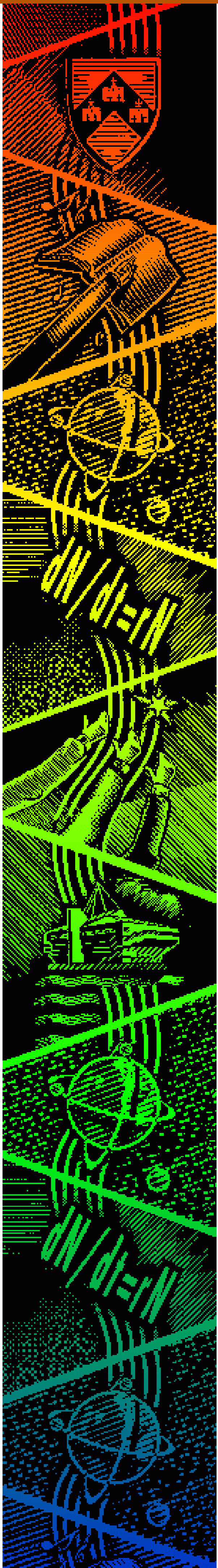

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Banks' Performance over the Business Cycle: A Panel Analysis on Italian Intermediaries

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BANKS' PERFORMANCE OVER THE BUSINESS CYCLE: A PANEL ANALYSIS ON ITALIAN INTERMEDIARIES

Mario Quagliariello*

Abstract

Supervisors and policy makers pay increasing attention to the possible procyclical nature of banks' behaviour. Indeed, to guarantee macro and financial stability, it is important to understand if, and to what extent, banks are affected by the macroeconomy and if there are second round effects. This paper provides a comprehensive investigation on these issues using a large dataset of Italian intermediaries over the period 1985-2002. In particular, estimating both static and dynamic models, it investigates whether loan loss provisions, non-performing loans and the return on assets show a cyclical pattern. The estimated relations are then employed to carry out simple stress tests aiming at assessing the effects of macroeconomic shocks on banks' balance sheets.

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1. Introduction

In recent years the issue of the possible procyclicality of banks’ activity has drawn the attention of both academics and policy makers. Indeed, to guarantee macro and financial stability, it is crucial to understand if, and to what extent, banks are affected by the evolution of the macroeconomic environment and if there are second round impacts. On the one hand, if the business cycle does influence banks, financial surveillance may need to be strengthened during recessionary phases, when it is more likely that banks’ fragility arises. On the other hand, if banks’ reaction to macroeconomic shocks does exacerbate the effects of the downturn, it is appropriate to establish rules aiming at alleviating the procyclicality of banks’ operations.

The stylised facts suggest that, at the beginning of an expansionary phase in the economy, firms’ profits tend to increase, asset prices rise and customers’ expectations are optimistic. Expansion of aggregate demand leads to a remarkable, often more than proportional, growth in bank lending and in economy’s indebtedness. During the boom, banks may underestimate their risk exposures, relaxing credit standards and reducing provisions for future losses.

After the peak of the cyclical upturn, customers’ profitability worsens, borrower’s creditworthiness deteriorates and non-performing assets are revealed, thus causing losses in banks’ balance sheets (cyclicality). This may be associated with a fall of asset prices that, in turn, further affects customers’ financial wealth and depresses the value of collaterals. Besides, the possible rise of unemployment reduces households’ disposable income and their ability to repay their debts. Banks’ risk exposure increases, thus requiring larger provisions and higher levels of capital, exactly when it is more expensive or simply not available. Intermediaries may react by reducing lending, especially if they have thin capital buffers above the minimum capital requirement, thus exacerbating the effects of the economic downturn (procyclicality).

The approaching reform of the Basel Accord on banks’ capital requirements (Basel II) has given rise to new concerns about the behaviour of the financial intermediaries through the business cycle. It is well known that the main goal of the new accord is to make capital requirements more risk-sensitive by substituting in their calculation the fixed weights attached to categories of borrowers with weights determined on the basis of the individual creditworthiness, as measured by agencies' ratings or banks' internal ratings. It has been argued that higher sensitivity of capital requirements could amplify the procyclicality of banks' activity. In fact, in bad times, increased risk would lead to higher capital requirements which, in turn, may cause a contraction of credit supply.

In principle, many banking variables are potentially able to convey signals about the evolution of banks' health over the business cycle; however, loan loss provisions and bad debts have been generally considered the "transmission channels" of the macroeconomic shocks to banks' balance sheets.

Banks make loan loss provisions against profits when they believe that borrowers will default; this is the tool they can use for adjusting the (historical) value of loans to reflect their true value. Provisions affect both banks' profitability, since they represent a cost for the intermediary, and capital, since they reduce the book value of the assets.

It is common to distinguish between static (specific) and dynamic (general) provisions, where the former are based on current conditions of debtors and are made only when losses are known to occur, while the latter are set against expected losses on non-impaired loans[1]. The principle that justifies dynamic provisions is that when a loan is granted, there is already a positive and measurable probability that the bank will incur losses due to the debtor's inability to honour his obligations. If loan loss provisions were forward-looking, the volume of bank capital should be related to the size of the unexpected losses and the procyclical effects of provisioning policies would be limited. Prudent banks might also use loan loss provisions to stabilise their earnings over time, by reducing/increasing the flow of provisions when their performance worsens/improves.

In practice, loan loss provisions are often backward-looking, as banks tend to underestimate future losses in periods of economic expansion because of disaster myopia (Guttentag *et al.*, 1986), herding behaviour (Rajan, 1994) or because higher provisions are interpreted by stakeholders as a signal of lower quality portfolios (Ahmed *et al.*, 1996).

[1] Cavallo and Majoni (2002) point out that specific provisions are thus similar to write offs. This may explain also why provisions and write offs are very often contemporaneous, even though the former should logically precede the latter.

Banks tend to provision against actual rather than expected losses also because of accounting and fiscal rules that allow specific provisions only against impaired debts and do not permit tax deductibility for general provisions, since they cannot be documented and can potentially be exploited by banks to reduce their fiscal burden.

Sub-standard loans are also considered as a good proxy for asset quality and a reliable leading indicator for bank fragility. In fact, there is clear evidence that the proportion of non-performing loans dramatically increases before and during banking crises (Demirguc-Kunt and Detragiache, 1998; Gonzales-Hermosillo, 1999). The stock of the outstanding bad debts is however a rough measure of credit quality, in fact it can decrease just because some of the credits are written off. For this reason, the flow of new bad debts, i.e. the amount of loans classified as bad debts for the first time in the reference period, can be considered to be a more precise indicator of the banks' portfolio riskiness.

Much empirical work has tried to verify the correctness of these stylised facts. Such investigations have generally focussed on a single banks' performance indicator, using relatively small datasets; cross-country comparisons are prevalent, while cross-bank investigations (within the same country) are less common.

This paper contributes to this stream of research using a large panel of Italian intermediaries whose data are available for the period 1985-2002. With respect to previous works, the paper attempts to provide a more comprehensive framework, though in a reduced-form modelling context, analysing the movements of loan loss provisions, new bad debts and profitability over the business cycle. Both static fixed-effects and dynamic models are estimated to verify if banks' performance is linked (also) to the general economic climate and to understand the timing of banks' reactions to economic changes. The outcomes of models are then employed to carry out stress tests that simulate the impact of some macroeconomic shocks on the Italian banking system.

The remainder of the paper is structured as follows. In the next section I review the empirical literature dealing with the procyclicality of banks' behaviour. Sections 3 and 4 are devoted to the description of the data used in the empirical exercise and of the econometric methodology. Sections 5 and 6 present the estimated models, their main findings and some robustness checks. In the last section, a sensitivity analysis is carried out on the basis of the estimated coefficients. Some concluding remarks are finally provided.

1. The review of the literature

There is a huge empirical literature studying the linkages between banking sector performance and the business cycle. The starting point of the analyses on procyclicality is that the models of banks performance that only include financial ratios as explanatory variables cannot take into account systematic problems arising from an adverse evolution of the macroeconomic environment. The general framework is therefore the following:

$$\textit{Bank-specific variable}_{it} = \textit{bank specific}_{it\text{-}j} + \textit{macroeconomic variables}_{it\text{-}j}$$

where the bank data might be either at single bank or banking system level and the regressors either coincident or lagged. The specification can thus be a simple static model (i=1 and j=0), a distributed lag model (i=1 and j>0) or a panel (i>1, either cross-bank or cross-country).

Since credit risk is still the main source of instability for most banks, the dependent variable is very often a measure of loan quality.

For instance, Salas and Saurina (2002) analyse the relation between problem loans and the economic cycle in Spain, over the period 1985-1997. They observe that, during economic booms, banks tend to expand lending activity to increase their market share; this result is often reached by lending to borrowers of lower credit quality. They report that bad loans increase in recessionary phases and that the contemporary impact is remarkably higher than the delayed one, concluding that macroeconomic shocks are quickly transmitted to banks' balance sheets. Conversely, non-financial sector's fragility indicators such as households and firms' indebtedness appear to be not significant.

In the same spirit, focusing on the banking crises of four Nordic countries (Denmark, Norway, Sweden and Finland), Pesola (2001) assesses the usefulness of macroeconomic shocks in explaining two different indicators of bank distress such as the ratio of loan losses to lending and the number of non-financial companies' bankruptcies per capita. According to his results, the high level of both corporate and households' indebtedness along with an increase in the interest rate above the expected one and a GDP growth below the forecasts contributed to the banking crises in Sweden, Norway and Finland; the deregulation dummy and lending growth variables come out to be significant as well.

The analysis performed by Gambera (2000) is quite different in style. He uses bivariate VAR systems and impulse response functions to study how economic development affects bank loan quality. With respect to panel estimation, the VAR methodology allows all variables to be endogenously determined and has the advantage of fully capturing the interactions between bank and macro variables. The author uses the ratio of delinquencies to total loans and the ratio of non-performing loans to total loans as alternative indicators of financial distress and estimates a bivariate system for each series of macroeconomic variables. His results suggest that a narrow number of macroeconomic variables (namely bankruptcy filings, farm income, annual product, housing permits and unemployment) are good predictors for the problem loans ratio.

Other authors focus on the evolution of provisioning policies through the business cycle since loan loss provisions should reflect changes of borrowers' creditworthiness and banks' sentiment concerning the health of the real economy.

Understanding banks' provisioning behaviour is, for instance, the goal of Cavallo and Majnoni (2002) and Laeven and Majnoni (2003). The latter authors analyse large commercial banks' policies in various countries to verify whether intermediaries use provisions for stabilising their income. They find that bankers, on average, smooth their earnings, but they create too little provision in good (macroeconomic) times. In other words, they find a negative relation between provisions and loan and GDP growth, suggesting that banks provision during and not before recessions, thus magnifying the effects of the negative phase of the business cycle. Similar evidence is provided by the European Central Bank (2001) in its survey on provisioning practices in the EU; the report points out also that there is an almost simultaneous relation between provisions and non-performing loans; in other words, banks seem to record provisions only when credit risk actually materialises. With reference to the relation between provisions and profitability, there is no clear evidence of income-smoothing.

Similarly to Laeven and Majnoni, Pain (2003) and Arpa et al. (2001) investigate the influence of the business cycle on loan loss provisions of UK and Austrian banks respectively. The former author considers a large set of explanatory variables proxying macroeconomic disturbances, firms and households' indebtedness, financial and real asset prices shocks, and documents that provisions exhibit some cyclical dependence. He also finds that bank specific factors are relevant as well: lending to riskier sectors is generally associated with higher provisions; in particular, mortgage banks provision less than commercial banks since their loans are typically collateralized. Arpa et al. (2001), estimating a simple distributed lag model, conclude that provisions increase in periods of falling real GDP growth. They also find evidence that provisions are higher in times of rising bank profitability, supporting the income-smoothing hypothesis.

