio riskiness.[3]

Since default rates from the Central Credit Register are available at the bank level, we can exploit the cross-sectional dimension and work at different levels of aggregation, from the whole banking system to each single bank's portfolio.

The initial dataset on individual banks goes from 1989Q1 to 2005Q2 with a total of 44,293 bank-quarter observations. The first quarter is deleted to compute the default rate. We have also excluded those banks with incomplete (or missing) information or those characterized by extreme observations for the variables of interest. We have then balanced the panel so that the resulting final dataset includes 212 banks spanning from 1990Q1 to 2005Q2 for a total of 13,144 observations. In the final sample we have 73 limited banks, 18 cooperative banks and 121 mutual banks for 62 quarters.

Regarding the proxy for the Italian business cycle, we focus on the output gap, defined as the difference between the actual and the potential gross domestic product. We compute a first measure of the output gap as the difference between the actual output and an estimate of the potential given by a linear trend (GAPT). For robustness, as alternative proxies, we employ also the deviations of the GDP series from the Hodrick-Prescott filtered series (GAPHP) and the usual GDP growth rate (GDPG).[4] Figure 1 depicts all the three macroeconomic time series. The shaded areas show the recessions in the Italian economy according to the *Istituto di Studi e Analisi Economica*

[3] A stock measure can be misleading because of write-offs and securitizations, which reduce the total amount of bad loans regardless the actual change in portfolio's riskiness.

[4] The use of regional breakdowns for GDP may provide valuable insights on possible differences across different geographical areas. Unfortunately, these data are not available on a quarterly basis.

(ISAE).[5] Within our sample period, the ISAE identifies 3 recessions: 1992Q2-1993Q2, 1995Q4-1996Q3 and 2001Q1-2004Q4. While the two measures of output gap correctly signal all the three recessions, the GDP growth is more ambiguous for the last one. This is due to the fact that the 2001-2004 recession is in reality a period of prolonged stagnation, as suggested by the ISAE which refers to this period as an anomalous cycle.

[Figure 1 about here]

Table 1 reports the summary statistics of the final sample, both the bank level and the macro data on alternative indicators of the Italian business cycle. The disaggregated default rate is related to the final sample of 212 banks while the aggregate one gives the characteristics of the time series. The individual default rate has a mean of about 0.30% and a median of 0.26% with a right-skewed distribution. The time series of the aggregate default rate shows a mean of 0.55% and a less skewed distribution with respect to the individual series. The second micro variable is the logarithm of all banks' total assets (in million of euros) which is used as a proxy for banks' size. The last micro variable is the difference between the loan growth rate of each bank *i* at time *t* and the average loan growth rate for each quarter. This variable is added to control for more active banks in lending activities, which may relax credit standards and have riskier portfolios, *ceteris paribus*.[6]

[Table 1 about here]

[5] The ISAE is an Italian Research Institute which provides an 'almost' official chronology of the Italian business cycle. We say 'almost' official because in Italy there is not an officially accepted business cycle chronology as that one of the NBER for the United States. To take care of the specific features of the Italian economy, the ISAE does not adopt the NBER methodology, but the one suggested by Altissimo *et al.* (2000).

[6] Also, the use of the loan growth rate could duplicate the signal from the business cycle indicator.

III. Single Threshold Model at the Aggregate level with Two Regimes

A. The Model

Our starting hypothesis is that the default rate is affected by the business cycle and that such impact is subject to one or more regime-switches that characterize asymmetries. If the observed data on the dependent variable (default rate) are $dr_1, \dots, dr_T$, the simplest model that relates the latter with macroeconomic conditions (proxied by a measure of the output gap, GAP_t) under the hypothesis of one regime only (i.e. with no thresholds) can be written as

$$dr_t = \beta_{01} + \beta_{11} GAP_{t-1} + e_t \tag{1}$$

where e_t is assumed to be a martingale difference sequence with respect to the sigma algebra generated by the past history of the variables. This model can be simply estimated by OLS. A more general model allows for the presence of two regimes defined by an observable threshold variable q_t that can be either the dependent or the independent variable.[7] In the former case, the model becomes

$$dr_t = \left(\beta_{01} + \beta_{11} GAP_{t-1}\right) I\left(dr_t \le \gamma\right) + \left(\beta_{02} + \beta_{12} GAP_{t-1}\right) I\left(dr_t > \gamma\right) + e_t \tag{2}$$

[7] Threshold regression models are regime-switching models where each regime is determined by the value of a particular observable threshold variable. These models differ from the regime-switching models *à la* Hamilton (Hamilton, 1989) because in the latter each regime is governed by an unobserved state variable which is usually modeled as a first-order Markov chain. For details see Hamilton (1994) or Franses and Van Dijk (2000).

where $I(\cdot)$ is the indicator function and γ is the threshold.[8] In this case we are distinguishing the two regimes with respect to the overall credit risk conditions. The model gives an estimate of γ which can be viewed as the threshold $\hat{\gamma}$ that characterizes good credit risk conditions, i.e. $I(dr_t \leq \hat{\gamma})$, from bad credit risk conditions, i.e. $I(dr_t > \hat{\gamma})$.

When the threshold variable is the independent variable, the model becomes

$$dr_t = (\beta_{01} + \beta_{11} GAP_{t-1}) I(GAP_{t-1} \leq \gamma) + (\beta_{02} + \beta_{12} GAP_{t-1}) I(GAP_{t-1} > \gamma) + e_t \qquad (3)$$

Here we characterize each regime depending on the general macroeconomic conditions, distinguishing between recessionary conditions $I(GAP_{t-1} \leq \hat{\gamma})$ and expansionary phases $I(GAP_{t-1} > \hat{\gamma})$. The models can be more compactly represented as

$$dr_t = GAP_{t-1}(\gamma)'\theta + e_t \qquad (4)$$

where $GAP_{t-1}(\gamma) = \left(GAP'_{t-1} I(q_t \leq \gamma), GAP'_{t-1} I(q_t > \gamma)\right)$, $GAP'_{t-1} = (1, GAP_{t-1})'$ and $\theta = (\beta_{01}, \beta_{02}, \beta_{11}, \beta_{12})$. The parameters of interest are the coefficients θ and the threshold γ. Even though the regression equation (4) is non linear in the parameters, it can be estimated through least squares (LS). Under the additional assumption that $e_t \sim N(0, \sigma^2)$, LS is equivalent to maximum likelihood estimation. These models can be estimated by sequential conditional LS. For any given value of γ, the LS estimate of θ is

[8] For convenience, throughout the paper we use γ or γ_j to indicate the threshold independently of the threshold variable.

$$\hat{\theta}(\gamma)=\left(\sum_{t=1}^{T}GAP_{t-1}(\gamma)GAP_{t-1}^{'}(\gamma)\right)^{-1}\left(\sum_{t=1}^{T}GAP_{t-1}(\gamma)dr_t\right) \tag{5}$$

with residuals $\hat{e}_t(\gamma)=dr_t-GAP_{t-1}^{'}(\gamma)\theta(\gamma)$ and residual variance $\hat{\sigma}_T^2(\gamma)=T^{-1}\sum_{t=1}^{T}\hat{e}_t(\gamma)^2$. The LS estimate of γ is the value that minimizes the residual variance, i.e.

$$\hat{\gamma}=\arg\min_{\gamma\in\Gamma}\hat{\sigma}_T^2(\gamma) \tag{6}$$

where $\Gamma=\left[\underline{\gamma},\overline{\gamma}\right]$. The minimization problem in (6) can be solved by direct search. The residual variance $\hat{\sigma}_T^2(\gamma)$ takes on at most T distinct values as γ varies. Thus, to obtain the LS estimates of (6) we can run OLS regression of (4) for $\gamma\in\Gamma$, where the elements of Γ are slightly less than T because we have to take a certain percentage $(\eta\%)$ of observations out to ensure that each regime has a minimum number of observations. Then the value of γ that minimizes the residual variance is the LS estimate of the threshold parameter. The LS estimates of the coefficients θ are then found as $\hat{\theta}=\hat{\theta}(\hat{\gamma})$. Similarly, the LS residuals are $\hat{e}=dr_t-GAP_{t-1}(\hat{\gamma})'\hat{\theta}$, with sample variance $\hat{\sigma}_T^2=\hat{\sigma}_T^2(\hat{\gamma})$.[9]

An important question is whether it is statistically sensible to move from the linear specification in (1) to the model in (2). The relevant null hypothesis that there are no asymmetries in the relationship between credit risk and business cycle is

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[9] Since the estimated threshold is superconsistent (Chan, 1993), to make inference on the slope parameters we can act as if the threshold were known using standard asymptotic theory for LS estimates. Thus our confidence intervals for the estimated parameters are throughout the paper conditional on the estimated threshold. Nevertheless, following Hansen (1999), to make inference on the estimated thresholds we invert the LR test.

$H_0 : \beta_{j1} = \beta_{j2}$, $j = 0,1$. From an econometric point of view this testing problem is non standard because there are some parameters that under the null are not identified (the so-called 'Davies' problem'). Based on the theories of Davies (1977, 1987) and Andrews and Ploberger (1994), Hansen (1996) shows that if the errors are *iid*, a test with near-optimal power against alternatives distant from the null hypothesis is the standard *F*-statistic

$$F_T = T\left(\frac{\tilde{\sigma}_T^2 - \hat{\sigma}_T^2}{\hat{\sigma}_T^2}\right) \tag{7}$$

where $\tilde{\sigma}_T^2 = T^{-1}\sum_{t=1}^{T}\left(dr_t - GAP_{t-1}'\tilde{\theta}\right)^2$ is the residual variance under the null hypothesis and $\tilde{\theta}$ is the OLS estimate under the null of no threshold, i.e.

$$\tilde{\theta} = \left(\sum_{t=1}^{T} GAP_{t-1}GAP_{t-1}'\right)^{-1}\left(\sum_{t=1}^{T} GAP_{t-1}dr_t\right) \tag{8}$$