An attractive view is provided by Bikker and Hu (2002), who estimate an unbalanced panel to evaluate the procyclicality of banks' provisions for a sample of 26 OECD countries between 1979 and 1999. They find that the coefficients on GDP growth and inflation have a negative sign, while that of unemployment rate is significantly positive. However, in years of higher net interest income the amount of provisions is higher, thus supporting the income-smoothing hypothesis. Therefore, the authors claim that, even if provisions go down in favourable (macroeconomic) times, banks tend to reserve more in good years (i.e., when profits are higher); as a result, banks are less procyclical than it would appear just looking at their dependence on the business cycle.

In a recent paper, Valckx (2003) considers the loan loss provisioning policy of EU banks using a sample of 15 European banking systems and a small panel of large EU banks. According to his results, loan loss provisions are determined by GDP growth, interest rates and some bank specific indicators both at sector level and for individual banks. The positive relation between income margin and provisions suggests that the income-smoothing hypothesis for EU banks applies, thus contradicting the ECB's findings.

Although credit quality is considered one of the main indicators of bank fragility, a relevant part of the literature on procyclicality focuses on other variables, typically P&L account ratios, to get a more detailed picture of banks' health over the business cycle.

For instance, Arpa et al. (2001) widen the focus of the analysis and examine the relation between economic activity and banks' profitability. They observe that falling interest rates, rising real estate prices and inflation positively affect operating income; while net interest income appears to be uncorrelated with GDP growth. Similarly, Meyer and Yeager (2001), employing a sample of US rural banks, find that state-level coincident macroeconomic variables are significant in explaining banks' performance.

In their model of banks' profitability, Bikker and Hu (2002) find that both the contemporaneous and the lagged coefficient of GDP growth are significant and positive, while the unemployment rate turns out to have a negative coefficient. Neither the short and long-term interest rates nor share prices and money supply seem to have significant explanatory power.

The role of the business cycle in determining banks' profits is also confirmed by Gambacorta, Gobbi and Panetta (2001) who estimate a panel regression for eight euro-countries, UK and USA over the period 1980-1997. They find that GDP growth positively affects the return on equity (ROE), while inflation has a negative impact on banks' earnings. The evolution of interest rates has an ambiguous effect on profitability.

Very recently, Gerlach et al. (2003) analyse the effect of macroeconomic developments on profitability and asset quality of banks in Hong Kong. Their results are consistent with the bulk of the previous empirical evidence. Furthermore, working on bank-level data, they notice that small banks tend to be more sensitive to macroeconomic shocks than larger ones. They argue that this is probably the consequence of small banks' larger exposures towards more risky firms that are more likely to be affected by the business cycle.

Summing up, good economic conditions positively affect the quality of banks' portfolios as measured by some kind of sub-standard loan ratio; business cycle also affects bank profitability. Moreover, there is some evidence on the issue of whether intermediaries tend to use loan loss provisions to smooth their income (i.e., they provision more when earnings increase). However, it happens that they do not make enough provision in good macroeconomic times (i.e., when GDP and loan growth are high). Therefore, when economic conditions reverse, loan losses start to emerge, provisions rise, profitability decreases and credit supply tends to decrease, thus amplifying the effects of the recession.

3. The data and the sample

The empirical analysis in this paper aims at investigating how Italian banks' performance is affected by the changes of the general economic conditions. Following the existing literature, the analysis focuses on the evolution of loan loss provisions (hereafter, LLP), new bad debts and the return on assets (ROA), to test if they show the expected cyclical pattern.

With reference to the sample, I select an unbalanced panel of 207 Italian intermediaries whose accounting ratios are available for at least 5 years in the period between 1985 and 2002. The sample excludes all the mutual banks (*banche di credito* *cooperativo*) and, to reduce measurement errors, the outliers[2]. The resulting sample represents around 90 per cent of Italian banking system's consolidated total assets[3]. Along with this large unbalanced sample, I use a smaller panel of 11 large banks whose data are available for the whole period under exam (18 years) to carry out robustness checks[4].

A summary of the characteristics of the two samples is provided in table 1.

Table 1

Accounting ratios for the individual institutions are built up using the supervisory statistics that intermediaries are required to report to the Bank of Italy and the information of the Italian Credit Register; all the macroeconomic variables are drawn from the database of the Research Department of the Bank of Italy that collects data from various sources. In general, the macroeconomic variables and most of the bank specific indicators are available at a quarterly frequency and over quite a long time span, even though data homogeneity may be an issue for some time series. Unfortunately, P&L account ratios are only available on a semi-annual basis since 1993; before that date they were annual. Since the focus of the paper is on the evolution of banks' performance through the business cycle, the longer time span is preferred to the higher frequency of the observations. Annual data are therefore used.

Tables 2, 3 and 4 summarise the variables I consider in the analysis and provide some descriptive statistics. Although I largely rely on supervisory data, most of the indicators can be built up using alternative and (very often) publicly available sources (tab. 2).

Tables 2,3,4

Some of the dependent variables, namely loan loss provisions (LLP) and the flow of new bad debts (RISKFL) vary by construction between 0 and 1; some authors have suggested to use the log-odds transformation of such variables to create an unbounded

[2] I exclude outlier banks by eliminating the observations with values of the banks specific variables (except SIZE) above and below the last and the first percentile respectively.

[3] During the Nineties, the Italian banking system experienced an intense process of mergers and acquisitions. To deal with the impact of these operations on the sample, I assumed that they took place at the beginning of the sample period, consolidating the balance-sheet items of the banks involved.

[4] The sample includes banks with total assets equal to at least 20 billion euros; it represents more than 65 per cent of Italian banks' consolidated total assets.

series between minus and plus infinity. Actually, this seems more a philosophical than a practical issue. In fact, these variables are typically in the range 0-0.1, the correspondent log-odds ratios are very far from varying between plus/minus infinite as well (tab. 4).

Finally, some concerns may derive from the presence of unit roots in the series considered in the analysis. Im, Pesaran and Shin's unit root tests for panel data are therefore carried out; results for the three dependent variables are reported in table 5[5].

Table 5

Tests are performed including both a constant and a constant and time trend and considering both the raw and the demeaned data. The t-bar statistics are always significant at any conventional level, thus confirming that the series for loan loss provisions, new bad debts and return on assets are stationary.

4. The econometric methodology

The analysis in this paper is carried out using a simple estimation strategy. I start with a static (reduced form) regression using the least square dummy variable (LSDV) model, since fixed effects seem *a priori* able to catch the heterogeneity across individuals, without imposing restrictive conditions on the correlation between the regressors and the error term[6].

I select the starting set of regressors according to the insights provided by the economic theory and the empirical results that emerged in previous analyses. In principle, several variables might be employed as proxies for the phase of the business cycle; however, a preliminary investigation suggested to include GDP growth as the main

[5] For simplicity I present only the unit root tests for the dependent variables; tests are however carried out for all the regressors as well. For the microeconomic explanatory variables, except RISKST, the tests generally do not find significant evidence of the presence of a unit root. Interestingly, the standard Augmented Dickey Fuller tests (ADF) performed on the aggregate time series fail to reject non-stationarity, thus confirming the advantage in terms of power of also exploiting cross-sectional information. Finally, it is worth noting that most of the macroeconomic series, even the first-differenced ones, seem to be non-stationary according to the ADF tests. This result is however affected by the low power of the test, especially in small samples and for near unit root processes (Enders, 1995).

[6] It is beyond the scope of this paper to set up a complete structural model, even though a system of simultaneous equations might be an appealing tool to describe the co-movements of the explanatory variables.

indicator of the aggregate economic activity[7].

The lag structure of the explanatory variables takes into account the plausible delay with which macroeconomic shocks affect banks, the frequency of the observations and the need to start from a quite general model without losing excessive degrees of freedom.

Therefore, as a general rule, the explanatory variables enter in the regressions with the current value and one lag; GDP changes enter with 2 lags. Other bank specific variables may have a different lag structure according to the particular dependent variable; details will be provided in the following section. As a consequence of the insertion of lagged variables, the period under examination is 1987-2002. At this stage, all the explanatory variables are assumed to be exogenous[8].

The most parsimonious specification is subsequently chosen through the general-to-simple approach, dropping the less significant variable at each stage and ending up with a set of regressors significant at (at least) 5 per cent level. A preliminary diagnostic revealed the presence of both groupwise heteroskedasticity and first order autocorrelation. I consequently use the Newey-West robust standard errors for carrying out inference.

As robustness checks the most parsimonious representations are re-estimated using the pooled regression and the random effect model.

Although the static model is the natural starting point for analysing the relation between economic activity and banks' stability, there is no consensus on its appropriateness for explaining the behaviour of LLP and non-performing loans through the business cycle[9].

For instance, with regard to LLP, Pain (2003) wonders if banks register in their balance sheets the full amount of any probable losses as soon as the borrower defaults (suggesting that the static model is appropriate) or rather if they update the assessment of the probable losses according to new information in each period (suggesting that provisions

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[7] Indeed, the inclusion of investment and consumption changes produced some puzzling results. The use of firms and households' indebtedness, which are frequently found as important signals of fragility of the real sector, did not significantly improve the performance of the model and dramatically reduced the sample span, since homogeneous figures for these variables are available since 1990; moreover, there is not clear-cut evidence on the expected effects of these variables (Salas and Saurina, 2002; Pain, 2003).

[8] This finds some support in the results of the Hausman tests performed on the starting specification.

[9] Valckx (2003), ECB (2001), Cavallo and Majnoni (2002) use a static model only, Salas and Saurina (2002) prefer the dynamic equation, while Pain (2003) estimates both the static and the dynamic specifications.

are systematically related and, therefore, the dynamic specification may be better).

As far as non-performing loans are concerned, Salas and Saurina (2002) use a dynamic equation under the assumption that the one-period variable is likely to be related to that of the previous periods since problem loans are not immediately written off and they can remain in the balance sheet for a long time.

To address these issues, the equations for loan loss provisions and new bad loans are re-estimated using a dynamic specification. A relevant advantage of the dynamic model is that it allows releasing the assumption of exogeneity of the regressors, which is unlikely to hold, at least for some of the current levels of the bank specific variables.

When the lagged dependent variable is included in the set of the explanatory variables, OLS estimates become inconsistent since regressors are no longer uncorrelated with the error term. These problems can be addressed first-differencing the model, thus eliminating the individual effects, and using instrumental variable estimators such as those proposed by Anderson and Hsiao (1981) and Arellano and Bond (1991). The two procedures produce consistent estimates; however the Arellano and Bond generalised method of the moments (GMM) estimator is more efficient and is the one used herewith.

Following Arellano-Bond methodology, the differences of the strictly exogenous regressors are instrumented with themselves and the dependent and predetermined/endogenous variables are instrumented with their lagged levels[10]. In particular, while predetermined variables are instrumented using their levels lagged by one or more periods, the dependent and the other endogenous variables are instrumented with their levels lagged by two ore more periods. The procedure requires that there is no second order correlation in the differenced equation; indeed, while the presence of first-order autocorrelation in the error terms does not imply inconsistency of the estimates, the presence of second-order autocorrelation makes estimates inconsistent (Arellano and Bond, 1991).