Since F_T is a monotonic function of $\hat{\sigma}_T^2$, it has been shown that $F_T = \sup_{\gamma\in\Gamma} F_T(\gamma)$ where $F_T(\gamma) = T\left(\tilde{\sigma}_T^2 - \hat{\sigma}_T^2(\gamma)\right)/\hat{\sigma}_T^2(\gamma)$ is the pointwise *F*-statistic against the alternative $H_1 : \beta_{j1} \neq \beta_{j2}$ when γ is known. Since γ is not identified, the asymptotic distribution of F_T is not a χ^2. Hansen (1996) shows that the asymptotic distribution of F_T can be approximated by a bootstrap procedure. Letting u_t^*, $t = 1,\ldots,T$ be *iid* $N(0,1)$ and setting $dr_t^* = u_t^*$, we can regress dr_t^* on the observations GAP_{t-1} to obtain $\tilde{\sigma}_T^{*2}$ and on $GAP_{t-1}(\gamma)$ to obtain $\hat{\sigma}_T^{*2}$. Thus we can form the statistic $F_T^*(\gamma) = T\left(\tilde{\sigma}_T^{*2} - \hat{\sigma}_T^{*2}(\gamma)\right)/\hat{\sigma}_T^{*2}(\gamma)$ and $F_T^* = \sup_{\gamma\in\Gamma} F_T^*(\gamma)$. Hansen (1996) shows that the distribution of F_T^* converges weakly in probability to the null distribution of F_T

under local alternatives for θ. Therefore, repeated bootstrap draws from F_T^* can be used to approximate the asymptotic null distribution of F_T. The bootstrap approximation to the asymptotic *p*-value of the test is constructed by counting the percentage of bootstrap samples for which F_T^* exceeds the observed F_T. If the errors are conditionally heteroskedastic, it is necessary to replace the *F*-statistic $F_T(\gamma)$ with a heteroskedasticity consistent Wald or Lagrange multiplier test. Setting $R = [I \quad -I]$, $M_T(\gamma) = \sum_{t=1}^{T} GAP_{t-1}(\gamma) GAP_{t-1}(\gamma)'$ and $V_T(\gamma) = \sum_{t=1}^{T} GAP_{t-1}(\gamma) GAP_{t-1}(\gamma)' \hat{e}_t^2$, then the pointwise Wald statistic is

$$W_T(\gamma) = \left(R\hat{\theta}(\gamma)\right)' \left[R\left(M_T(\gamma)^{-1} V_T(\gamma) M_T(\gamma)^{-1}\right) R' \right]^{-1} R\hat{\theta}(\gamma) \tag{9}$$

and the appropriate test for the null is $W_T = \sup_{\gamma \in \Gamma} W_T(\gamma)$. To obtain the bootstrap *p*-value, it is sufficient to repeat the bootstrap procedure as before setting $dr_t^* = \hat{e}_t u_t^*$.

B. *Empirical Results*

Table 2 reports the results for the two-regime threshold model estimated using aggregate data. Given the short time span of our data, in our preferred parsimonious model, the default rate *dr* only depends on one-quarter lag of the business cycle indicator. The results for model 1 confirm the well-known negative relationship between default rates and business cycle, when there are no regime changes.[10]

[10] A negative coefficient on the output gap means that during recessionary conditions (i.e. when the output gap is negative) banks' riskiness increases.

Our second set of results show the impact of the business cycle depending on the level of banks' riskiness, proxied by either contemporaneous or lagged default rate (*dr*), respectively models 2 and 3. We note that there is a regime switch when bank borrowers' default rates are above a threshold of 0.54% which is very close to both the mean and median of the aggregate default rate.[11] In particular, the statistical significance and magnitude of β_{12} suggest that when asset quality is lower, economic conditions have a statistically significant impact on banks' riskiness. By contrast, in less-risky periods (i.e. when *dr* is below the threshold) the impact of the business cycle on default rates is almost nil and not significant. The LR test for the null of no regime switch is significant at any conventional level, suggesting that the model is appropriate.[12]

As we mentioned above, an advantage of our methodology is that it allows to obtain an endogenous estimate of the threshold. Looking at Table 2, we observe that the value of the threshold is very similar across models and specifications, ranging between 0.54 and 0.58%. Taken at its face value, this means that when the aggregate default rate is above these figures, the banking system tends to be more sensitive to macroeconomic turbulences. In a macro prudential perspective, this advises supervisory authorities to reinforce monitoring activities in these periods.

[Table 2 about here]

[11] Using quantiles as the thresholds might be an alternative to our approach. However, our methodology has the significant advantage of determining endogenously the threshold, without imposing any a priori assumption on its value.

[12] To check the robustness of our results we estimated the same models with different proxies of the business cycle and more lags for the threshold variable. Our results (not reported for the sake of brevity) are not affected by the choice of a longer lag for the threshold variable and are robust to the use of different proxies for the business cycle (GAPHP and GDP growth).

With model 4, we try to assess whether the impact of the business cycle on Italian banks is also subject to a second kind of regime switch, which depends on the phase of the business cycle itself. Our results suggest that in recessions the impact of the business cycle on credit risk is statistically significant and more pronounced than in expansionary phases when the impact is less intense and insignificant. Again, these results are generally robust to the use of different business cycle indicators.

C. Different Bank Categories

In order to check the robustness of our results, we re-estimate the models at different levels of aggregation. In particular, we classify banks into three different institutional categories (limited companies, cooperative banks and mutual banks) that present different risk-levels. As a matter of fact, mutual and cooperative banks have a lower riskiness than limited companies while mutual banks have the lowest riskiness compared to the other two institutional categories. This may be related to the fact that mutual and cooperative banks operate more locally than limited banks, thus having a better knowledge of their borrowers' creditworthiness. Table 3 shows that the econometric results are substantially unchanged with respect to those presented above for the aggregate case.

[Table 3 about here]

The impact of macroeconomic conditions on credit risk is negative and statistically significant when the quality of banks' portfolios is lower, while it is not significant when portfolios are less risky. β_{11} is significant at the 10 per cent level for limited banks; however, its magnitude is considerably lower than that of β_{12}. The LR tests reject the null of no regime switch at any conventional level. The estimated thresholds are very close across the three categories and similar to those obtained with the aggregate models. When *GAPT* is the threshold variable, the results for models 4, 8 and 12 confirm that the relationship between business cycle and credit risk is significantly negative only during recessions.

The results presented so far are very supportive of the hypothesis that credit risk is cyclical. However, they also seem to suggest that the issue of cyclicality, as described hitherto by the empirical literature, has been somehow misinterpreted. Indeed, according to our evidence, the negative relationship between banks' portfolio riskiness and the business cycle holds only in either unfavorable economic conditions or when average credit quality is already unsatisfactory. By contrast, it does not seem to be statistically significant in good times (i.e., when either economic conditions improve or loan riskiness is low).

However, the small sample size leads us to interpret these preliminary results at the aggregate level with some caution and to deepen our analysis, exploiting the cross-sectional dimension of our rich dataset to account for banks' heterogeneity.

IV. Panel Data model with a Single Threshold Variable and Multiple Regimes

Using the detailed information on borrowers' default rates available on a bank-by-bank basis and panel data techniques, we can analyze whether the impact of the business cycle on riskier and less-risky banks is asymmetric. At a first glance, we expect riskier banks to have more cyclical portfolios than less-risky ones. The sample size (more than fifteen years of quarterly data at the individual level) allows us to exploit a more articulated econometric representation, with multiple thresholds over the same variable.

A. The Model

As in Hansen (1999) we start assuming that the observed data are from a balanced panel $\{dr_{it}, x_{it}, q_{it}\}$ with $1 \le i \le N$ and $1 \le t \le T$. The scalar dr_{it} is the dependent variable, the *k* vector x_{it} contains the exogenous (or predetermined variables), while q_{it} is an *s* vector $(s \ge 1)$ containing the threshold variables. The subscript *i* indicates the individual bank, while *t* designates the time period (in our case the quarter).

The simplest version of the model is a static panel data model with two regimes

$$\begin{aligned} dr_{it} &= \mu_i + \alpha_1 \ln(TA_{it}) + \alpha_2 \ln(TA_{it})^2 + \alpha_3 \ln(TA_{it})^3 + \alpha_4 \mathrm{lgr}_{it} + \alpha_5 \mathrm{lgr}_{it}^2 + \alpha_6 \mathrm{lgr}_{it}^3 \\ &+ \alpha_7 \ln(TA_{it}) \cdot \mathrm{lgr}_{it} + \beta_{11} GAP_{t-1} I(dr_{it} \le \gamma_1) + \beta_{12} GAP_{t-1} I(dr_{it} > \gamma_1) + e_t \end{aligned} \tag{10}$$

where μ_i are individual fixed effects, $\ln(TA_{it})$ and lgr_{it} are the log of total assets and the loan growth rate of bank *i* at time *t*, respectively, while $I(\cdot)$ is the indicator function. The logarithm of total assets is included to control for banks' size, while loan growth rate controls for different lending policies. Following Hansen (1999), the nonlinear terms are included to reduce the possibility of spurious correlations due to omitted variable bias.[13]

In model (10) the observations are divided into two regimes depending on whether the default rate of bank *i* at time *t* is smaller or larger than the threshold γ_1. This threshold is endogenously determined by the model and separates banks with less and more cyclical portfolios. Each regime is characterized by different regression slopes β_{1j}, $j = 1, 2$ and to identify them it is required that both the regressors and the threshold variables are not time invariant. The errors e_{it} are assumed to be *iid* with zero mean and finite variance σ^2. The asymptotic analysis is performed with fixed *T* and $N \to \infty$.

Model (10) can be generalized in two ways. Firstly, as we did in equation (3), we can identify different business cycle regimes by using a measure of output gap as the threshold variable, i.e.

$$\begin{aligned} dr_{it} &= \mu_i + \alpha_1 \ln(TA_{it}) + \alpha_2 \ln(TA_{it})^2 + \alpha_3 \ln(TA_{it})^3 + \alpha_4 \mathrm{lgr}_{it} + \alpha_5 \mathrm{lgr}_{it}^2 + \alpha_6 \mathrm{lgr}_{it}^3 \\ &\quad + \alpha_7 \ln(TA_{it}) \mathrm{lgr}_{it} + \beta_{11} GAP_{t-1} I(GAP_{t-1} \le \gamma_1) + \beta_{12} GAP_{t-1} I(GAP_{t-1} > \gamma_1) + e_t \end{aligned} \tag{11}$$

In this way, the first regime is characterized by recessionary conditions, while in the second one we have booming conditions (the output gap is greater than a certain threshold, γ_1). Secondly, we can generalize model (10) by considering the possibility of more than two regimes over the same threshold variable. For example we can consider three regimes over the banks' riskiness indicator (that is slightly risky, risky and very risky banks) with the following model

[13] Lack of bank data at higher frequencies does not allow the estimation of models with a richer set of bank-specific variables.

$$
\begin{aligned}
dr_{it} = \mu_i + \alpha_1 \ln\left(TA_{it}\right) + \alpha_2 \ln\left(TA_{it}\right)^2 + \alpha_3 \ln\left(TA_{it}\right)^3 + \alpha_4 \text{lgr}_{it} + \alpha_5 \text{lgr}_{it}^2 + \alpha_6 \text{lgr}_{it}^3 \\
+\alpha_7 \ln\left(TA_{it}\right) \cdot \text{lgr}_{it} + \beta_{11} GAP_{t-1} I\left(dr_{it} \le \gamma_1\right) + \beta_{12} GAP_{t-1} I\left(\gamma_1 < dr_{it} \le \gamma_2\right) \\
+\beta_{13} GAP_{t-1} I\left(dr_{it} > \gamma_2\right) + e_t
\end{aligned} \tag{12}
$$

where $\gamma_1 < \gamma_2$.