[10] In the following analysis, a regressor x_{it} is considered: strictly exogenous if $E[x_{it}\varepsilon_{is}]=0$ for all t and s; predetermined if $E[x_{it}\varepsilon_{is}]=0$ for $s \geq t$ and $E[x_{it}\varepsilon_{is}] \neq 0$ if $s<t$; endogenous if $E[x_{it}\varepsilon_{is}]=0$ for $s>t$ and $E[x_{it}\varepsilon_{is}] \neq 0$ if $s \leq t$.

5. The models and the results

5.1 Credit quality: loan loss provisions

In Italy, the rules banks must respect in the evaluation of their loans are established by Legislative Decree 87/1992 on banks' individual and consolidated accounts (implementing Directive 86/635/EEC) and by the Bank of Italy supervisory guidelines.

Loan loss provisions are typically raised on a case-by-case basis to cover potential losses on non-performing loans (specific provisions); portfolio-specific general provisions are allowed for homogeneous categories of loans, such as sectoral loans and country risk exposures. Along with these adjustments, which are not reported as contra-assets, banks can charge general provisions to the profit and loss account to create prudential reserves; they are therefore set up against unforeseen events and do not have an asset-adjustment function, but can be computed in the Tier 2 capital up to 1.25 per cent of the risk weighted assets.[11]

Since, as mentioned above, the stock of LLP may decrease not only because of the improvement of the debtors' financial conditions but also because the underlying credits are written off, the stock ratios are not necessarily timely indicators of banks' health; I therefore employ a flow rather than a stock measure.

Table 6 presents the correlation coefficients between loan loss provisions and some of the possible explanatory variables over the period 1985-2002.

Table 6

It emerges quite clearly that LLP are negatively related to GDP and credit growth implying that, on average, banks provision less in favourable economic times. However, a more careful analysis shows that the correlation between LLP and GDP is not stable over time[12]. Looking at figure 1, which plots the LLP ratio and the GDP growth, it is not possible to individuate a clear-cut linkage.

Fig. 1

[11] In Italy, fiscal regulations allow banks to deduct from their gross income value adjustments on credits (i.e. specific provisions) and general provisions up to 0.6 per cent of their total loans.

Indeed, while the evidence for some years (e.g., 1986, 1993 and 2000) confirms that banks provision less in good times, in other periods the relation tends to reverse and banks seem to adopt more forward-looking and counter-cyclical provisioning policies.

5.1.1 Static model

The estimated model for loan loss provisions is the following:

$$LLP_{it} = \alpha + BSV_{it-j}\beta + MV_{t-j}\delta + u_i + \varepsilon_{it}$$

i= 1,..., 207; t= 1987,..., 2002; j= 0, 1, 2 depending on the variable

where LLP is the loan loss provision ratio, BSV are the bank specific variables, MV the macroeconomic indicators, u the individual unobservable effects and ε the error term.

The starting model includes the following bank specific variables:

- CREDGR (contemporaneous and lagged by 1-year) is the growth of performing loans for each bank. It might signal either a positive phase of the business cycle if it is led by demand factors (suggesting a negative sign) or an aggressive supply policy of the banks that, in turn, entails the exposure to excessive risks and higher future provisions (suggesting a positive sign). It is hence plausible that CREDGR shows a negative sign when current values are considered and positive when lagged (Salas and Saurina, 2002). However, the empirical evidence for other countries is somewhat mixed and does not allow me to conclude that rapid credit growth automatically implies future problems. It is interesting to note that if provisions were dynamic the contemporaneous CREDGR should have a positive effect on LLP as well.
- The cost-to-income ratio (CIRATIO) is a commonly used indicator of banks' efficiency; banks with higher values of the ratio are expected to be also less effective in the selection of the borrowers and, in turn, to make higher provisions. Besides, as reported by Pain (2003) inefficient banks may be tempted to engage in riskier lending.

[12] This is not completely unexpected. Pain (2003) finds that the relation between LLP and business cycle for UK banks is not stable as well; for instance, he notices that provisions did not increase significantly during the early eighties recession.

- The return on assets (ROA) is a measure of profitability before loan loss provisions are registered on banks' balance sheet. It can be thus used to test whether banks use provisions to smooth their income. If the income-smoothing hypothesis held, the coefficient of the ROA should have a positive sign.

- RISKST provides a reliable proxy of the overall quality of bank's portfolio. The worse the creditworthiness of the customers, the higher the provisions against loan losses. From a logical point of view, loan loss provisions should precede the emergence of bad debts. In fact the amount of provisions is typically determined on the basis of the losses experienced in the past. Therefore, one lag of the variable is included as well.

- RISKFL should pick up banks' ability to select good new borrowers. The expected sign is positive since banks that are not able to screen potential debtors are more likely to incur loan losses in the future.

- SIZE has been preliminarily included as a control variable and subsequently dropped to avoid perplexing results probably due to its interaction with the individual effects.

For the macroeconomic determinants, the selected indicators are:

- GDPCC is the main and most direct measure of the aggregate economic activity and, according to the prevailing view that banks do not provision in good times, it is expected to be inversely related to loan loss provisions. Along with the contemporaneous value, two lags are introduced in the specification to understand the delay with which the worsening of the real economy affects credit quality.

- BTPR is the interest rate on long-term Treasury bonds. Higher interest rates entail an increasing debt burden for banks' borrowers. Households and firms may thus face greater difficulties in paying their loans back, especially if they are hugely indebted (Benito et al. 2002). On the other hand, interest rates are typically higher in expansionary phases when provisions are more likely to be low. The sign of the coefficient is therefore ambiguous.

- MIBC is the appreciation/depreciation of the stock exchange index and is a very rough proxy for the state of health of financial markets. In periods of bullish markets, the net wealth of households and firms tends to increase, thus making it easier to honour financial obligations (negative association). On the other hand, when the value of collateral appears particularly high, banks may be tempted to reduce their screening activity making their portfolios riskier (positive association). Finally, financial markets often show a boom and bust pattern; in other words, the bullish phase might precede a sharp decline of asset prices; according to this view, one would expect a negative sign for the lagged coefficient and a positive sign for the contemporaneous one.

- The change of the unemployment rate (URC) is usually not considered as a leading indicator; however, it influences the income of households and, in turn, their debt servicing ability. Since this transmission mechanism is not instantaneous, it is reasonable to consider the contemporaneous as well as the lagged values of the variable.
- The SPREAD between loans and deposits' rates is a proxy for banks' risk taking behaviour that might lead to future problem loans and higher provisions. More generally, the widening of financial spreads may anticipate cyclical movements in aggregate activity and the increase of default risk (Davis and Henry, 1994).

Table 7 presents the regression results. Newey-West standard errors are calculated assuming an autocorrelation up to order 2, but results are very similar when I use a higher number of lags.

Table 7

Consistently with the findings of the literature, Italian banks seem to be short-sighted to a certain extent. Indeed, they reduce their provisions when credit supply (CREDGR) and GDP (GDPCC) increase, thus reinforcing the idea that provisions are not dynamic and that intermediaries systematically underprovision during the upswing phases of the cycle. However, GDP growth turns out to be significant only when lagged by 1 and 2 years and the coefficient of the second lag is larger than that of the first one, implying that the cyclical impacts are not instantaneous, but delayed. The overall long-run partial effect of 1 per cent change of GDP is equal to around –0.23, comparable with the values provided by Pain (2003), Valckx (2003) and Bikker and Hu (2002).

Turning to credit growth, as already mentioned it might be led by both demand and supply factors; it is therefore difficult to use such a variable to decide whether banks pursuing higher lending growth rates are more likely to accept riskier borrowers. Since this is a relevant issue, I re-estimate the model using a sort of "abnormal" growth indicator (i.e. the difference between the single bank's growth rate and the average for the banking system), which should mainly reflect supply-side determinants. The estimated coefficients for this modified indicator remain negative, indicating that it is not necessarily true that more aggressive lending policies imply a less accurate selection of the customers.

As far the profitability indicator is concerned, the positive sign of the current ROA coefficient indicates that banks tend to use provisions to stabilise their income over time, as found by Arpa *et al.* (2001), Bikker and Hu (2002) and Valckx (2003). Banks' cyclical behaviour appears therefore to be partially offset by income-smoothing policies.

The negative sign of URC is quite puzzling; a possible explanation is that GDPCC already captures the effects of the business cycle. Lagged interest rate spread shows, as expected, a positive association with LLP, making plausible the hypotheses that it either proxies risk taking or anticipates cyclical downturns; however, it is worth underlining that the indicator is calculated for the banking system as a whole and can therefore hide differences across banks.

The coefficient on the treasury bond rate (BTPR) shows a negative sign, which should support the idea that the variable represents a generic business cycle indicator rather than a proxy for debt burden. As in previous empirical analysis financial asset prices (MIBC) show a boom and bust cycle with negative lagged coefficients and positive contemporaneous coefficients; the overall long-run effect is negative, but it does not seem particularly relevant. Finally, as expected, banks provision according to the overall riskiness of their portfolio (RISKST) and to their ability to effectively select new customers (RISKFL). The past history of bad debts is therefore an important element in banks' choice of their provisioning policies.

As far as the overall goodness of fit is concerned, the value of the R-squared (0.5 per cent) is acceptable and in line with the previous literature. Moreover, the model picks up the main turning points of the evolution of LLP and the confidence intervals for the (in-sample) predictions are reasonably small (fig. 2).

Fig. 2

The fixed effect model seems appropriate as confirmed by the Breusch-Pagan Lagrange multiplier and the Hausman tests that reject the pooled regression and the random effect model respectively. The F-test confirms that the individual dummies are jointly significant at any conventional level. In any case, coefficient estimates seem robust to different estimations techniques; for instance, the partial effect of GDPCC is not dramatically different in the three specifications[13].

5.1.2 Dynamic model

Although the static estimates appear very supportive of the conjecture that loan loss provisions are cyclical, the exercise is replicated including some dynamics.

The resulting regression is the following:

$$LLP_{it} = \alpha + \Sigma\gamma_j LLP_{it\text{-}j} + BSV_{it\text{-}j}\beta + MV_{t\text{-}j}\delta + u_i + \varepsilon_{it}$$

i= 1,..., 207; t= 1987,..., 2002; j= 0, 1, 2 depending on the variable

that, once first differenced, reduces to:

$$\Delta LLP_{it} = \Sigma\gamma_j \Delta LLP_{it\text{-}j} + \Delta BSV_{it\text{-}j}\beta + \Delta MV_{t\text{-}j}\delta + \Delta\varepsilon_{it}$$

The need to difference the equation reduces the time period available for the estimation by one further year. Compared with the static model, I introduce two lags of the dependent variable and I start with a relatively more general specification.

I treat all the explanatory variables as strictly exogenous, except the contemporaneous values of the bank specific indicators, which are treated as endogenous. In principle, also some of the current macroeconomic variables might be endogenous, since banking system performance is likely to have second round effects on the real economy. Granger causality tests carried out on the aggregated series generally exclude that microeconomic variables

[13] In this kind of investigation the reliability of the empirical results may be undermined by the presence of structural changes. As far as Italian banks are concerned, a possible break may be due to the reform of the banking law in 1993 (which came into force in 1994). Problems of multicollinearity in sub-samples make it difficult to carry out a complete Chow test for the stability of the coefficients. However, since GDP growth is the key variable of the analysis, I include a time intercept dummy (D94 equal to 1 from 1994 and 0 otherwise) and two slope dummies for the lagged values of GDPCC (D94*L1GDPCC and D94*L2GDPCC) and tested their joint significance. The coefficients of the dummies turn out to be significant, picking up some possible break; nonetheless, the good performance of the fitted values allows not to attach excessive emphasis to this problem.

Granger cause macroeconomic ones[14]; therefore, even though Granger non-causality is weaker than the condition for exogeneity, I treat macroeconomic indicators as exogenous. Finally, since the number of instruments may become very high using the Arellano-Bond estimator, I allow up to 5 lags of the instrumented variables.

The one-step estimation results for the Arellano-Bond model are reported in table 8.

Table 8

They show an acceptable convergence with the outcomes of the static exercise. Virtually all the relevant bank specific variables of the static model remain significant in the dynamic equation and most of their coefficients turn out to be very close in magnitude to the static ones. Both the stock and the flow riskiness indicators are highly significant and, not surprisingly, are confirmed as the main microeconomic determinant of loan loss provisions. Interestingly, the lags added in the dynamic model are significant, even though the second lag of RISKST seems to absorb the information provided by the first lag, which ceases to be significant. The return on assets is no longer significant as well, indicating that the evidence of income-smoothing behaviour is not particularly robust, as suggested by previous works.

The first lag of the dependent variable is significant and shows the expected sign. Higher provisions in the past are therefore reflected in higher provisions now. The marginal effect is not excessively high (0.15), consistent with the fact that the dependent variable is a flow indicator.

As to the macroeconomic variables, apart from the stock exchange index changes (MIBC), all the other relevant indicators continue to be significant. In particular, the long-run effect of 1 per cent change in GDP on loan loss provisions is 0.13, as against 0.23 estimated with the static model. The 2-year delayed effect remains higher in size than the 1-year one.

Table 8 also reports the Arellano-Bond tests for serial correlation in the differenced residuals. The tests find evidence of significant negative first order autocorrelation, but fail to reject the null hypothesis of no second order autocorrelation at 5 per cent significance

[14] In particular, no dependent variable Granger causes GDP growth at any conventional significance level.

level. The Sargan test of over-identifying restrictions based on the two-step GMM estimator is not significant at any conventional level[15].

The plot of the actual and the fitted values is shown in figure 3[16].

Fig. 3

The comparison between the actual and the predicted values reveals that the model provides on average acceptable estimates, picking up the main turning points. However, it seems less precise at the beginning and at the end of the time-period under consideration; in particular, actual values lie outside the 95 per cent confidence interval in 1999. The fact that the model underestimates LLP in 2001 may be partly explained recalling that, in that year, some important Italian banks had to make relevant provisions to deal with the crises of several Latin American countries and some international conglomerates.

5.2 Credit quality: new bad debts

In Italy, according to the Legislative Decree 87/1992 and the supervisory guidelines, exposures are to be valued at their estimated realisable value. Loans are therefore classified as performing, substandard and bad debts depending on the intensity of the difficulties the debtor is dealing with. In particular, exposures are classified as bad loans when, regardless the existence of guarantees and collateral: i) the borrower has been declared insolvent or ii) the borrower is facing serious economic difficulties that may threaten permanently his ability to pay the loan back. Notwithstanding the lack of an objective definition of bad loans, Italian banks tend to correctly classify their exposures and with appropriate timing (Moody's 2003), making them a good indicator of the riskiness of banks' debtors. As for LLP, I use the flow measure rather than the stock; since the indicator is built up as the ratio of the loans classified as bad debts in the reference year to the performing loans outstanding at the end of the previous year, it can be interpreted as a default rate[17].

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[15] The Sargan test from the one-step estimator is not heteroskedasticity-consistent (see Arellano and Bond, 1991).

[16] Since the model is estimated in first difference and provides the one-step ahead changes of LLP, I add the estimated changes at time t to the actual levels at time t-1 to obtain the predictions for the levels.

[17] While the use of the flow of LLP is quite common in the empirical exercises (see, among the others, Cavallo and Majnoni, 2002; Pain, 2003; Valckx, 2003), the flow of new bad debts is less widespread, probably because of problems of data availability.

Table 9 reports the correlation coefficients between the new bad debt ratio and the relevant micro and macroeconomic indicators.

Table 9

Virtually all the macroeconomic variables are significantly correlated with banks' portfolio riskiness and, as expected, bad debts tend to decrease during upturns. However, as for loan loss provisions, the relation is not constant over time (fig. 4).

Fig. 4

For instance, the new bad debt ratio significantly increased during the 1993 recession, but it did not in the last downturn. In fact, in 2001 and 2002, notwithstanding the very negative economic conditions, bad debts did not show any significant increase. A possible explanation for this difference is that banks improved their borrowers' selection criteria in the last years; besides, the historically very low level of interest rates and the limited level of indebtedness may have helped firms and households to honour their debts even in such a recessionary period.

5.2.1 Static model

The estimated model is:

$$RISKFL_{it} = \alpha + BSV_{it\text{-}j}\beta + MV_{t\text{-}j}\delta + u_i + \varepsilon_{it}$$

$$i= 1,..., 207;\ t= 1987,..., 2002;\ j= 0, 1, 2 \text{ depending on the variable}$$

where RISKFL is the ratio of the flow of new bad debts to performing loans.

Most of the banks specific variables included in the model are the same employed in the LLP equation and, more specifically:

- CREDGR and CIRATIO, which should behave as described for the LLP equation.
- INTM, the ratio of interest income to total assets, is a proxy of the riskiness of the loans' portfolio since higher interest rates should be typically charged against lower quality credits, which are more likely to turn into bad debts. On the other hand, as pointed out by Salas and Saurina (2002), INTM might proxy managers' incentive to switch to riskier credit policy when things turn bad, as signalled by the curbing of

the margin. According to this second interpretation, the expected sign should be negative, at least for the lagged coefficients.

- EQCAPIT may be interpreted, in an agency cost framework, as a proxy for risk taking behaviour. The higher the riskiness of the bank, the higher is the share of equity capital the shareholders have to invest to convince other stakeholders to support the bank.

The macroeconomic indicators are the same (and with the same lag structure) selected for the LLP equation and namely: GDP changes (GDPC), T-bond interest rate (BTPR), Stock Exchange index changes (MIBC), unemployment rate changes (URC) and the loan-deposit rates spread (SPREAD).

The results for the bad debts equation are provided in table 10.

Table 10

A first interesting element arising from this equation is that only two bank specific variables (lagged CREDGR and CIRATIO) turn out to be significant. However, while the former shows the expected sign, the latter behaves in an odd way, changing its sign when lagged. The behaviour of CIRATIO might be justified on the basis of the idea that high values of the indicator not only reflect bank's inefficiency, but also the use of more advanced, but expensive, methodologies for screening borrowers (see Pain, 2003). This interpretation, even though appealing in this context, does not seem very convincing. All the proxies for risk taking behaviour (INTM and EQCAPIT) are not significant.

As far as the macroeconomic variables are concerned, bad debts increase in the negative phases of the business cycle; however, the effect of GDP changes is not immediate as suggested by previous work, but delayed by 1 and 2 years. In the long run, a 1 per cent GDP growth makes the new bad debt ratio decrease by 0.13 percentage points, quite close to the figure provided by Salas and Saurina. The evolution of interest rates seems to affect debtors' capacity to return their loans as shown by the positive coefficient of BTPR; by contrast the coefficient of the SPREAD between loan and deposit rate has an unexpected negative sign. Unemployment, which showed the wrong sign in the LLP equation, show now the expected positive association with bad debts, confirming that it affects borrowers' disposable income and, in turn, their ability to pay back the debt. Moreover, its marginal effect is relevant from an economic perspective, even though this largely depends on the way the indicator has been calculated.

Overall, the model fits data sufficiently well with a value of the R-squared equal to 0.5; the comparison between actual and fitted values is satisfying as well (fig. 5).

Fig. 5

There are some concerns on the suitability of the fixed effect model in this case since the Hausman test fails to reject the random effect estimates. However, the values of the coefficients in the RE regression are quite close to those of the LSDV one[18].

5.2.2 Dynamic model

The relation between the flow of new bad debts and the business cycle is re-estimated in the context of a dynamic model.

The specification is as follows:

$$RISKFL_{it} = \alpha + \Sigma\gamma_j RISKFL_{it\text{-}j} + BSV_{it\text{-}j}\beta + MV_{t\text{-}j}\delta + u_i + \varepsilon_{it}$$

i= 1,..., 207; t= 1987,..., 2002; j= 0, 1, 2 depending on the variable

Taking the first difference:

$$\Delta RISKFL_{it} = \Sigma\gamma j\Delta RISKFL_{it\text{-}j} + \Delta BSV_{it\text{-}j}\beta + \Delta MV_{t\text{-}j}\delta + \Delta\varepsilon_{it}$$

The starting model includes, along with the variable used in the static model, one lag of the dependent variable. As in the LLP equation, I consider the contemporaneous values of the banks' specific regressors as endogenous and all the other explanatory variables as exogenous. I allow up to 5 lags of the instrumented variables.

Table 11 shows the results for this model.

Table 11

The results show a satisfactory stability in terms of the coefficients' signs, even though some of the parameters are altered in magnitude. In particular, the effect of a 1 per cent GDP increase on the flow of new bad debts is equal to around 0.31, as against 0.13

found in the static model.

The lagged dependent variable is significant and, as expected, has a positive coefficient. The magnitude (0.15) is much lower than that reported by Salas and Saurina (around 0.5) who, however, use the stock of bad debts that are obviously stickier and more persistent than the flow indicator.

In terms of the diagnostics, Arellano-Bond tests find significant negative first order autocorrelation and no evidence of second order serial correlation; the Sargan test fails to reject the null hypothesis of the validity of the instruments at 5 per cent level. The model's fit appears adequate as shown in figure 6.

Fig. 6

The fitted values are generally close to the actual ones. However, there is some evidence that the model is not completely accurate at the end of the estimation period. In particular, in 2001 and 2002 the model tends to over-estimate the new bad debt ratio, while actual data suggest that the recent downturn has not affected credit quality as heavily as in the past, possibly because of the lower level of the interest rates or the improvement of banks' credit risk management.

5.3 Profitability: return on assets

The return on assets is a common measure of profitability (gross of provisions). With respect to other indicators (such as the return on equity), it has the remarkable advantage of not being affected by banks' different balance-sheet policies and by fiscal issues.

Table 12 shows the correlation between the return on assets and some selected explanatory variables. As suggested by common sense, GDP growth positively affects banks' income as well as high interest rates and bullish financial markets.

Table 12

Apart for the second half of the eighties, the relation between ROA and the business cycle appears to be stable, even though the magnitude of the reaction of banks' profits to

[18] As for the LLP equation, I carried out a test for the stability of the coefficients that failed to reject

macroeconomic shocks varies. For example, after the 1993 crisis, banks tended to recover acceptable profitability levels quite slowly with respect to other periods of distress (fig. 7).

Fig. 7

5.3.1 Static model

The estimated model is:

$$ROA_{it} = \alpha + BSV_{it\text{-}j}\beta + MV_{t\text{-}j}\delta + u_i + \varepsilon_{it}$$

i= 1,..., 207; t= 1988,..., 2002; j= 0, 1 depending on the variable

With respect to banks' riskiness, profitability should reflect the overall condition of the economy more quickly; besides, it should primarily reflect structural bank specific factors. I thus employ a simpler specification, in which only the contemporaneous values of most of the explanatory variables are considered (1-lag has been included for GDP changes, credit growth, and the stock riskiness indicator).

The bank specific variables included in the most general model are:

- CREDGR (contemporaneous and lagged) is expected to present a positive sign, as the favourable evolution of the volumes managed by the banks is likely to produce greater interest profits in the future.
- cost-to-income ratio (CIRATIO) is clearly negatively related to the overall profitability of the bank: less efficient intermediaries are less likely to register high profits.
- the EQCAPIT effect is not well defined ex ante; in fact high capital and reserves may signal that the bank is involved in risky operations and therefore more likely to incur in losses; on the other hand, riskier investments may carry higher returns.
- RISKST has clearly a negative effect on bank's profits, since bad loans increase losses charged in the P&L account. Since the timing of the transformation of non-performing loans into loan losses is not certain, 1-lag is introduced along with the current value of the indicator.