We can generalize further the model by including a third threshold, so that we can characterize four credit risk regimes. The same strategy can be adopted for model (11) with different business cycle regimes.

A more compact way to represent models (10), (11) and their generalizations is

$$dr_{it} = \mu_i + \theta' x_{it}\left(\gamma\right) + e_{it} \tag{13}$$

where $\theta = \left(\alpha_1, ..., \alpha_7, \beta_{11}, \beta_{12}, ...\right)$ and

$$x_{it}\left(\gamma\right) = \left(\ln\left(TA_{it}\right), \ln\left(TA_{it}\right)^2, \ln\left(TA_{it}\right)^3, \text{lgr}_{it}, \text{lgr}_{it}^2, \text{lgr}_{it}^3, \text{lgr}_{it} \cdot \ln\left(TA_{it}\right), GAP_t \cdot I\left(dr_{it} \le \gamma_1\right), GAP_t \cdot I\left(dr_{it} > \gamma_1\right)\right)' \tag{14}$$

in case of model (10). To estimate this class of models we can employ a fixed effects transformation by removing the individual effects. We can take the averages over time of (13) getting

$$\overline{dr}_i = \mu_i + \theta' \overline{x}_i\left(\gamma\right) + \overline{e}_i \tag{15}$$

where $\overline{dr}_i = T^{-1}\sum_t dr_{it}$, $\overline{e}_i = T^{-1}\sum_t e_{it}$ and $\overline{x}_i\left(\gamma\right) = T^{-1}\sum_t x_{it}\left(\gamma\right)$. Taking the differences between (13) and (15) yields

$$dr_{it}^* = \theta' x_{it}^*\left(\gamma\right) + e_{it}^* \tag{16}$$

where $dr_{it}^* = dr_{it} - \overline{dr}_i$, $x_{it}^*(\gamma) = x_{it}(\gamma) - \overline{x}_i(\gamma)$ and $e_{it}^* = e_{it} - \overline{e}_i$. Stacking data and errors for each individual i with the first time period deleted and then stacking what results over individuals we get the vector of the dependent variable Y^*, the independent variables $X^*(\gamma)$ and that of the errors e^*. With this notation, (13) is equivalent to

$$Y^* = X^*(\gamma)\theta + e^* \tag{17}$$

and for any given value of the threshold γ this model can be estimated by OLS, i.e.

$$\hat{\theta}(\gamma) = \left[X^*(\gamma) X^*(\gamma)^{'}\right]^{-1} X^*(\gamma)^{'} Y^* \tag{18}$$

with regression residuals $\hat{e}^*(\gamma) = Y^* - X^*(\gamma)\hat{\theta}(\gamma)$ and sum of squared errors (SSE)

$$S(\gamma) = \hat{e}^*(\gamma)^{'} \hat{e}^*(\gamma) = Y^{*'}\left[I - X^*(\gamma)\left[X^*(\gamma)^{'} X^*(\gamma)\right]^{-1} X^*(\gamma)^{'}\right] Y^* \tag{19}$$

Chan (1993) and Hansen (1999) recommend to estimate γ by LS minimizing the concentrated SSE in (19). Thus the LS estimator of γ becomes

$$\hat{\gamma} = \underset{\gamma = [\underline{\gamma}, \overline{\gamma}]}{\arg\min}\, S(\gamma) \tag{20}$$

Since it is undesirable for a threshold $\hat{\gamma}$ to be selected when it sorts too few observations in one regime, we can exclude this by restricting the minimization in (20) to values of γ such that a minimal percentage of observations (e.g. 1 or 5%) lie in each regime. Once $\hat{\gamma}$ is obtained the slope estimate becomes $\hat{\theta} = \hat{\theta}(\hat{\gamma})$, the residual vector is $\hat{e}^* = \hat{e}^*(\hat{\gamma})$ and the residual variance is $\hat{\sigma}^2 = \left[n(T-1)\right]^{-1} \hat{e}^{*'}\hat{e}^* = \left[n(T-1)\right]^{-1} S(\hat{\gamma})$. Since the SSE $S(\gamma)$ depends on the threshold only through the indicator functions, the

SSE is a step function with at most *NT* steps. The minimization in (20) can thus be reduced to a search over at most *NT* different values of the threshold variable. This is achieved by sorting the threshold eliminating the smallest and the largest δ% to ensure a minimum number of observations in each regime. However, since this procedure might be numerically intensive with long time spans and large panels, Hansen (1999) suggests using 393 quantiles, reducing the grid search over $\{1.00\%, 1.25\%, 1.50\%, ..., 98.75\%, 99.00\%\}$.[14]

As in the aggregate case, it is important to test whether the models in (10) and (11) are statistically significant relative to their linear specifications in which there are no thresholds. The relevant null hypothesis of no threshold (or one regime) can be represented as $H_0 : \beta_{11} = \beta_{12}$. Again, under the null the thresholds γ's are not identified ('Davies' problem'), implying that classical tests have non-standard distributions. We again adopt the bootstrap procedure suggested by Hansen (1996, 1999) to simulate the asymptotic distribution of the test under the null hypothesis of no thresholds. Under the null, the model can be compactly represented as

$$dr_{it} = \mu_i + \theta' x_{it} + e_{it} \tag{21}$$

or as in (16) under the fixed effects transformation. The regression parameter θ can be estimated by OLS, yielding the restricted estimate $\tilde{\theta}$, residuals $\tilde{e}_{it}^*$ and sum of squared

[14] In our four-regime models we adopt a different approach from Hansen (1999) to estimate the thresholds. Instead of estimating the third threshold keeping the first two fixed, we continue with another full sequence of estimations. Once the third threshold is estimated, we estimate the first one keeping the second and third one fixed. Then we keep fixed the first and the third one to estimate the second one. Finally we estimate the third one, keeping the first two thresholds fixed. This procedure consistently estimates all the thresholds in case of more than three regimes. For other details on the estimation of these models, see Hansen (1999) and Marcucci and Lotti (2007).

errors $S_0 = \tilde{e}_{it}^{*'}\tilde{e}_{it}^{*}$. Thus, the likelihood ratio test of H_0 against the alternative of a threshold is based on

$$F_{10} = \frac{S_0 - S_1\left(\hat{\gamma}_1\right)}{\hat{\sigma}^2} \tag{22}$$

where $\hat{\sigma}^2 = \left[n\left(T-1\right)\right]^{-1} S_1\left(\hat{\gamma}_1\right)$.

We can get asymptotically valid tests by using the bootstrap. Keeping the regressors and threshold variable fixed in repeated bootstrap samples, we adopt the following procedure. First we estimate the model grouping the regression residuals $\tilde{e}_{it}^{*}$ by individual, i.e. for each i we construct $\tilde{e}_i^{*} = \left(\tilde{e}_{i1}^{*},\ldots,\tilde{e}_{iT}^{*}\right)$ treating the sample $\tilde{e}^{*} = \left\{\tilde{e}_1^{*},\ldots,\tilde{e}_N^{*}\right\}$ as the empirical distribution for the bootstrap. Then we draw with replacement a sample of size N from the empirical distribution and use these errors $\tilde{e}^{*(b)}$, where the superscript indicates the *b*-th bootstrap replication, to create a bootstrap sample under the null, i.e. $\tilde{dr}_{it}^{*(b)} = \tilde{\theta}' x_{it}^{*} + \tilde{e}_{it}^{*(b)}$. Using the bootstrap sample $\tilde{dr}_{it}^{*(b)}$, we estimate the model under the null, i.e. $\tilde{dr}_{it}^{*(b)} = \theta' x_{it}^{*} + u_{it}$ and under the alternative of a threshold, i.e. $\hat{dr}_{it}^{*(b)} = \theta' x_{it}^{*}\left(\gamma_1\right) + v_{it}$. Therefore, we compute the bootstrap value of the likelihood ratio statistic F_{10} as in (22), repeating this procedure a large number (say B) of times. We finally calculate the bootstrap *p*-value as the percentage of draws for which the simulated statistic exceeds the actual value.

B. *Empirical Results with the Default Rate as the Threshold Variable: Credit Risk Regimes*

The results of the estimated panel data models with two or more regimes over the same threshold variable are provided in Table 4. We start with the simple model 1, which includes only a single threshold, and move on to models 2 and 3, which include two and three thresholds, respectively. The use of multiple thresholds (with the same threshold variable) makes it possible to identify up to four regimes (from the least to the most cyclical), in which we classify banks depending on their portfolios' riskiness (for simplicity, from the lowest to the highest threshold, we can refer to them as less risky, slightly risky, fairly risky and riskier banks).

When a single threshold is introduced, we find that both less-risky and riskier banks are significantly affected by the business cycle, but the magnitude of the coefficient on the business cycle indicator is larger for those banks with lower asset quality (i.e., riskier banks are also more cyclical). In particular, the increase of *dr* as the result of 1 percentage point decrease of GAP is almost 9 times higher for riskier banks than for less risky ones.

[Table 4 about here]

Models 2 and 3 provide further support to the application of regime-switching models for analyzing credit risk. We find that the magnitude of the coefficients on GAP monotonically increases as we move from lower-risk to higher-risk intermediaries. In particular, looking at the results for model 3, we note that β is equal to -0.02 and -0.11 for less risky and slightly risky banks, respectively, while such impact jumps to -0.20 and -0.33 for fairly risky and riskier banks, respectively, which are therefore much more cyclical than the previous ones.[15] These are quite substantial differences also corroborated by a series of Wald tests which all reject the null hypothesis of equal coefficients. We note that the first and second thresholds are very stable, since they remain unchanged as the number of regimes increases. This suggests that the use of multiple regimes is not very helpful for classifying less cyclical banks, but it is extremely important for identifying more accurately fragile intermediaries.

This evidence is confirmed when lagged *dr* is employed as the threshold variable (models 5, 6 and 7). Here we can notice that more cyclical banks are already selected with the two-regime model (i.e., model 5). As we add further thresholds, we discriminate more precisely among less cyclical banks.[16]

For models 1, 2 and 3 the LR test for the null of one, two and three regimes, respectively, is significant at any conventional level. This indicates that the model with four regimes (three thresholds) is adequate. When we use the lagged *dr* as the threshold variable, the LR tests for the null of one and two regimes are rejected at 5%, while we cannot reject the null of three regimes.

The endogenously determined thresholds can be used to assess the evolution of the Italian banks' riskiness over time. The three charts of panel A in Figure 2 depict the percentages of Italian banks in the more cyclical regimes in each quarter for the models with two, three and four regimes (models 1, 2 and 3 of Table 4) along with the ISAE

[15] In model 2, banks in the higher risk regime are affected by the business cycle almost 13 times more than those less risky. In model 3, riskier banks are affected by macroeconomic conditions 20 times more than the less risky ones. In particular, the impact of business cycle on the slightly risky banks is 7 times higher than that for the less risky ones, while the impact of fairly risky ones is twice as much higher as that for the slightly risky ones. Finally, the effect of economic conditions on riskier banks is twice as much higher as that for the fairly risky ones. This monotonicity is shared by all the models we considered.

[16] As a robustness check, we also estimated the models for different institutional categories of banks. The results for these specifications are consistent with those presented above for the whole system and are therefore not reported for the sake of brevity.

recessions (shaded areas). We can notice that banks tended to migrate towards more cyclical regimes in both the 1992Q2-1993Q2 and the 1995Q4-1996Q3 recessions. However, no significant migration is apparent in the 2001Q1-2004Q4 recession, notwithstanding the stagnant economic conditions. A possible explanation is that banks have improved borrower selection criteria in the last years due to the increasing importance of risk management. Furthermore, the very low level of interest rates and the limited level of indebtedness may have helped firms and households to honor their obligations even in unfavorable times. Another explanation is the more and more important credit risk transfer market, which allows many financial intermediaries to transfer credit risk to other institutions/investors through a plethora of new financial instruments. All this factors may have alleviated the cyclicality of credit risk.

We also notice that the share of banks under the fourth regime is almost unaffected by the economic environment. This extreme risk-category (dr>1.44%) is probably more affected by idiosyncratic factors than systemic ones.

The three charts of Panel B in Figure 2 show the same percentages as Panel A when the lagged default rate is used as the threshold (models 5, 6 and 7 of Table 4). The results are quite similar to those already discussed. Notice that using the lagged default rate as a threshold allows us to disentangle the same behavior observed in the previous panel but now more banks fall in the fourth regime (the one of more cyclical banks). Many Italian banks migrated towards more cyclical regimes in both the 1992Q2-1993Q2 and the 1995Q4-1996Q3 recessions, but no significant migration is evident in the 2001Q1-2004Q4 recession for the same reasons explained above.

[Figure 2 about here]

In principle, our analysis may be improved including more bank-specific variables in the econometric specification. For example, some indicators based on banks' financial statement may help to control the possible causes of cyclicality. Unfortunately, lack of data with a sufficient time-span and above all at higher frequencies than yearly did not allow us to perform this check.

In order to provide some further evidence of heterogeneous bank behavior we have analyzed some characteristic of riskier and thus more cyclical banks. In particular, we have focused on intermediaries classified as fairly risky and riskier by our model 3 of Table 4 (four-regime panel data) between 1992 and 2004. These banks are very often small banks; on average their market share on either total assets or loans represented less than 4 per cent of the whole banking system. Their average solvency ratio is equal, on average, to 15%, which is not only much higher than the regulatory minimum but also of the other banks' figures. However, we note that in Italy smaller banks are generally better capitalized than larger ones also for regulatory reasons (in particular, mutual banks are subject to specific rules concerning profit allocation). Therefore, it is difficult to argue that more cyclical banks tend – prudently – to keep higher capital buffers than less-cyclical ones. Indeed, the loan-loss provision ratio, which can be considered another proxy of a cautious risk management, appears very similar between these two categories of banks.

C. *Empirical Results with the Output Gap as the Threshold Variable: Business Cycle Regimes*

When GAPT is used as the threshold variable (model 4 of Table 4), we find further evidence that the relationship between credit risk and business cycle is stronger in recessionary conditions rather than in booms. This is consistent with our previous results for the aggregate case. Unfortunately, the LR test fails to reject the null hypothesis of one regime (i.e., no threshold). However, a Wald test on the equality of the coefficients β_{11} and β_{12} is rejected at any usual significance level, indicating that the model still captures some of the features of the relationship between credit risk and business cycle in different phases.

Based on the estimated thresholds for GAPT, we can identify periods in which economic conditions tend to affect banks' portfolios to a larger extent than in normal times. In unreported results, we identify four "high-impact" periods: between 1993-Q1 and 1994-Q2, in 1997-Q1/Q2, 1999-Q1 and 2005-Q2. We note that these periods do not necessarily overlap with the ISAE recessionary phases.

D. Robustness checks and a Monte Carlo exercise

As a first step to check the robustness of our results we have estimated both panel data models with one threshold variable for different subsamples. First we have split our full sample in two subsamples: 1990Q1-1997Q4 and 1998Q1-2005Q2. In the first subsample we have almost two complete business cycles, while in the second one we have almost one complete cycle. In both subsamples the estimated thresholds (unreported) are in line with those estimated for the full sample. In addition, the previously found negative relationship between credit risk and business cycle still holds as well as the monotonic relationship between coefficients in different regimes. As a further robustness check, we have estimated both models on a sequence of rolling five-year subsamples starting from 1990Q1-1994Q4 through 2001Q1-2005Q2. All the previous findings are again confirmed. Besides, the estimated thresholds are quite consistent in the various subsamples; they are on average close to the full sample estimates. For example, for the model with two regimes and dr_t as the threshold we obtained two high values (around unity) for those subsamples characterized by the 1993 and 1995 recessions.[17]

Furthermore, we set up a Monte Carlo experiment to check the robustness of our models out of sample. We split our sample in two parts. The first one is the in-sample one where we select 160 banks. This in-sample part is used to estimate each model. The second part is the out-of-sample one where we leave the other 52 banks. This part is used to test our model out-of-sample. Since in our full sample of 212 banks we have 73 limited banks (34%), 18 cooperative banks (9%) and 121 mutual banks (57%), we have decided to maintain the same percentages in both the in-sample and out-of-sample parts. Therefore, in-sample we have 55 limited banks, 14 cooperative banks and 91 mutual banks whereas out-of-sample we have 18 limited banks, 4 cooperative banks and 30 limited banks. At each iteration we randomly select the 52 banks that remain out-of-sample. We estimate the model with the 160 banks in-sample, we save both the estimated coefficients and thresholds and use them to compute the fitted values of the default rate (our dependent variable) for our 52 banks out-of-sample. Since we have the realized values of such default rates, we compute two measures of goodness of fit. The first one is the difference in absolute value between the fitted values of the default rates out-of-sample and their realized values which is called L_{ABS}. The second one is the

[17] As a further robustness check we estimated both models including more dynamics in the business cycle indicators. We added up to four lags of our business cycle indicator (i.e. GAPT) at each regime in each model. We found that almost all coefficients are negative but only the first lag coefficients are significant. We also estimated the models considering all the possible quantiles of each threshold variable rather than the 393 suggested by Hansen (1999). Unreported results show that using 393 quantiles is sufficient to correctly estimate the unknown thresholds. As a further check we estimated our models with the default rate at time *t-2* as the threshold variable and all the previous results still hold.

squared difference between the fitted values out-of-sample of the default rates and their realized values, called L_{SQ}.

Table 6 reports the summary results for the Monte Carlo exercises for all models estimated in this paper with 1,000 iterations. For each model we present both the median and mean value of all the coefficients and thresholds along with the average values of the two measures of goodness of fit (L_{ABS} and L_{SQ}). For all models of this section, both the average and median values of the absolute and squared differences are quite small suggesting that these models give a good description of the relationship between credit risk and business cycle both in-sample and out-of-sample. These findings also suggest that these models can be adopted to carry out real out-of-sample exercises. All the regime-dependent coefficients both on average and in median terms are close to the estimated values for our full sample. Furthermore, the mean and median thresholds are consistent with the estimates obtained with the full sample for all models with one threshold variable and two or more regimes.

V. Combining Credit Risk and Business cycle: panel data model with two threshold variables and four regimes

A. The Model

As an extension of Hansen's (1999) model, we can use a four-regime panel data model where the regimes are determined by two different threshold variables, as suggested by Marcucci and Lotti (2007). The simplest version of the model takes the form

$$
\begin{aligned}
dr_{it} = {} & \mu_i + \alpha_1 \ln\left(TA_{it}\right) + \alpha_2 \ln\left(TA_{it}\right)^2 + \alpha_3 \ln\left(TA_{it}\right)^3 + \alpha_4 \mathrm{lgr}_{it} + \alpha_5 \mathrm{lgr}_{it}^2 + \alpha_6 \mathrm{lgr}_{it}^3 \\
& + \alpha_7 \ln\left(TA_{it}\right) \cdot \mathrm{lgr}_{it} + \beta_{11} GAP_{t-1} I\left(dr_{it} \le \gamma_1\right) I\left(GAP_{t-1} \le \gamma_2\right) \\
& + \beta_{12} GAP_{t-1} I\left(dr_{it} \le \gamma_1\right) I\left(GAP_{t-1} > \gamma_2\right) + \beta_{13} GAP_{t-1} I\left(dr_{it} > \gamma_1\right) I\left(GAP_{t-1} \le \gamma_2\right) \\
& + \beta_{14} GAP_{t-1} I\left(dr_{it} > \gamma_1\right) I\left(GAP_{t-1} > \gamma_2\right) + e_t
\end{aligned} \tag{23}
$$

where μ_i are individual fixed effects, $\ln\left(TA_{it}\right)$ and lgr_{it} are the log of total assets and the loan growth rate of bank *i* at time *t*, respectively, while $I\left(\cdot\right)$ is the indicator function.

In model (23) the observations are divided into four regimes depending on both the default rate of each bank and the output gap. With this model we can study less risky and riskier banks in both booming and recessionary conditions. In this way we can look at their different behavior over different phases of the business cycle. As before, each regime is characterized by different slopes ($\beta_{1j}, j = 1,...,4$) and to identify them it is required that both the regressors and threshold variables are not time invariant. The errors are assumed to be *iid* with zero mean and finite variance while the asymptotic analysis is again performed with fixed T and $N \to \infty$.

To estimate this model we can employ the fixed effects transformation as with the two-regime panel data model discussed before. We can then apply conditional LS minimizing the concentrated SSE as in (20). As before, it is fundamental to test whether the model (23) is statistically significant relative to the simplest models with only one threshold. The null hypothesis in this case is that of one threshold. Thus, we again have the problem of some parameters not identified under the null, implying a non-standard testing problem. We can therefore adopt the bootstrap procedure suggested by Marcucci and Lotti (2007) which is similar to that one discussed before in the case of only one threshold. An approximate likelihood ratio test of one threshold against two thresholds can be based on the statistic

$$F_{21} = \frac{S_1(\tilde{\gamma}_1) - S_2(\hat{\gamma}_1, \hat{\gamma}_2)}{\hat{\sigma}^2} \tag{24}$$

where $\hat{\sigma}^2 = \left[n(T-1)\right]^{-1} S_2(\hat{\gamma}_1, \hat{\gamma}_2)$. The null hypothesis of one threshold is rejected for large values of F_{21}. We can use a similar bootstrap procedure as in the two-regime panel data model to obtain the approximate asymptotic distribution of the test. To generate the bootstrap samples we hold both the regressors and thresholds fixed in repeated bootstrap samples. Then we follow the same steps discussed before to obtain the bootstrap *p*-value of the test.