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the null of parameter constancy.

- FSERVIN measures the contribution of the earnings stemming from financial services to banks' profitability and proxies the ability of the intermediary to diversify among different sources of income. More diversified banks are expected to register on average higher returns.

- SIZE is the standard control variable.

The macroeconomic indicators are:

- GDPCC, which is obviously expected to show a positive association with banks' profits.

- BTPR should positively affect the ROA since banks' loans generally have a long-term horizon and therefore customers pay an interest rate linked to the long-term one. Along with this direct effect, there could also be a second round effect, since high long term rates tend to worsen economic growth; however, the former effect is likely to be much more relevant than the latter (Bikker and Hu, 2002).

- MIBC affects banks' profits both directly, by increasing the market value of the assets in their own portfolios, and indirectly through the increase of the commissions charged to households and firms for financial services.

- URC typically signals recessionary phases and can lead to the contraction of the demand for banking services. Its effect is thus indirect.

- SPREAD, along with CREDGR, is the basic determinant of the income arising from the traditional banking activity and should present a positive sign.

The econometric results for this specification are reported in table 13.

Table 13

In general, most of the variables show the expected sign, even though it may appear surprising that neither the contemporaneous nor the lagged values of CREDGR are significant.

Considering the microeconomic variables, more diversified (higher FSERVIN) banks tend to show higher profits; by contrast, less efficient ones (higher CIRATIO) are – as expected – generally less profitable. EQCAPIT as well as the lagged value of RISKST have the expected sign. It is plausible that the deterioration of the loan portfolio affects profitability with some delay. Bank's SIZE is significant and negative.

As far as macroeconomic variables are concerned, it is interesting to notice that the favourable evolution of the GDP positively affects banks' profits, but with some delay probably due to demand factors. This supports the inclusion of the lagged value of this variable. Moreover, higher interest rates and bullish financial markets help banks' profitability; SPREAD variable turns out to be not significant. As in the specification for loan loss provisions, the change of the unemployment rate (URC) shows the wrong sign; the use of a larger lag structure for this variable does not change this outcome.

The R-squared for the final specification is equal to 0.85; the plot of the actual and fitted values and the 95 per cent confidence interval for the ROA specifications are reported in figure 8. Except for 1989, the fitted values pick up the relevant turning points of banks' profitability.

Fig. 8

Finally, it is worth noting that both the pooled regression and the random effect model are respectively rejected by the Breusch-Pagan and the Hausman tests; moreover, the null hypothesis that the coefficients of the individual effects are jointly equal to zero is rejected at all conventional level, confirming that the fixed effect model is adequate.

6. Robustness checks

In this section I carry out some robustness checks. First, I use a small panel of large intermediaries to assess whether the econometric relations estimated so far are common to different categories of banks. Second, I analyse whether the effects of GDP changes are asymmetric, i.e. if their magnitude is different during upturns and downturns.

6.1 Are large banks different?

To verify whether the results obtained in the previous section are common for different categories of banks, I re-estimate the fixed effect models using the balanced panel of large banks. In general, I do not necessarily expect the microeconomic determinants of banks' behaviour to be exactly the same for larger intermediaries. However, I do assume that the basic macroeconomic indicators remain significant and exhibit the same kind of association with the dependent variables.

The results of the regressions are reported in table 14.

Table 14

The outcomes are fairly similar to those obtained with the unbalanced panel, even though there are some puzzling results regarding the bank specific variables, especially for the ROA equation.

As in the unbalanced panel, provisions tend to decrease as a share of total assets when GDP grows, but the current effect becomes positive and the long-run multiplier decreases in magnitude. Moreover, the banks specific variables are never significant when lagged. This evidence is somewhat puzzling; indeed it suggests, on the one hand, that large banks tend to be less backward-looking in setting their provisioning policies, on the other, that they make provisions only when problem loans actually materialise in their portfolios and do not use them to smooth their income. This is consistent with the findings of the ECB (2001); however, the small sample size recommends interpreting these results with caution.

Considering the new bad debt ratio, the evidence for large banks confirms that credit quality deteriorates during the recessionary phases of the business cycle; the long-run impact of GDP changes increase substantially in size, possibly suggesting that large banks are more affected by the fluctuations of the real economy.

As already noted, the regression for the return on assets produces very ambiguous results; nevertheless, it at least confirms the positive relation between GDP growth and banks' profits.

6.2 Do macroeconomic shocks have asymmetric effects?

In theory, the magnitude of the impact of GDP changes on banks' performance might differ depending on whether the economic system is in recessionary or expansionary phases. If this is the case, it might be appropriate to use models that allow for this asymmetry.

To deal with this issue, I re-estimate the static specifications introducing two slope dummy variables that interact with GDP growth. The first dummy (DOWN) is equal to 1 during downswings and 0 otherwise; the second (UP), conversely, is equal to 1 during upswings and 0 otherwise. If GDP changes had asymmetric effects during expansions/recessions, the coefficients of the interaction regressors should be significantly different each other.

For dating the recessionary phases, I rely on the studies by Altissimo *et al.* (2000) and Bruno and Otranto (2004), whose results are considered a very consistent description of the evolution of the business cycle in Italy. During the period 1987-2002, they identify three main recessions: the first one from March 1992 to July 1993, the second from November 1995 to November 1996, and the third at the end of 2001; I thus set DOWN equal to 1 for 1992-1993, 1996 and 2002.

Table 15 shows the coefficients of the interaction terms; the effects of the other regressors remained roughly unchanged and are therefore omitted.

Table 15

It is interesting to note that the coefficients on the 1-year lagged GDPCC turn out to be not significant during downturns for both the LLP and the RISKFL equations, possibly suggesting that good economic conditions affect credit quality more rapidly than bad or that the improvement of loan portfolios is reported by banks relatively quicker than their deterioration.

However, the overall long-run impact of GDP changes on loan loss provisions, new bad loans and the return on assets appears quite similar in the different sub-periods. Most importantly, the F-tests generally fail to reject the null hypothesis that the coefficients are equal during downswings and upswings; hence, data tend to exclude the presence of significant asymmetries in the transmission of the macroeconomic shocks.

7. A possible supervisory use: stress tests

Stress tests are increasingly used by the supervisory authorities to assess the resilience of the financial system to adverse macroeconomic disturbances, thus enhancing their action.

The Basel Committee on Banking Supervision underlined the need for stress testing when it published the "Amendment to the Capital Accord to Incorporate Market Risks" in 1996; banking supervisors have then established the use of stress tests as an important component of the intermediaries' internal-models approach to market risk monitoring.

According to the new Capital Accord, the intermediaries will be required to run stress tests for credit risk under the control of the national authorities, to ascertain if the capital buffers are adequate.

Besides, in the context of the Financial Sector Assessment Programmes (FSAP), the IMF, in addition to asking a sample of intermediaries to evaluate the impact of macroeconomic shocks on their balance sheets, may invite national authorities to perform the same task on an aggregate basis.

When setting up the framework for stress testing exercises, it is necessary to identify the kind of risks that have to be considered and the range of factors to be included; indeed, stress tests can be used to analyse the impact of a change in a single risk factor (sensitivity test) or the effect of a simultaneous change in several risk factors (scenario analysis). It is also important to determine whether the exercise should be based on historical scenarios, assuming that past shocks may happen again, or rather on hypothetical scenarios, that is on extreme but plausible changes in the external environment regardless of the historical experience (Blaschke *et al.*, 2001; Hoggarth *et al.*, 2004)[19].

Specific methodological issues arise when aggregate stress tests have to be carried out to identify structural vulnerabilities and the overall risk exposure of the banking system (Hoggarth and Whitley, 2003). In principle, two solutions are available for the aggregation rule: supervisors can define the macroeconomic shock, let the intermediaries evaluate its impact on their balance sheets and then aggregate the bank-level outcomes to get the overall effect (bottom-up approach) or, conversely, they can directly apply the shock to some sort of banking system-level portfolio and analyse the aggregate effect (top-down approach). Of course, in the bottom-up methodology, the issue of comparability is a relevant one since each intermediary may employ different methodologies and modelling assumptions, making the aggregation less reliable. Conversely, the top-down approach enhances the comparability of the results, but it is typically based on historical relations[20].

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[19] The construction of historical scenarios is relatively straightforward, but stress test based on this method are eminently backward-looking and may be not very reliable over time, as market and institutional structures change. By contrast, hypothetical scenarios are more flexible in the selection of potential events and, therefore, they tend to be more forward-looking; on the other hand, it is often a hard task to quantify the likelihood of a given event.

20 During the UK's Financial Sector Assessment Programme, the Bank of England and the Financial Services Authority set up detailed macroeconomic scenarios and supplied them to the UK banks as inputs

In this section, I use the econometric relations estimated so far to simulate the impact of some macroeconomic shocks on the Italian banking system. In particular, employing the coefficients of the static models, I carry out both single factor stress tests, which are only a rough attempt to quantify the aggregate effects of GDP changes, and scenario analyses, which replicate the recessionary conditions of 1993 and the following recovery in 1994.

For the sensitivity analyses, I assume that all the variables for 2002 are constant, apart from the GDP changes. Although GDP growth rates are not chosen according to any historical/probabilistic criterion, the lower values include very extreme events; in particular, a 1 per cent contraction of GDP has been experienced only once in the 18 years under consideration, in the aftermath of the European Monetary System crisis in 1992-93. By contrast, in the scenario analyses, all the relevant macroeconomic regressors are set at their 1993-1994 levels, *ceteris paribus.*

Table 16 shows the outcomes of the exercise.

Table 16

The results of the sensitivity analysis imply that, with respect to the 2002 baseline scenario, two consecutive years of GDP decline would cause the loan loss provision ratio to double and the new bad debt ratio to increase by 35 per cent.

Conversely, under the stress scenario that assumes a recession like the 1993 one, the LLP ratio would increase from 0.82 in the baseline scenario to 1.35 per cent (1993 scenario); however, during the recovery period, the ratio would fall to 0.87 (1994 scenario). With reference to the new bad debt ratio, it would increase from 1.28 to 3.4 per cent at the through of the cycle (2.6 per cent during the following recovery period). ROA would not fall, but this is mainly due to the effect of the stock exchange variable, whose values in 2002 were much worse than those recorded in 1993 and 1994.

To assess the resilience of the banking system, these figures can be compared with the pre-tax profit of banks and the level of supervisory capital above the minimum requirements (i.e. the buffer against losses beyond banks' income).

As far as loan loss provisions are concerned, over the period 2000-2002, the pre-tax

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for their internal models; the results were compared with those obtained by the authorities (see Hoggarth and Whitley, 2003).

profit amounted, on average, to 2 per cent of total loans, a figure sufficient to cover the extra-provisions resulting from the assumed shocks.

Regarding bad debts, under the very unfavourable scenario of insufficient earnings, banks should cover loan losses by depleting the supervisory capital. During 2000-2002, as a percentage of performing loans, excess capital was equal, on average, to 3.5. Assuming a 50 per cent loss-given-default, which is the historical figure for Italy, the excess capital would be largely above the potential losses arising from bad debts (around 1.7 per cent of performing loans). Banks could therefore deal with such an adverse shock while still keeping capital levels above the regulatory minimum.

This kind of simulation presents of course some shortcomings. First of all, the *ceteris paribus* hypothesis is not completely satisfactory, since micro and macroeconomic variables generally move together. Second, the exercise neglects either any potential second round effect or policy response. Results must thus be interpreted with caution; however, with this *caveat* in mind, they provide some useful insights about the potential effects of the business cycle on the stability of the Italian banking system.