B. Empirical Results

The final set of results is obtained estimating a model with two different threshold variables: the micro variable *dr* and the business cycle indicator (GAPT). In this way, we try to depict a more comprehensive picture of the evolution of credit risk across banks and through the business cycle. It is not straightforward to guess the impact of business cycle conditions on banks with different portfolios. However, our a priori belief is that less risky banks should be less affected by the overall economic conditions than riskier ones. In other words, less risky banks should be less cyclical, while riskier banks should be more cyclical. In addition, as suggested by our previous results, for the latter intermediaries, the impact should be stronger in unfavorable times.

Table 5 shows the results for the four-regime panel data models with two different threshold variables. In model 1, where the thresholds are dr_{it} and $GAPT_{t-1}$, we notice that the coefficient on GAP is negative, as expected, only for less-risky banks in expansionary periods and for riskier banks during recessions. The magnitude of the coefficient is higher for riskier banks (a ratio of about 3), confirming the results we provided in the previous paragraphs. However, it is puzzling that the coefficient turns out to be positive and statistically significant for less risky banks in recession and riskier banks in expansion. Since we suspect that contemporaneous dr_{it} may suffer some endogeneity problems, we also estimate the four-regime panel data model with the lagged default rate and *GAPT* as the threshold variables.

[Table 5 about here]

With model 2 where the lagged default rate is used as the threshold we have more clear-cut results. In fact, all the β_{1j}, $j = 1,...,4$ coefficients are negative and significant. In addition, the monotonic relationships we previously found, both between less risky and riskier banks and between recessionary and expansionary phases, are all confirmed. Riskier banks are affected by the business cycle during recessions more than four times as much as the same type of banks in expansion. In addition the impact of macroeconomic conditions on riskier banks in recessionary phases is more than three times as much as that on less risky banks. Finally, less risky banks are also affected by the business cycle during recessions almost twice as much as similar banks are affected in booming phases.[18]

[18] Models 3, 4 and 5 are the same as model 1 for limited, cooperative and mutual banks respectively. The results we obtain are quite similar to the previous ones for the whole sample with some counter-intuitive evidence. In particular, the coefficients for less risky banks in recession and those for riskier banks in expansion are positive and significant. This is less evident from the estimates of models 6, 7 and 8 that are the same as model 2 but for limited, cooperative and mutual banks respectively. Here, only the coefficients for riskier banks in expansion are slightly significant and positive both for limited and cooperative banks except for mutual ones. However, the same picture found both at the aggregate level and at the individual level with simpler models still holds. We keep on having monotonicity and higher impacts both for riskier banks and during recessions.

In the last two columns of Table 6 we present the mean and median results of our out-of-sample Monte Carlo exercise described in Section IV for the two four-regime models with two different threshold variables. In both cases, the average and median estimated thresholds are close to those obtained for the full sample. In addition, the regime-dependent estimates are similar to those obtained from the full sample thus further corroborating our conclusions.[19]

These results can be extremely helpful for supervisory authorities in monitoring credit risk during different phases of the business cycle. However, further research is needed to ameliorate and calibrate these regime-switching models based on panel data and threshold regression.

VI. Concluding remarks

In this paper we try to make a step forward in explaining the macroeconomic determinants of credit risk and its evolution over the business cycle. With respect to most of the existing studies, which neglect asymmetric effects, we analyze whether the relationship between business cycle and credit risk is subject to regime switches determining endogenously the thresholds at which the model switches from one regime to the other.

[19] We also estimated these four-regime models with two different threshold variables in two subsamples: the first one is 1990Q1—1997Q4 and the second one is 1998Q1—2005Q2 obtaining similar results to the full sample.

Using a threshold regression approach combined with panel data and exploiting a unique dataset on Italian bank borrowers' default rates, we find that the impact of the business cycle is more pronounced when credit risk levels are higher and during unfavorable economic times. Moreover, our methodology allows us to identify the risk threshold(s) over/below which such impact is different, providing a powerful tool for financial stability monitoring.

As an example, in the two-regime panel threshold model, we find that both less-risky and riskier banks are significantly affected by the business cycle, but the impact is stronger for the latter. In particular, the increase of the default rate as a result of one percentage point decrease of the output gap is almost 9 times higher for riskier banks. This evidence is robust to the use of different proxies for the overall economic conditions and holds at various levels of aggregation. In addition, we find a certain degree of monotonicity in the impact of macroeconomic conditions on credit risk that is higher for riskier banks as well as during recessions.

By contrast, the evidence arising from our panel data model with two different threshold variables and four regimes is slightly less definite and leaves room for future research. Also, it may be valuable to test the out-of-sample performance of this kind of models as soon as longer time-series become available.

Overall, our results may provide some guidance to banks and supervisors in the assessment of capital buffers in the various phases of the business cycle, particularly under risk sensitive capital requirements. Furthermore, the methodology we propose may be easily employed by supervisors for selecting more cyclical institutions and for stress testing credit risk in banks' books.

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Table 1
Summary statistics

This table provides the summary statistics for the default rate *dr*, both at the bank and aggregate level, the total assets in logs, *ln(TA)*, the individual loan growth rate, *lgr*, the quarterly growth rate of GDP, *GDPG*, the output gap computed as the difference between the GDP and the Hodrick-Prescott (HP) filtered series, *GAPHP*, and the output gap computed as the difference between the GDP and a linear trend, *GAPT*. All data are quarterly from 1990:Q1 to 2005:Q2 for a total of 13,144 bank-quarters (212 banks and 62 quarters, balanced panel). The default rate is computed as the flow of new 'adjusted' bad debts in each quarter over the outstanding non-performing loans in the previous quarter. Total assets are in million of euros. The loan growth rate is the difference between the loan growth rate of each bank *i* at time *t* and the average loan growth rate for each quarter.

	Description	Min	25% Percentile	Median	75% Percentile	Max	Mean	Std. Dev.	Skewness	Kurtosis
Micro variables										
dr_{it}	*Individual default rate*	0.000	0.000	0.257	0.453	1.495	0.299	0.281	1.048	4.066
$ln(TA_{it})$	*Total Assets in logs*	1.792	5.011	5.964	7.279	12.304	6.252	1.738	0.697	3.320
lgr_{it}	*Loan growth rate*	-0.295	-0.028	-0.011	0.006	0.272	-0.010	0.036	0.599	10.193
Macro variables										
dr_t	*Aggregate default rate*	0.309	0.379	0.539	0.671	0.972	0.554	0.179	0.498	2.361
$GDPG_t$	*GDP growth rate*	-1.840	0.402	1.169	2.528	3.818	1.363	1.338	-0.115	2.368
$GAPHP_t$	*Output gap from HP-filtered GDP*	-2.126	-0.513	0.116	0.639	1.779	0.017	0.829	-0.313	2.588
$GAPT_t$	*Output gap from linear trend*	-3.001	-0.734	0.168	0.920	2.539	-0.037	1.298	-0.222	2.316

Table 2
Estimates for 2-regime threshold model at the aggregate level

This table presents the conditional LS estimates for the following threshold models with 2 regimes:

Model (1): $dr_t = \beta_{01} + \beta_{11} GAP_{t-1} + e_t$

Model (2): $dr_t = \left(\beta_{01} + \beta_{11} GAP_{t-1}\right) I\left\{dr_t \le \gamma\right\} + \left(\beta_{02} + \beta_{12} GAP_{t-1}\right) I\left\{dr_t > \gamma\right\} + e_t$

Model (3): $dr_t = \left(\beta_{01} + \beta_{11} GAP_{t-1}\right) I\left\{dr_{t-1} \le \gamma\right\} + \left(\beta_{02} + \beta_{12} GAP_{t-1}\right) I\left\{dr_{t-1} > \gamma\right\} + e_t$

Model (4): $dr_t = \left(\beta_{01} + \beta_{11} GAP_{t-1}\right) I\left\{GAP_{t-1} \le \gamma\right\} + \left(\beta_{02} + \beta_{12} GAP_{t-1}\right) I\left\{GAP_{t-1} > \gamma\right\} + e_t$

where *dr* is the aggregate default rate and GAP_{t-1} is $GAPT_{t-1}$. γ is the estimated threshold, N_1 and N_2 are the number of observations that lie in the first and second regime, respectively. *LR* is the likelihood ratio test for the null of no threshold whose *p*-value is computed through the bootstrap as suggested by Hansen (1996). *N. bootstrap* is the number of bootstrap replications used to compute the *p*-value. The trimming % is the percentage of observations that are excluded from the sample so that a minimal percentage of observations lie in each regime. Standard errors are in parenthesis. ***, ** and * indicate significance at 1, 5 and 10% respectively.

	Aggregate			
Model	(1)	(2)	(3)	(4)
β_{01}	0.5536 ***	0.4022 ***	0.4074 ***	0.4449 ***
	(0.0226)	(0.0127)	(0.0151)	(0.0259)
β_{02}	-	0.7118 ***	0.7020 ***	0.5559 ***
	-	(0.0157)	(0.0166)	(0.0653)
β_{11}	-0.0752 **	-0.0210	1.50E-05	-0.2183 ***
	(0.0303)	(0.0161)	(0.0277)	(0.0356)
β_{12}	-	-0.0676 ***	-0.0747 ***	-0.0084
	-	(0.0191)	(0.0203)	(0.0776)
γ	-	0.5387 **	0.5793 **	0.3005 **
R^2	0.1171	0.8214	0.7638	0.3200
N_1	58	30	30	36
N_2	-	28	28	22
LR Test	-	44.59 ***	40.00 ***	13.02 ***
p -value	-	0.000	0.000	0.001
N. bootstrap	-	1000	1000	1000
trimming %	-	0.15	0.15	0.15

Table 3
Estimates for 2-regime threshold model at the aggregate level for bank categories

This table reports the conditional LS estimates for the following threshold models with 2 regimes:

Models (1), (5) and (9): $dr_t = \beta_{01} + \beta_{11} GAP_{t-1} + e_t$, for limited, cooperative and mutual banks respectively.