8. Conclusions

Empirical observation suggests that banks behave procyclically since bad debts, provisions and loan losses are generally very low during booms. They start to be recorded at the peak of the upturn and rise significantly during the subsequent recession; this is often coupled with the contraction of earnings. The consequence is that banks tighten credit supply during downturns, thus further deepening the negative impact of the business cycle.

Several empirical works have investigated the issue of procyclicality in banking, generally concluding that banks' policies tend to be cyclical.

Following this stream of research, this paper analyses the behaviour of more than 200 Italian banks over almost two decades to understand if the stylised facts are confirmed in the Italian case. With respect to previous studies, this paper attempts to provide a more comprehensive framework, analysing the evolution of loan loss provisions, new bad debts and profitability over the business cycle.

The econometric outcomes confirm that banks' loan loss provisions, bad debts and profits are affected by the evolution of the business cycle; in particular, while the flow of new bad debts and the provisions against loan losses tend to increase when economic conditions deteriorate, bank profitability is higher during upturns. However, GDP growth turns out to be significant only when lagged by 1 and 2 years, implying that the cyclical impacts are not instantaneous, but delayed.

Variation in the premise of the models leaves the sign and the significance of the macroeconomic variables basically unchanged, although the magnitude of the effects may vary. For instance, the overall long-run partial effect of 1 per cent change of GDP on the ratio between loan loss provisions and total loans swings between 0.13 and 0.23, depending on the model; for the flow of new bad debts over performing loans, the long-run impact is in the range 0.13-0.31. These findings are consistent with the evidence for other countries.

Moreover, data provide some support to the idea that intermediaries exploit provisioning policies to stabilise their income over time; however, the evidence on the income-smoothing hypothesis remains somewhat mixed, since the positive relation between provisions and profits is not significant in all the specifications.

Along with the macroeconomic variables, several bank-level indicators are also relevant in explaining the changes in the evolution of riskiness and profitability. This corroborates the idea that the overall performance of the intermediaries is the result of the interaction between the general economic framework and banks' management.

Finally, the estimated relations are employed to stress test Italian banks' portfolios and, hence, to assess the resilience of the banking system to external shocks. The outcomes suggest that, with respect to the 2002 baseline scenario, a recession like that experienced in 1993 would make the LLP ratio increase from 0.82 to 1.35 per cent and the new bad loan ratio from 1.28 to 3.4 per cent. Even in such an unfavourable scenario, the level of Italian banks' earnings and capital buffers would be, on average, sufficient to absorb the effects of the shocks. Even though they depend on the underlying assumptions, these results represent an important step for quantifying the effects of the business cycle on the Italian banking system.

In the near future, the analysis will be extended by the use of alternative econometric methodologies such as VARs, the design of different scenarios and the direct involvement of banks in bottom-up exercises, since cross-checks are an essential part of stress testing and the prerequisite for policy implementation.

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Tables and figures

Tab. 1

THE SAMPLES						
	Years	**N. obs.**	**N. banks**	**Obs. per bank: min**	**Obs. per bank: max**	**Obs. per bank: avg**
Unbalanced	1985-2002	3207	207	5	18	15.5
Balanced	1985-2002	198	11	18	18	18

Tab. 2

SELECTED VARIABLES

Name	Description		Source	Publicly available?
Microeconomic				
CIRATIO	Cost-to-income ratio	%	Sup.statistics	YES
FSERVIN	Financial services revenue / gross income	%	Sup.statistics	YES
EQCAPIT	Equity capital / total assets	%	Sup.statistics	YES
SIZE	Log total assets	%	Sup.statistics	YES
ROA	ROA (operating profit / total assets)	%	Sup.statistics	YES
LLP	Loan loss provisions (flow) / total loans	%	Sup.statistics	YES
RISKST	Bad debts (gross of provisions) / total loans	%	Sup.statistics	YES
RISKFL	Flow of new bad debts (t) / performing loans (t-1)	%	Credit Register	NO
CREDGR	Credit growth	%	Sup.statistics	YES
INTM	Interest margin / total assets	%	Sup.statistics	YES
LLPODD	Ln (LLP / (100-LLP))			
RSKFLODD	Ln (RISKFL / (100-RISKFL))			
Macroeconomic				
MIBC	Milan Stock Exchange index - percentage change	%	R.D. database	YES
BOTR	Italian T-bill rate - level	%	R.D. database	YES
BTPR	Italian T-bond rate - level	%	R.D. database	YES
URC	Unemployment rate - percentage point change	%	R.D. database	YES
SPREAD	Spread between loan and deposit rate - level	%	R.D. database	YES
GDPCC	GDP - percentage change	%	R.D. database	YES
INVCC	Investment - percentage change	%	R.D. database	YES
CONCC	Consumption - percentage change	%	R.D. database	YES
FLEV	Firm leverage (debt / equity capital+debt) - level	%	R.D. database	YES
HOUD	Household indebtedness / GDP - level	%	R.D. database	YES

Tab. 3

MACROECONOMIC VARIABLES: DESCRIPTIVE STATISTICS

Variable	N. obs	Mean	STD	Min	Max	Median
MIBC	20	14.3	33.2	-27.7	104.1	14.6
BOTR	20	9.5	4.5	2.8	17.5	10.4
BTPR	20	9.9	4.3	3.7	17.7	10.8
URC	20	0.1	0.7	-1.1	1.6	0.1
SPREAD	20	5.5	1.1	3.6	8.5	5.5
GDPCC	20	2.0	1.1	-0.9	3.9	2.0
INVCC	20	2.2	3.9	-10.9	7.1	3.0
CONCC	20	2.0	1.3	-2.0	3.8	2.3
FLEV	13	48.0	8.0	36.0	58.0	50.8
HOUD	14	14.4	4.2	8.4	22.2	13.3

Tab. 4

BANK SPECIFIC VARIABLES: DESCRIPTIVE STATISTICS

Variable	N. obs	Mean	STD	Min	Max	Median
CIRATIO	3207	63.2	14.8	9.1	291.3	63.4
FSERVIN	3207	22.9	12.1	-53.4	87.6	22.6
EQCAPIT	3207	8.3	4.2	0.9	63.7	7.7
SIZE	3207	14.0	1.6	9.6	19.2	13.9
ROA	3207	1.8	0.8	-4.5	6.0	1.8
LLP	3207	1.1	1.0	0.0	7.7	0.8
RISKST	3207	6.7	5.1	0.0	37.7	5.5
RISKFL	3207	2.1	1.7	0.0	13.5	1.6
CREDGR	3207	13.3	21.1	-94.0	533.0	11.8
INTM	3207	3.7	1.2	0.0	7.1	3.7
LLPODD	3207	-4.9	1.0	-10.2	-2.5	-4.8
RSKFLODD	3207	-4.2	0.9	-8.6	-1.9	-4.1

Tab. 5

IPS TESTS FOR UNIT ROOTS (1)

Variable		t-bar statistics - 2 lags	
		Constant	Constant and trend
LLP	Raw data	-3.062 ***	-3.154 ***
	Demeaned	-3.276 ***	-3.417 ***
RISKFL	Raw data	-2.592 ***	-3.146 ***
	Demeaned	-3.039 ***	-3.422 ***
ROA	Raw data	-2.266 ***	-2.964 ***
	Demeaned	-2.382 ***	-2.841 ***

*, **, *** significant at 10, 5 and 1 per cent level respectively.

Notes: (1) Im, Pesaran and Shin tests for unit roots in panel data based on the mean of the individual Augmented Dickey-Fuller t-statistics of each unit in the panel (Ho: presence of a unit root). Tests are carried out on a balanced panel of 1802 obs. (Stata routine provided by C. F. Baum and F. Bornhorst).

Tab. 6

LOAN LOSS PROVISIONS - CORRELATION COEFFICIENTS

	LLP	CREDGR	CIRATIO	ROA	RISKST	RISKFL	GDPCC	L1GDPCC	L2GDPCC	BTPR	MIBC	URC	SPREAD
LLP	1.000												
CREDGR	**-0.148**	1.000											
CIRATIO	**0.128**	0.029	1.000										
ROA	-0.028	0.012	**-0.656**	1.000									
RISKST	**0.444**	**-0.211**	**0.169**	**-0.168**	1.000								
RISKFL	**0.419**	**-0.046**	**0.064**	0.018	**0.505**	1.000							
GDPCC	**-0.124**	**0.108**	-0.025	**0.058**	**0.062**	**-0.086**	1.000						
L1GDPCC	**-0.178**	**0.099**	**-0.083**	**0.104**	-0.048	**-0.119**	**0.364**	1.000					
L2GDPCC	**-0.206**	**0.060**	-0.049	**0.042**	**-0.110**	**-0.107**	**-0.066**	**0.341**	1.000				
BTPR	**-0.062**	**0.059**	**-0.063**	**0.219**	-0.043	**0.228**	**0.220**	**0.106**	**0.080**	1.000			
MIBC	0.016	-0.018	-0.022	**0.065**	**0.084**	**0.117**	**0.130**	**-0.018**	**-0.151**	-0.016	1.000		
URC	**0.112**	**-0.126**	0.001	**0.119**	**0.073**	**0.284**	**-0.308**	**-0.342**	**-0.264**	**0.241**	**0.464**	1.000	
SPREAD	-0.034	0.009	-0.034	**0.183**	-0.042	**0.192**	0.011	**0.089**	**0.069**	**0.826**	**-0.157**	**0.347**	1.000

Coefficients in bold are significant at 5 per cent level.

ECONOMETRIC RESULTS - UNBALANCED PANEL
LOAN LOSS PROVISIONS - STATIC SPECIFICATION (1)

Explanatory variable	Exp. Sign	Fixed effects (LSDV) Coeffic.	N-W SE (2)	Sign. Lev.	Pooled Regression Coeffic.	N-W SE (2)	Sign. Lev.	Random effects Coeffic.	SE	Sign. Lev.
Intercept		-0.3338	0.2098		-0.0906	0.1551		-0.0766	0.1438	
BANK SPECIFIC										
CREDGR	+/-	-0.0114	0.0015	***	-0.0065	0.0021	***	-0.0076	0.0010	***
L1CREDGR	+/-	-0.0058	0.0017	***	-0.0020	0.0013		-0.0025	0.0009	***
CIRATIO	+									
L1CIRATIO	+									
ROA	+	0.1406	0.0417	***	0.0787	0.0306	***	0.0887	0.0239	***
RISKST	+									
L1RISKST	+	0.0540	0.0075	***	0.0437	0.0062	***	0.0470	0.0045	***
RISKFL	+	0.1941	0.0215	***	0.1787	0.0209	***	0.1845	0.0118	***
L1RISKFL	+	0.0659	0.0189	***	0.0743	0.0182	***	0.0687	0.0122	***
MACRO										
BTPR	+/-	-0.0282	0.0096	***	-0.0313	0.0102	***	-0.0324	0.0095	***
L1BTPR	+/-	-0.0280	0.0136	**	-0.0220	0.0152		-0.0216	0.0148	
MIBC	+	0.0031	0.0007	***	-0.0220	0.0008	***	0.0030	0.0008	***
L1MIBC	-	-0.0039	0.0006	***	-0.0034	0.0006	***	-0.0036	0.0006	***
URC	+	-0.3087	0.0472	***	-0.2763	0.0498	***	-0.2846	0.0487	***
L1URC	+									
SPREAD	+									
L1SPREAD	+	0.2539	0.0443	***	0.2477	0.0467	***	0.2443	0.0402	***
GDPCC	-									
L1GDPCC	-	-0.0564	0.0191	***	-0.0514	0.0200	***	-0.0565	0.0191	***
L2GDPCC	-	-0.1701	0.0177	***	-0.1711	0.0197	***	-0.1731	0.0163	***
Nr. Obs.		2642			2642			2642		
R2		0.51			0.37					
Wald-test (3)		F (14, 2422) =89.36		***	F (14, 2627) = 41.21		***	Chi2 (14) = 1378.03		***
F-test all FE=0		F (205, 2442) =3.27		***						
B-P LM (4)					Chi2 (1) = 187.33		***			
Hausman (5)								Chi2 (14) = 139.93		***
Panel-hetero (6)		Chi2 (206) = 1.7e+31		***						
Panel-AR (1) (7)		F (1, 200) = 4.704		**						

*, **, *** significant at 10, 5 and 1 per cent level respectively.