Models (2), (6) and (10): $dr_t = \left(\beta_{01} + \beta_{11} GAP_{t-1}\right) I\left\{dr_t \le \gamma\right\} + \left(\beta_{02} + \beta_{12} GAP_{t-1}\right) I\left\{dr_t > \gamma\right\} + e_t$ for limited, cooperative and mutual banks respectively,

Models (3), (7) and (11): $dr_t = \left(\beta_{01} + \beta_{11} GAP_{t-1}\right) I\left\{dr_{t-1} \le \gamma\right\} + \left(\beta_{02} + \beta_{12} GAP_{t-1}\right) I\left\{dr_{t-1} > \gamma\right\} + e_t$, for limited, cooperative and mutual banks respectively,

Models (4), (8) and (12): $dr_t = \left(\beta_{01} + \beta_{11} GAP_{t-1}\right) I\left\{GAP_{t-1} \le \gamma\right\} + \left(\beta_{02} + \beta_{12} GAP_{t-1}\right) I\left\{GAP_{t-1} > \gamma\right\} + e_t$, for limited, cooperative and mutual banks respectively,

where *dr* is the aggregate default rate and GAP_{t-1} is $GAPT_{t-1}$. The threshold default rate is the overall default rate for all models, while the dependent variable refers the default rate of each bank category. γ is the estimated threshold, N_1 and N_2 are the number of observations that lie in the first and second regime, respectively. LR is the likelihood ratio test for the null of no threshold whose p-value is computed through the bootstrap as suggested by Hansen (1996) with N. bootstrap replications. The trimming % is the percentage of observations that are excluded from the sample so that a minimal percentage of observations lie in each regime. Standard errors are in parenthesis. ***, ** and * indicate significance at 1, 5 and 10% respectively.

	Limited Banks				Cooperative Banks				Mutual Banks			
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β_{01}	0.5765 ***	0.4206 ***	0.4257 ***	0.4685 ***	0.4894 ***	0.3603 ***	0.3589 ***	0.3998 ***	0.3661 ***	0.2930 ***	0.2756 ***	0.3023 ***
	(0.0228)	(0.0130)	(0.0154)	(0.0265)	(0.0198)	(0.0090)	(0.0085)	(0.0224)	(0.0142)	(0.0083)	(0.0068)	(0.0144)
β_{02}	-	0.7284 ***	0.7193 ***	0.5825 ***	-	0.6217 ***	0.6215 ***	0.5071 ***	-	0.4921 ***	0.4586 ***	0.3304 ***
	-	(0.0170)	(0.0176)	(0.0674)	-	(0.0168)	(0.0165)	(0.0540)	-	(0.0104)	(0.0136)	(0.0420)
β_{11}	-0.0780 **	-0.0223	-0.0018 *	-0.2198 ***	-0.0725 ***	-0.0084	-0.0042	-0.1888 ***	-0.0482 **	-0.0194	-0.0053	-0.1356 ***
	(0.0304)	(0.0174)	(0.0283)	(0.0371)	(0.0276)	(0.0121)	(0.0136)	(0.0363)	(0.0205)	(0.0124)	(0.0118)	(0.0225)
β_{12}	-	-0.0723 ***	-0.0791 ***	-0.0157	-	-0.0742 ***	-0.0726 **	-0.0354	-	-0.0517 ***	-0.0460 ***	0.0329
	-	(0.0205)	(0.0217)	(0.0799)	-	(0.0219)	(0.0222)	(0.0658)	-	(0.0098)	(0.0160)	(0.0519)
γ	-	0.5369 **	0.5387 **	0.3005 **	-	0.5387 **	0.5793 **	0.3005 **	-	0.6191 **	0.5793 **	0.3005 **
R^2	0.1227	0.8025	0.7501	0.3168	0.1375	0.7846	0.7880	0.3079	0.1216	0.8210	0.7473	0.3199
N_1	58	29	29	36	58	30	30	36	58	37	30	36
N_2	-	29	29	22	-	28	28	22	-	21	28	22
LR Test	-	43.76 ***	39.12 ***	12.83 ***	-	42.83 ***	42.21 ***	11.83 ***	-	41.92 ***	38.08 ***	12.22 ***
p-value	-	0.000	0.000	0.001	-	0.000	0.000	0.008	-	0.000	0.000	0.008
N. bootstrap	-	1000	1000	1000	-	1000	1000	1000	-	1000	1000	1000
trimming %	-	0.15	0.15	0.15	-	0.15	0.15	0.15	-	0.15	0.15	0.15

Table 4
Estimates for threshold regression panel data models with 2 or more regimes over the same threshold variable

This table displays the conditional LS estimates for the following threshold panel data model with 2 or more regimes (same threshold variable):

Model (1): $dr_{it} = \alpha_1 \ln\left(TA_{it}\right) + \alpha_2 \ln\left(TA_{it}\right)^2 + \alpha_3 \mathrm{lgr}_{it} + \alpha_4 \mathrm{lgr}_{it}^2 + \alpha_5 \mathrm{lgr}_{it}^3 + \alpha_6 \mathrm{lgr}_{it} \ \ln\left(TA_{it}\right) + \beta_{11} GAP_{t-1} I\left(dr_{it} \le \gamma_1\right)$
$+\beta_{12} GAP_{t-1} I\left(dr_{it} > \gamma_1\right) + e_t$

Model (2): $dr_{it} = \alpha_1 \ln\left(TA_{it}\right) + \alpha_2 \ln\left(TA_{it}\right)^2 + \alpha_3 \mathrm{lgr}_{it} + \alpha_4 \mathrm{lgr}_{it}^2 + \alpha_5 \mathrm{lgr}_{it}^3 + \alpha_6 \mathrm{lgr}_{it} \ \ln\left(TA_{it}\right) + \beta_{11} GAP_{t-1} I\left(dr_{it} \le \gamma_1\right)$
$+\beta_{12} GAP_{t-1} I\left(\gamma_1 < dr_{it} \le \gamma_2\right) + \beta_{13} GAP_{t-1} I\left(dr_{it} > \gamma_2\right) + e_t$

Model (3): $dr_{it} = \alpha_1 \ln\left(TA_{it}\right) + \alpha_2 \ln\left(TA_{it}\right)^2 + \alpha_3 \mathrm{lgr}_{it} + \alpha_4 \mathrm{lgr}_{it}^2 + \alpha_5 \mathrm{lgr}_{it}^3 + \alpha_6 \mathrm{lgr}_{it} \ \ln\left(TA_{it}\right) + \beta_{11} GAP_{t-1} I\left(dr_{it} \le \gamma_1\right)$
$+\beta_{12} GAP_{t-1} I\left(\gamma_1 < dr_{it} \le \gamma_2\right) + \beta_{13} GAP_{t-1} I\left(\gamma_2 < dr_{it} \le \gamma_3\right) + \beta_{14} GAP_{t-1} I\left(dr_{it} > \gamma_3\right) + e_t$

Model (4): $dr_{it} = \alpha_1 \ln\left(TA_{it}\right) + \alpha_2 \ln\left(TA_{it}\right)^2 + \alpha_3 \mathrm{lgr}_{it} + \alpha_4 \mathrm{lgr}_{it}^2 + \alpha_5 \mathrm{lgr}_{it}^3 + \alpha_6 \mathrm{lgr}_{it} \ \ln\left(TA_{it}\right) + \beta_{11} GAP_{t-1} I\left(GAP_{t-1} \le \gamma_1\right)$
$+\beta_{12} GAP_{t-1} I\left(GAP_{t-1} > \gamma_1\right) + e_t$

Model (5), (6) and (7): same as (1), (2) and (3) respectively with threshold dr_{it} replaced by dr_{it-1}

where *dr* is the individual default rate and GAP_{t-1} is $GAPT_{t-1}$. γ_j, $j = 1, 2, 3$ are the estimated thresholds. *LR* is the likelihood ratio test for i) the null of no threshold in models (1), (4) and (5), ii) the null of one threshold in models (2) and (6), and iii) the null of two thresholds for models (3) and (7). Its *p*-value is computed through the bootstrap as suggested by Hansen (1996) with *N. bootstrap* replications. The trimming % is the percentage of observations that are excluded from the sample so that a minimal percentage of observations lie in each regime. Standard errors are in parenthesis. ***, ** and * indicate significance at 1, 5 and 10% respectively.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α_1	0.1493 ***	0.1503 ***	0.1505 ***	0.1833 ***	0.1633 ***	0.1654 ***	0.1651 ***
	(0.0189)	(0.0189)	(0.0188)	(0.0187)	(0.0186)	(0.0186)	(0.0186)
α_2	-0.0204 ***	-0.0205 ***	-0.0205 ***	-0.0234 ***	-0.0219 ***	-0.0221 ***	-0.0220 ***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
α_3	-0.6173 ***	-0.6199 ***	-0.6227 ***	-0.6265 ***	-0.6089 ***	-0.6003 ***	-0.6073 ***
	(0.1840)	(0.1837)	(0.1837)	(0.1870)	(0.1862)	(0.1860)	(0.1861)
α_4	-0.1134 **	-0.1083 **	-0.1089 **	-0.1118 **	-0.1238 ***	-0.1183 **	-0.1188 **
	(0.0447)	(0.0446)	(0.0446)	(0.0466)	(0.0463)	(0.0461)	(0.0462)
α_5	0.1927 ***	0.1912 ***	0.1910 ***	0.2115 ***	0.2072 ***	0.2038 ***	0.2034 ***
	(0.0286)	(0.0283)	(0.0283)	(0.0302)	(0.0299)	(0.0297)	(0.0298)
α_6	-0.0531 **	-0.0523 **	-0.0518 **	-0.0621 **	-0.0648 **	-0.0650 **	-0.0634 **
	(0.0266)	(0.0264)	(0.0265)	(0.0273)	(0.0271)	(0.0270)	(0.0270)
β_{11}	-0.0170 ***	-0.0165 ***	-0.0165 ***	-0.0513 ***	-0.0241 ***	-0.0181 ***	-0.0181 ***
	(0.0013)	(0.0013)	(0.0013)	(0.0034)	(0.0017)	(0.0021)	(0.0021)
β_{12}	-0.1484 ***	-0.1111 ***	-0.1110 ***	-0.0210 ***	-0.0878 ***	-0.0340 ***	-0.0289 ***
	(0.0093)	(0.0082)	(0.0082)	(0.0019)	(0.0058)	(0.0028)	(0.0034)
β_{13}	-	-0.2091 ***	-0.2000 ***	-	-	-0.0878 ***	-0.0421 ***
		(0.0190)	(0.0192)			(0.0058)	(0.0047)
β_{14}	-	-	-0.3305 ***	-	-	-	-0.0878
			(0.0804)				(0.0058)
γ_1	0.735 **	0.721 **	0.721 **	-1.822 **	0.743 **	0.317 **	0.317 **
γ_2	-	0.988 **	0.988 **	-	-	0.743 **	0.513 **
γ_3	-	-	1.437 **	-	-	-	0.743 **
N. of banks	212	212	212	212	212	212	212
N. of quarters	61	61	61	61	61	61	61
N. of quantiles	393	393	393	393	393	393	393
Trimming %	0.01	0.01	0.05	0.01	0.01	0.01	0.05
LR Test	1099.92 ***	95.20 ***	18.83 ***	474.70	561.93 **	21.55 **	5.73
p-value	0.000	0.000	0.005	0.390	0.020	0.015	0.695
N. bootstrap	300	300	300	300	300	300	300

Figure 1
Italian business cycle indicators.

This figure depicts the Italian business cycle as measured by three different indicators. GAPHP (left-hand scale) is the real GDP minus the HP-filtered GDP series. GAPT ((left-hand scale)) is the GDP minus the potential output proxied by a fitted linear trend. GDPG (right-hand scale) is the series of the GDP q/q growth rate. Shaded areas indicate the recessions according to the ISAE chronology.

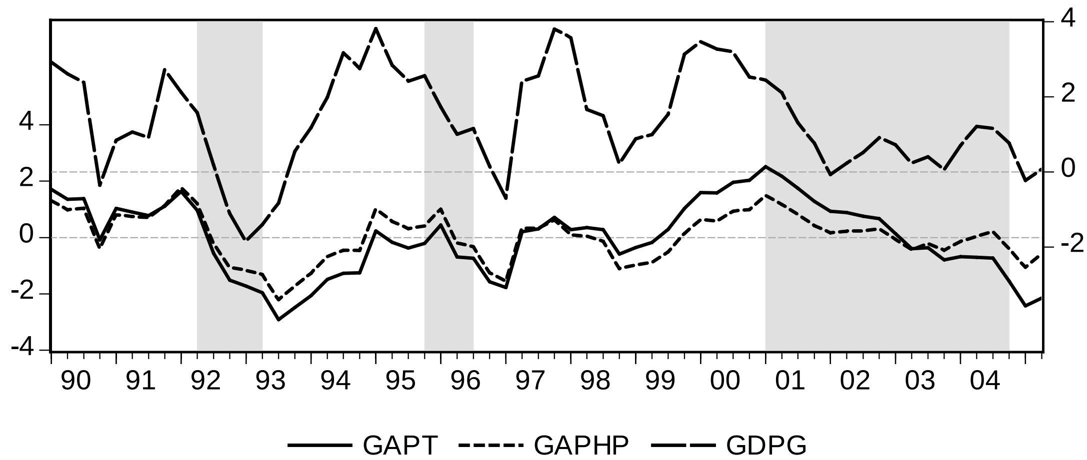
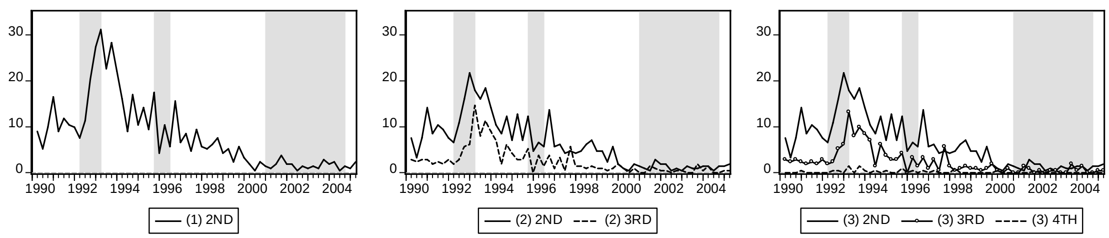


Figure 2
Percentage of banks in each regime by quarter (Threshold panel data model with 2 or more regimes).

This figure displays the percentage of the 212 banks that fall in the more cyclical regimes within the threshold panel data model with 2 or more regimes (see Table 4). Panel A depicts the percentage of banks in the second regime, the second and the third regimes and the second, the third and the fourth regimes, respectively from left to right, when the threshold variable is the contemporaneous default rate. For example, in model (1) the first chart on the left of panel A shows the percentage of banks for which $dr_{it} > \gamma_1$.Panel B displays the same charts for models where the threshold variable is the lagged default rate. For example, in model (5) the first chart on the left of panel A shows the percentage of banks for which $dr_{it-1} > \gamma_1$.

Panel A: Models (1), (2) and (3): threshold dr_{it}



Panel B: Models (5), (6) and (7): threshold $dr_{i,t-1}$

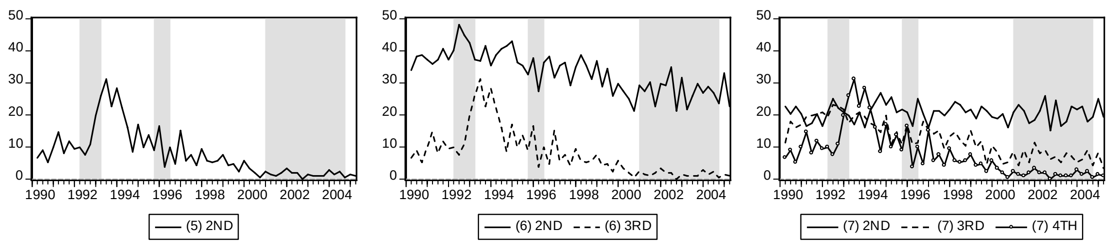


Table 5
Estimates for threshold regression panel data models with 4 regimes over different threshold variables

This table presents the conditional LS estimates for the following threshold panel data model with 4 regimes (different threshold variable: one micro and one macro):

Model (1):
$$dr_{it} = \alpha_1 \ln(TA_{it}) + \alpha_2 \ln(TA_{it})^2 + \alpha_3 \mathrm{lgr}_{it} + \alpha_4 \mathrm{lgr}_{it}^2 + \alpha_5 \mathrm{lgr}_{it}^3 + \alpha_6 \mathrm{lgr}_{it} \ln(TA_{it}) + \beta_{11} GAP_{t-1} I(dr_{it} \le \gamma_1) I(GAP_{t-1} \le \gamma_2) + \beta_{12} GAP_{t-1} I(dr_{it} \le \gamma_1) I(GAP_{t-1} > \gamma_2)$$
$$+ \beta_{13} GAP_{t-1} I(dr_{it} > \gamma_1) I(GAP_{t-1} \le \gamma_2) + \beta_{14} GAP_{t-1} I(dr_{it} > \gamma_1) I(GAP_{t-1} > \gamma_2) + e_t$$

Model (2):
$$dr_{it} = \alpha_1 \ln(TA_{it}) + \alpha_2 \ln(TA_{it})^2 + \alpha_3 \mathrm{lgr}_{it} + \alpha_4 \mathrm{lgr}_{it}^2 + \alpha_5 \mathrm{lgr}_{it}^3 + \alpha_6 \mathrm{lgr}_{it} \ln(TA_{it}) + \beta_{11} GAP_{t-1} I(dr_{it-1} \le \gamma_1) I(GAP_{t-1} \le \gamma_2) + \beta_{12} GAP_{t-1} I(dr_{it-1} \le \gamma_1) I(GAP_{t-1} > \gamma_2)$$
$$+ \beta_{13} GAP_{t-1} I(dr_{it-1} > \gamma_1) I(GAP_{t-1} \le \gamma_2) + \beta_{14} GAP_{t-1} I(dr_{it-1} > \gamma_1) I(GAP_{t-1} > \gamma_2) + e_t$$

Model (3), (4) and (5): same as (1) with dr_{it} replaced by dr_{it}^{LTD}, dr_{it}^{CO} and dr_{it}^{MU} respectively. Model (6), (7) and (8): same as (2) with dr_{it-1} replaced by dr_{it-1}^{LTD}, dr_{it-1}^{CO} and dr_{it-1}^{MU} respectively,

where *dr* is the individual default rate and GAP_{t-1} is $GAPT_{t-1}$. γ_1 and γ_2 are the estimated micro and macro threshold, respectively. *LR* is the likelihood ratio test for the null of one micro threshold whose *p*-value is computed through the bootstrap as suggested by Hansen (1996) with *N. bootstrap* replications. The trimming % is the percentage of observations that are excluded from the sample so that a minimal percentage of observations lie in each regime. Standard errors are in parenthesis. ***, ** and * indicate significance at 1, 5 and 10% respectively.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α_1	0.0496 ***	0.1656 ***	0.0556 **	0.1803 ***	0.0072	0.0995 ***	0.2576 ***	0.1662 ***
	(0.0147)	(0.0186)	(0.0240)	(0.0173)	(0.0199)	(0.0299)	(0.0233)	(0.0287)
α_2	-0.0066 ***	-0.0216 ***	-0.0097 ***	-0.0160 ***	-0.0017	-0.0179 ***	-0.0235 ***	-0.0216 ***
	(0.0011)	(0.0014)	(0.0015)	(0.0011)	(0.0019)	(0.0018)	(0.0014)	(0.0027)
α_3	-0.4834 ***	-0.6327 ***	-1.5294 ***	-1.8760 ***	-0.2234	-1.8381 ***	-2.4589 ***	0.0520
	(0.1419)	(0.1861)	(0.3030)	(0.2502)	(0.1608)	(0.3622)	(0.3184)	(0.2171)
α_4	-0.1002 ***	-0.1045 **	-0.0416	-0.0900 **	-0.1699 ***	-0.0102	-0.0187	-0.1542 ***
	(0.0355)	(0.0460)	(0.0383)	(0.0363)	(0.0303)	(0.0446)	(0.0419)	(0.0401)
α_5	0.1198 ***	0.2078 ***	0.2120 ***	0.0650 ***	0.0936 ***	0.2810 ***	0.1868 ***	0.1664 ***
	(0.0205)	(0.0296)	(0.0253)	(0.0236)	(0.0156)	(0.0305)	(0.0277)	(0.0220)
α_6	-0.0215	-0.0590 **	0.0864 **	0.1610 ***	-0.0522	0.0830 *	0.1780 ***	-0.1889 ***
	(0.0221)	(0.0271)	(0.0366)	(0.0291)	(0.0329)	(0.0426)	(0.0369)	(0.0425)
β_{11} (good bank/recession)	0.0522 ***	-0.0333 ***	0.0439 ***	0.0240 ***	0.0558 ***	-0.0152 ***	-0.0315 **	-0.0224 ***
	(0.0025)	(0.0035)	(0.0025)	(0.0022)	(0.0024)	(0.0033)	(0.0023)	(0.0045)
β_{12} (good bank/expansion)	-0.0688 ***	-0.0187 ***	-0.0707 ***	-0.0532 ***	-0.0696 ***	-0.0336 ***	-0.0176 ***	-0.0131 ***
	(0.0026)	(0.0020)	(0.0023)	(0.0019)	(0.0026)	(0.0027)	(0.0018)	(0.0023)
β_{13} (bad bank/recession)	-0.2046 ***	-0.1130 ***	-0.1750 ***	-0.1906 ***	-0.2344 ***	-0.1092 ***	-0.1903 ***	-0.0578 ***
	(0.0043)	(0.0067)	(0.0032)	(0.0037)	(0.0056)	(0.0037)	(0.0057)	(0.0061)
β_{14} (bad bank/expansion)	0.2289 ***	-0.0263 ***	0.1648 ***	0.1679 ***	0.2942 ***	0.0116 *	0.0341 *	-0.0147 ***
	(0.0071)	(0.0099)	(0.0053)	(0.0058)	(0.0084)	(0.0064)	(0.0174)	(0.0046)

Table 5 (Continued)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ_1	0.44	0.729	0.508	0.561	0.372	0.546	0.888	0.324
γ_2	-0.178	-1.614	-0.178	-0.178	-0.178	-0.219	-0.782	-1.822
N. of banks	212	212	73	18	121	73	18	121
N. of quarters	61	61	61	61	61	61	61	61
N. of quantiles (micro)	393	393	393	393	393	393	393	393
N. of quantiles (macro)	60	60	60	60	60	60	60	60
Trimming %	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
LR Test	7000.58 ***	78.54 ***	5601.92 ***	5497.42 ***	9494.10 ***	274.64 ***	308.69 ***	40.90 ***
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N. bootstrap	300	300	100	100	100	100	100	100

Table 6
Summary Results of Monte Carlo Exercises

This table reports the summary results for the Monte Carlo out-of-sample exercises for all models estimated in this paper. The models are the following:

Model (1): $dr_{it} = \alpha_1 \ln\left(TA_{it}\right) + \alpha_2 \ln\left(TA_{it}\right)^2 + \alpha_3 \lg r_{it} + \alpha_4 \lg r_{it}^2 + \alpha_5 \lg r_{it}^3 + \alpha_6 \lg r_{it} \ln\left(TA_{it}\right) + \beta_{11} GAP_{t-1} I\left(dr_{it} \le \gamma_1\right) + \beta_{12} GAP_{t-1} I\left(dr_{it} > \gamma_1\right) + e_t$. Model (2) is the same as model (1) with dr_{it} replaced by dr_{it-1}.