Notes: (1) Static model in which the ratio of loan loss provisions to total loans is the dependent variable. The most parsimonious specification of the LSDV model has been selected via general-to-simple approach. The coefficients of the individual effects are not reported. (2) Newey-West robust standard errors; the errors are assumed to be heteroskedastic and autocorrelated up to 2 lags (Stata routine provided by D. Roodman). (3) Wald test that all the coefficients (except intercept and FE) are jointly not significant. (4) Breusch-Pagan Lagrange multiplier for the pooled model (Ho: pooled regression against Ha: RE). (5) Hausman test for random effects (Ho: RE against Ha: FE). (6) Modified Wald statistic for groupwise heteroskedasticity in fixed effect model (Stata routine provided by C. F. Baum). (7) Wooldridge test for first order serial correlation (Stata routine provided by D. M. Drukker).

ECONOMETRIC RESULTS - UNBALANCED PANEL
LOAN LOSS PROVISIONS - DYNAMIC SPECIFICATION (1)

		First differenced equation		
Explanatory variable	**Exp. Sign**	**Coeffic.**	**Robust SE (2)**	**Sign. Lev.**
Intercept		0.0347	0.0124	***
BANK SPECIFIC				
L1LLP	+	0.1534	0.0401	***
L2LLP	+			
CREDGR	+/-	-0.0105	0.0019	***
L1CREDGR	+/-	-0.0059	0.0024	**
L2CREDGR	+/-			
CIRATIO	+			
L1CIRATIO	+			
ROA	+			
RISKST	+			
L1RISKST	+			
L2RISKST	+	0.0387	0.0116	***
RISKFL	+	0.1946	0.0325	***
L1RISKFL	+	0.0549	0.0187	***
L2RISKFL	+	0.0480	0.0161	***
MACRO				
BTPR	+/-			
L1BTPR	+/-	-0.0445	0.0140	***
MIBC	+			
L1MIBC	-			
URC	+			
L1URC	+	-0.2512	0.0471	***
L2URC	+	0.2365	0.0336	***
SPREAD	+	0.2833	0.0372	***
L1SPREAD	+			
GDPCC	-			
L1GDPCC	-	-0.0557	0.0197	***
L2GDPCC	-	-0.0709	0.0197	***
Nr. Obs.		2400		
Wald-test (3)		Chi2(26) = 698.58		***
Sargan (4)		Chi2(270) = 193.51		
Arellano-Bond AR (1) (5)		z = -7.79		***
Arellano-Bond AR (2) (5)		z = 1.92		*

*, **, *** significant at 10, 5 and 1 per cent level respectively.

Notes: (1) Dynamic (first differenced) model in which the ratio of loan loss provisions to total loans is the dependent variable. The results are from the one-step GMM estimator. All the regressors are treated as exogenous, except the contemporaneous bank-specific variables that are considered endogenous. The most parsimonious specification has been selected via general-to-simple approach. (2) Heteroskedasticity robust standard errors. (3) Wald test that all the coefficients are jointly not significant. (4) Sargan test of over-identifying restrictions from the two-step estimator. (5) Arellano-Bond test for first and second order autocorrelation in the residuals.

Tab. 9

FLOW OF NEW BAD DEBTS: CORRELATION COEFFICIENTS

	RISKFL	CREDGR	CIRATIO	INTM	EQCAPIT	GDPCC	L1GDPCC	L2GDPCC	BTPR	MIBC	URC	SPREAD
RISKFL	1.000											
CREDGR	**-0.046**	1.000										
CIRATIO	**0.064**	0.029	1.000									
INTM	**0.193**	-0.010	**-0.127**	1.000								
EQCAPIT	0.038	-0.035	**-0.081**	**0.170**	1.000							
GDPCC	**-0.086**	**0.108**	-0.025	**0.063**	**-0.191**	1.000						
L1GDPCC	**-0.119**	**0.099**	**-0.083**	**0.072**	**-0.206**	**0.364**	1.000					
L2GDPCC	**-0.107**	**0.060**	-0.049	**0.038**	**-0.147**	**-0.066**	**0.341**	1.000				
BTPR	**0.228**	**0.059**	**-0.063**	**0.420**	**-0.171**	**0.220**	**0.106**	**0.080**	1.000			
MIBC	**0.117**	-0.018	-0.022	**0.053**	**-0.112**	**0.130**	**-0.018**	**-0.151**	-0.016	1.000		
URC	**0.284**	**-0.126**	0.001	**0.238**	-0.041	**-0.308**	**-0.342**	**-0.264**	**0.241**	**0.464**	1.000	
SPREAD	**0.192**	0.009	-0.034	**0.391**	**-0.093**	0.011	**0.089**	**0.069**	**0.826**	**-0.157**	**0.347**	1.000

Coefficients in bold are significant at 5 per cent level.

ECONOMETRIC RESULTS - UNBALANCED PANEL
FLOW OF NEW BAD DEBTS - STATIC SPECIFICATION

		Fixed effects (LSDV)			Pooled Regression			Random effects		
Explanatory variable	Exp. sign	Coeffic.	N-W SE (2)	Sign. Lev.	Coeffic.	N-W SE (2)	Sign. Lev.	Coeffic.	SE	Sign. Lev.
Intercept		3.0092	0.3915	***	1.9571	0.3101	***	2.4020	0.2646	***
BANK SPECIFIC										
CREDGR	+/-									
L1CREDGR	+/-	-0.0057	0.0022	***	-0.0063	0.0020	***	-0.0056	0.0015	***
CIRATIO	+	0.0094	0.0027	***	0.0157	0.0032	***	0.0113	0.0027	***
L1CIRATIO	+	-0.0166	0.0040	***	-0.0144	0.0036	***	-0.0149	0.0031	***
INTM	+									
L1INTM	+									
EQCAPIT	+									
L1EQCAPIT	+									
MACRO										
BTPR	+/-	0.0496	0.0188	***	0.0437	0.0237	*	0.0494	0.0192	***
L1BTPR	+/-	0.1113	0.0179	***	0.1172	0.0219	***	0.1123	0.0175	***
MIBC	+									
L1MIBC	-									
URC	+	0.4413	0.0736	***	0.4164	0.0877	***	0.4354	0.0705	***
L1URC	+									
SPREAD	+	-0.2344	0.0448	***	-0.2146	0.0520	***	-0.2319	0.0450	***
L1SPREAD	+									
GDPCC	-									
L1GDPCC	-	-0.0719	0.0313	**	-0.0782	0.0388	*	-0.0726	0.0325	**
L2GDPCC	-	-0.0603	0.0248	**	-0.0501	0.0312		-0.0572	0.0237	**
Nr. Obs.		2642			2642			2642		
R2		0.5			0.15					
Wald-test (3)		F(9, 2427) = 67.08		***	F(9, 2632) = 29.77		***	Chi2 (9) = 663.23		***
F-test all FE=0		F (205, 2427) = 8.20		***						
B-P LM (4)					Chi2 (1) = 1920.89		***			
Hausman (5)								Chi2 (9) = 8.71		
Panel-hetero (6)		Chi2 (206) = 3.3e+31		***						
Panel-AR (1) (7)		F(1, 200) = 26.485		***						

*, **, *** significant at 10, 5 and 1 per cent level respectively.

Notes: (1) Static model in which the ratio of the flow of new bad debts to total loans is the dependent variable. The most parsimonious specification of the LSDV model has been selected via general-to-simple approach. The coefficients of the individual effects are not reported. (2) Newey-West robust standard errors; the errors are assumed to be heteroskedastic and autocorrelated up to 2 lags (Stata routine provided by D. Roodman). (3) Wald test that all the coefficients (except intercept and FE) are jointly not significant. (4) Breusch-Pagan Lagrange multiplier for the pooled model (Ho: pooled regression against Ha: RE). (5) Hausman test for random effects (Ho: RE against Ha: FE). (6) Modified Wald statistic for groupwise heteroskedasticity in fixed effect model (Stata routine provided by C. F. Baum). (7) Wooldridge test for first order serial correlation (Stata routine provided by D. M. Drukker).

ECONOMETRIC RESULTS - UNBALANCED PANEL
FLOW OF NEW BAD DEBTS - DYNAMIC SPECIFICATION (1)

Explanatory variable	Exp. Sign	First differenced equation Coeffic.	Robust SE (2)	Sign. Lev.
Intercept		-0.0446	0.0202	**
BANK SPECIFIC				
L1RISKFL		0.1501	0.0325	***
CREDGR	+/-			
L1CREDGR	+/-	-0.0085	0.0028	***
CIRATIO	+			
L1CIRATIO	+	-0.0149	0.0051	***
INTM	+			
L1INTM	+			
EQCAPIT	+			
L1EQCAPIT	+			
	+			
MACRO				
BTPR	+/-	0.0884	0.0250	***
L1BTPR	+/-	0.1070	0.0240	***
MIBC	+	0.0049	0.0016	***
L1MIBC	-			
URC	+	0.4081	0.0938	***
L1URC	+			
SPREAD	+	-0.3118	0.0585	***
L1SPREAD	+	-0.2066	0.0794	***
GDPCC	-	-0.2122	0.0482	***
L1GDPCC	-			
L2GDPCC	-	-0.1049	0.0356	***
Nr. Obs.		2400		
Wald-test (3)		Chi2(11) = 250.62		***
Sargan (4)		Chi2(134) = 157.88		*
Arellano-Bond AR (1) (5)		z = -7.54		***
Arellano-Bond AR (2) (5)		z = 0.69		

*, **, *** significant at 10, 5 and 1 per cent level respectively.

Notes: (1) Dynamic (first differenced) model in which the ratio of the flow of new bad debts to total loans is the dependent variable. The results are from the one-step GMM estimator. All the regressors are treated as exogenous, except the contemporaneous bank-specific variables that are considered endogenous. The most parsimonious specification has been selected via general-to-simple approach. (2) Heteroskedasticity robust standard errors. (3) Wald test that all the coefficients are jointly not significant. (4) Sargan test of over-identifying restrictions from the two-step estimator. (5) Arellano-Bond test for first and second order autocorrelation in the residuals.