Model (3): $dr_{it} = \alpha_1 \ln\left(TA_{it}\right) + \alpha_2 \ln\left(TA_{it}\right)^2 + \alpha_3 \lg r_{it} + \alpha_4 \lg r_{it}^2 + \alpha_5 \lg r_{it}^3 + \alpha_6 \lg r_{it} \ln\left(TA_{it}\right) + \beta_{11} GAP_{t-1} I\left(GAP_{t-1} \le \gamma_1\right) + \beta_{12} GAP_{t-1} I\left(GAP_{t-1} > \gamma_1\right) + e_t$.

Model (4): $dr_{it} = \alpha_1 \ln\left(TA_{it}\right) + \alpha_2 \ln\left(TA_{it}\right)^2 + \alpha_3 \lg r_{it} + \alpha_4 \lg r_{it}^2 + \alpha_5 \lg r_{it}^3 + \alpha_6 \lg r_{it} \ln\left(TA_{it}\right) + \beta_{11} GAP_{t-1} I\left(dr_{it} \le \gamma_1\right) + \beta_{12} GAP_{t-1} I\left(\gamma_1 < dr_{it} \le \gamma_2\right) + \beta_{13} GAP_{t-1} I\left(dr_{it} > \gamma_2\right) + e_t$. Model (5) is the same as model (4) with dr_{it} replaced by dr_{it-1}.

Model (6): $dr_{it} = \alpha_1 \ln\left(TA_{it}\right) + \alpha_2 \ln\left(TA_{it}\right)^2 + \alpha_3 \lg r_{it} + \alpha_4 \lg r_{it}^2 + \alpha_5 \lg r_{it}^3 + \alpha_6 \lg r_{it} \ln\left(TA_{it}\right) + \beta_{11} GAP_{t-1} I\left(dr_{it} \le \gamma_1\right) + \beta_{12} GAP_{t-1} I\left(\gamma_1 < dr_{it} \le \gamma_2\right) + \beta_{13} GAP_{t-1} I\left(\gamma_2 < dr_{it} \le \gamma_3\right) + \beta_{14} GAP_{t-1} I\left(dr_{it} > \gamma_3\right) + e_t$. Model (7) is the same as model (6) with dr_{it} replaced by dr_{it-1}.

Model (8):
$$dr_{it} = \alpha_1 \ln\left(TA_{it}\right) + \alpha_2 \ln\left(TA_{it}\right)^2 + \alpha_3 \lg r_{it} + \alpha_4 \lg r_{it}^2 + \alpha_5 \lg r_{it}^3 + \alpha_6 \lg r_{it} \ln\left(TA_{it}\right) + \beta_{11} GAP_{t-1} I\left(dr_{it} \le \gamma_1\right) I\left(GAP_{t-1} \le \gamma_2\right) + \beta_{12} GAP_{t-1} I\left(dr_{it} \le \gamma_1\right) I\left(GAP_{t-1} > \gamma_2\right)$$
$$+\beta_{13} GAP_{t-1} I\left(dr_{it} > \gamma_1\right) I\left(GAP_{t-1} \le \gamma_2\right) + \beta_{14} GAP_{t-1} I\left(dr_{it} > \gamma_1\right) I\left(GAP_{t-1} > \gamma_2\right) + e_t$$

Model (9):
$$dr_{it} = \alpha_1 \ln\left(TA_{it}\right) + \alpha_2 \ln\left(TA_{it}\right)^2 + \alpha_3 \lg r_{it} + \alpha_4 \lg r_{it}^2 + \alpha_5 \lg r_{it}^3 + \alpha_6 \lg r_{it} \ln\left(TA_{it}\right) + \beta_{11} GAP_{t-1} I\left(dr_{it-1} \le \gamma_1\right) I\left(GAP_{t-1} \le \gamma_2\right) + \beta_{12} GAP_{t-1} I\left(dr_{it-1} \le \gamma_1\right) I\left(GAP_{t-1} > \gamma_2\right)$$
$$+\beta_{13} GAP_{t-1} I\left(dr_{it-1} > \gamma_1\right) I\left(GAP_{t-1} \le \gamma_2\right) + \beta_{14} GAP_{t-1} I\left(dr_{it-1} > \gamma_1\right) I\left(GAP_{t-1} > \gamma_2\right) + e_t$$

For each model, the Monte Carlo exercises are performed as follows. At each iteration, we randomly select an out-of-sample of 52 banks, leaving 160 banks in sample. Since in the full sample of 212 banks we have 73 limited banks (34%), 18 cooperative banks (9%) and 121 mutual banks (57%), we decided to maintain the same percentages for each category in both samples. Therefore in the out-of-sample we have 18 limited banks, 4 cooperative banks and 30 mutual banks. We then estimate all models in sample, saving the estimated coefficients and thresholds. We thus use these estimated coefficients and thresholds to compute the fitted default rates out-of-sample for the 52 banks. We then compute two measures of goodness of fit. The absolute difference between the out-of-sample real value and the fitted one (L_{ABS}) and the squared difference between the realized and the fitted value of the default rate (L_{SQ}). This table reports for each model the mean and median of all coefficients, thresholds and the two measures of fit.

Model	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
	2 regimes						**3 regimes**				**4 regimes**				**4 regimes**			
Threshold Variable	*dr(t)*		*dr(t-1)*		*GAPT(t-1)*		*dr(t)*		*dr(t-1)*		*dr(t)*		*dr(t-1)*		*dr(t), GAP(t-1)*		*dr(t-1), GAPT(t-1)*	
Coefficients	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
α_1	0.1494	0.1480	0.1603	0.1588	0.1840	0.1822	0.1489	0.1628	0.1614	0.1597	0.1483	0.1470	0.1610	0.1596	0.0585	0.0566	0.1527	0.1508
α_2	-0.0203	-0.0202	-0.0215	-0.0213	-0.0231	-0.0230	-0.0202	-0.0192	-0.0215	-0.0214	-0.0202	-0.0200	-0.0215	-0.0213	-0.0077	-0.0079	-0.0201	-0.0199
α_3	-0.7103	-0.7029	-0.7049	-0.6976	-0.7291	-0.7237	-0.7190	-0.6336	-0.7089	-0.7013	-0.7182	-0.7134	-0.7063	-0.6979	-0.5504	-0.5488	-0.7431	-0.7297
α_4	-0.0867	-0.0866	-0.0972	-0.0961	-0.0814	-0.0807	-0.0829	-0.0649	-0.0944	-0.0933	-0.0816	-0.0808	-0.0941	-0.0933	-0.0720	-0.0716	-0.0760	-0.0793
α_5	0.1984	0.1958	0.2141	0.2111	0.2180	0.2151	0.1986	0.2101	0.2104	0.2072	0.1983	0.1963	0.2108	0.2077	0.1287	0.1276	0.2108	0.2086
α_6	-0.0390	-0.0409	-0.0500	-0.0517	-0.0457	-0.0484	-0.0378	-0.0252	-0.0474	-0.0489	-0.0379	-0.0396	-0.0480	-0.0500	-0.0148	-0.0151	-0.0402	-0.0426
β_{11}	-0.0200	-0.0199	-0.0256	-0.0256	-0.0563	-0.0563	-0.0184	-0.0178	-0.0209	-0.0212	-0.0180	-0.0181	-0.0205	-0.0208	0.0520	0.0521	-0.0249	-0.0231
β_{12}	-0.1550	-0.1536	-0.0978	-0.0985	-0.0221	-0.0222	-0.1107	-0.1022	-0.0454	-0.0455	-0.0928	-0.0981	-0.0453	-0.0444	-0.0699	-0.0702	-0.0207	-0.0211
β_{13}	-	-	-	-	-	-	-0.2314	-0.2095	-0.0997	-0.0992	-0.1671	-0.1738	-0.0756	-0.0868	-0.1935	-0.1932	-0.1083	-0.1035
β_{14}	-	-	-	-	-	-	-	-	-	-	-0.2703	-0.2683	-0.1110	-0.1124	0.2045	0.2018	0.0048	0.0063

Table 6 (Continued)

Model		(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
		2 regimes						**3 regimes**				**4 regimes**				**4 regimes**			
	Threshold Variable	*dr(t)*		*dr(t-1)*		*GAPT(t-1)*		*dr(t)*		*dr(t-1)*		*dr(t)*		*dr(t-1)*		*dr(t), GAP(t-1)*		*dr(t-1), GAPT(t-1)*	
Thresholds																			
γ_1		0.767	0.765	0.739	0.742	-1.688	-1.614	0.717	0.714	0.480	0.512	0.696	0.711	0.454	0.512	0.454	0.451	0.606	0.545
γ_2		-	-	-	-	-	-	1.044	0.986	0.759	0.743	0.912	0.945	0.695	0.741	-0.178	-0.178	-0.393	-0.219
γ_3		-	-	-	-	-	-	-	-	-	-	1.202	1.174	0.985	1.065	-	-	-	-
Measures of fit																			
L_{ABS}		0.225	0.224	0.192	0.192	0.165	0.165	0.290	0.280	0.193	0.192	0.326	0.322	0.203	0.200	0.132	0.131	0.164	0.162
L_{SQ}		0.085	0.083	0.064	0.064	0.051	0.051	0.135	0.126	0.065	0.064	0.170	0.164	0.071	0.069	0.032	0.031	0.050	0.049