Tab. 12

RETURN ON ASSETS: CORRELATION COEFFICIENTS

	ROA	CREDGR	CIRATIO	EQCAPIT	SIZE	RISKST	FSERVIN	GDPCC	L1GDPCC	BTPR	MIBC	URC	SPREAD
ROA	1.000												
CREDGR	**0.012**	1.000											
CIRATIO	**-0.656**	0.029	1.000										
EQCAPIT	**0.222**	-0.035	**-0.081**	1.000									
SIZE	**-0.265**	**-0.088**	-0.036	**-0.232**	1.000								
RISKST	**-0.168**	**-0.211**	**0.169**	0.044	**-0.098**	1.000							
FSERVIN	**-0.122**	**0.086**	**0.241**	-0.006	**0.177**	**-0.150**	1.000						
GDPCC	**0.058**	**0.108**	-0.025	**-0.191**	**-0.095**	**0.062**	-0.018	1.000					
L1GDPCC	**0.104**	**0.099**	**-0.083**	**-0.206**	**-0.082**	-0.048	-0.039	**0.364**	1.000				
BTPR	**0.219**	**0.059**	**-0.063**	**-0.171**	**-0.153**	-0.043	**-0.374**	**0.220**	**0.106**	1.000			
MIBC	**0.065**	**-0.018**	-0.022	**-0.112**	**-0.076**	**0.084**	0.022	**0.130**	**-0.018**	-0.016	1.000		
URC	**0.119**	**-0.126**	0.001	-0.041	**-0.074**	**0.073**	**-0.160**	**-0.308**	**-0.342**	**0.241**	**0.464**	1.000	
SPREAD	**0.183**	0.009	-0.034	**-0.093**	**-0.111**	-0.042	**-0.357**	0.011	**0.089**	**0.826**	**-0.157**	**0.347**	1.000

Coefficients in bold are significant at 5 per cent level.

ECONOMETRIC RESULTS - UNBALANCED PANEL

RETURN ON ASSETS - STATIC SPECIFICATION

Explanatory variable	Exp. sign	Fixed effects(LSDV) Coeffic.	N-W SE (2)	Sign. Lev.	Pooled Regression Coeffic.	N-W SE (2)	Sign. Lev.	Random effects Coeffic.	SE	Sign. Lev.
Intercept		7.7209	0.8483		4.8858	0.3371	***	5.7926	0.2302	
BANK SPECIFIC										
CREDGR	+									
L1CREDGR	+									
CIRATIO	-	-0.0393	0.0070	***	-0.0385	0.0034	***	-0.0395	0.0007	***
EQCAPIT	+/-	0.0347	0.0050	***	0.0345	0.0061	***	0.0333	0.0026	***
SIZE	+/-	-0.2649	0.0298	***	-0.1286	0.0106	***	-0.1734	0.0146	***
RISKST	-									
L1RISKST	-	-0.0224	0.0051	***	-0.0107	0.0033	***	-0.0203	0.0019	***
FSERVIN	+	0.0123	0.0036	***	0.0134	0.0018	***	0.0121	0.0009	***
MACRO										
BTPR	+	0.0334	0.0055	***	0.0515	0.0040	***	0.0406	0.0024	***
MIBC	+	0.0007	0.0003	**	0.0011	0.0004	***	0.0009	0.0003	***
URC	-	0.0784	0.0180	***	0.1190	0.0196	***	0.0906	0.0116	***
SPREAD	+									
GDPCC	+									
L1GDPCC	+	0.0361	0.0163	**	0.0829	0.0120	***	0.0484	0.0070	***
Nr. Obs.		2911			2911			2911		
R2		0.85			0.6					
Wald-test (3)		F(9, 2695) = 252.53		***	F(9, 2901) = 100.05		***	Chi2 (9) = 5707.70		***
F-test all FE=0		F (206, 2695) = 22.32		***						
B-P LM (4)					Chi2 (1) = 4562.34		***			
Hausman (5)								Chi2 (9) = 46.99		***
Panel-hetero (6)		Chi2 (207) = 1.1e+05		***						
Panel-AR (1) (7)		F (1, 202) = 17.680		***						

*, **, *** significant at 10, 5 and 1 per cent level respectively.

Notes: (1) Static model in which the return on assets is the dependent variable. The most parsimonious specification of the LSDV model has been selected via general-to-simple approach. The coefficients of the individual effects are not reported. (2) Newey-West robust standard errors; the errors are assumed to be heteroskedastic and autocorrelated up to 2 lags (Stata routine provided by D. Roodman). (3) Wald test that all the coefficients (except intercept and FE) are jointly not significant. (4) Breusch-Pagan Lagrange multiplier for the pooled model (Ho: pooled regression against Ha: RE). (5) Hausman test for random effects (Ho: RE against Ha: FE). (6) Modified Wald statistic for groupwise heteroskedasticity in fixed effect model (Stata routine provided by C. F. Baum). (7) Wooldridge test for first order serial correlation (Stata routine provided by D. M. Drukker).

ECONOMETRIC RESULTS - BALANCED PANEL
FIXED EFFECTS (LSDV) (1)

Explanatory variable	Loan loss provisions Coeffic.	N-W SE (2)	Sign. Lev.	New bad debts Coeffic.	N-W SE (2)	Sign. Lev.	Return on assets Coeffic.	N-W SE (2)	Sign. Lev.
Intercept	-0.2952	0.2894		0.8946	1.0366		4.0958	0.1987	***
BANK SPECIFIC									
CREDGR	-0.0136	0.0057	**						
L1CREDGR				-0.0173	0.0073	**	-0.0073	0.0040	*
CIRATIO				0.0275	0.0107	**	-0.0565	0.0034	***
L1CIRATIO				-0.0286	0.0129	**			
ROA									
RISKST	0.0557	0.0181	**				0.0140	0.0073	*
L1RISKST									
RISKFL	0.1395	0.0768	*						
L1RISKFL									
INTM									
L1INTM									
EQCAPIT							0.0531	0.0192	***
L1EQCAPIT				0.1396	0.0746	**			
FSERVIN									
MACRO									
BTPR							0.0257	0.0055	***
L1BTPR	-0.0803	0.0181	***	0.1711	0.0238	***			
MIBC				0.0098	0.0030	***			
L1MIBC	-0.0038	0.0018	**	0.0066	0.0025	***			
URC	-0.2870	0.1130	**				0.0426	0.0194	**
L1URC									
SPREAD									
L1SPREAD	0.3197	0.0690	***						
GDPCC	0.1135	0.0433	***	-0.2231	0.0550	***			
L1GDPCC	-0.1282	0.0551	**				0.0614	0.0194	***
L2GDPCC	-0.0955	0.0475	**	-0.1665	0.0464	***			
Nr. Obs.	176			176			187		
R2	0.57			0.76			0.88		
Wald-test (3)	F(10, 155) = 7.39		***	F(9, 156) = 17.01		***	F(7, 169) = 55.22		***
F-test all FE=0	F(10, 155) = 3.82		***	F(10, 156) = 19.17		***	F(10, 169) = 19.31		***
Panel-hetero (4)	Chi2 (11)= 181.91		***	Chi2 (11) = 562.77		***	Chi2 (11) = 339.88		***
Panel-AR (1) (5)	F(1, 10) = 2.212			F(1, 10) = 0.555			F(1, 10) = 11.677		***

*, **, *** significant at 10, 5 and 1 per cent level respectively.

Notes: (1) Grey areas denote the variables included in the most general specification for each equation; the most parsimonious specification has been selected via general-to-simple approach. The coefficients of the individual effects are not reported. (2) Newey West standard errors; the errors are assumed to be heteroskedastic and autocorrelated up to 2 lags (Stata routine provided by D. Roodman). (3) Wald test that all the coefficients (except intercept and FE) are jointly not significant. (4) Modified Wald statistic for groupwise heteroskedasticity in fixed effect model (Stata routine provided by C. F. Baum). (5) Wooldridge test for first order serial correlation (Stata routine provided by D. M. Drukker).

Tab. 15

IMPACT OF GDP GROWTH DURING DOWNTURNS/UPTURNS (1)

	L1GDPCC*		L2GDPCC*	
	DOWN	UP	DOWN	UP
LLP equation	0.020	-0.068 (***)	-0.232 (***)	-0.177 (***)
F-test down=up (2)	F(1, 2420) = 2.99 *		F(1, 2420) = 1.17	
RISKFL equation	-0.012	-0.083 (***)	-0.131 (**)	-0.051 (**)
F-test down=up (2)	F(1, 2425) = 0.79		F(1, 2425) = 1.39	
ROA equation	0.044 (***)	0.032 (*)	n.a.	n.a.
F-test down=up (2)	F(1, 2694) = 1.81			

*, **, *** significant at 10, 5 and 1 per cent level respectively.

Notes: (1) The table reports the coefficients of GDP growth for the static models in different phases of the business cycle. Two intercept dummies interact with L1GDPCC and L2GDPCC: DOWN equal to 1 during recessions (1992, 1993, 1996 and 2002) and 0 otherwise; UP equal to 1 during expansions and 0 otherwise. (2) F-test that the coefficients of DOWN*L1GDPCC and UP*L1GDPCC (DOWN*L2GDPCC and UP*L2GDPCC) are equal each other.

STRESS TEST

	Baseline scenario (2002) (1)	GDP Changes (2)				Scenario 1993 (3)	Scenario 1994 (3)
		-1%	0	1%	2%		
LLP	0.82	1.69	1.46	1.23	1.01	1.35	0.87
RISKFL	1.28	1.73	1.60	1.46	1.33	3.40	2.63
ROA	1.52	1.42	1.46	1.49	1.53	1.85	1.74

Notes: (1) GDP changes in 2000 and 2001 were 3.1 and 1.8 per cent respectively. (2) The exercise (sensitivity analysis) simulates the impact on LLP, bad loans and ROA of different GDP growth rates (assuming that L1GDPCC=L2GDPCC), *ceteris paribus*. The static models and the 2002 values of all the relevant regressors are used for the simulation. (3) All macroeconomic variables are set at 1993 and 1994 levels. The static models and the 2002 values of all the microeconomic regressors are used for the simulation.

FIG. 1 - LOAN LOSS PROVISIONS OVER THE BUSINESS CYCLE

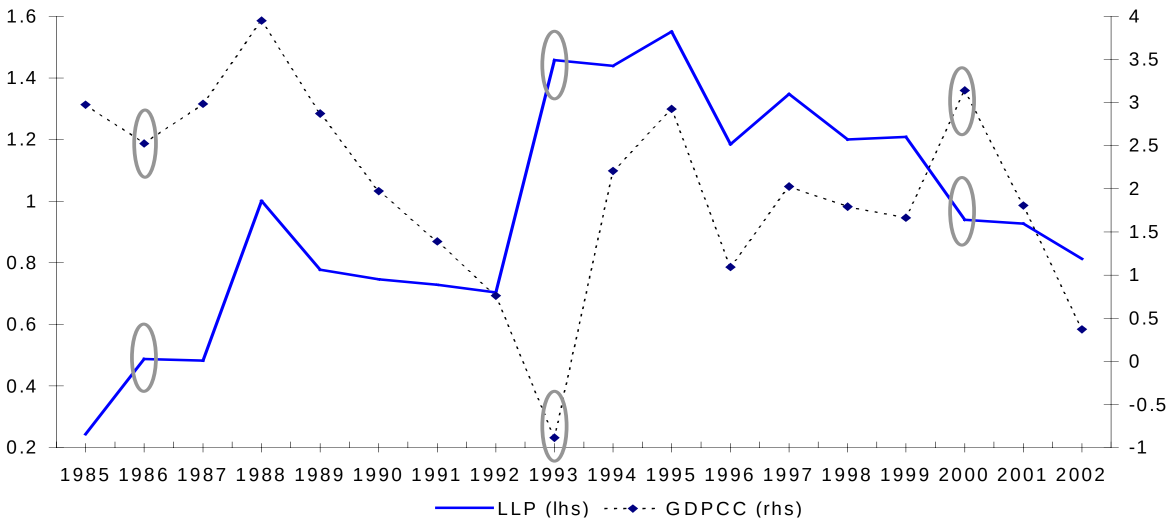

FIG. 2 - LLP - STATIC MODEL
Actual and fitted values
(averaged across banks)

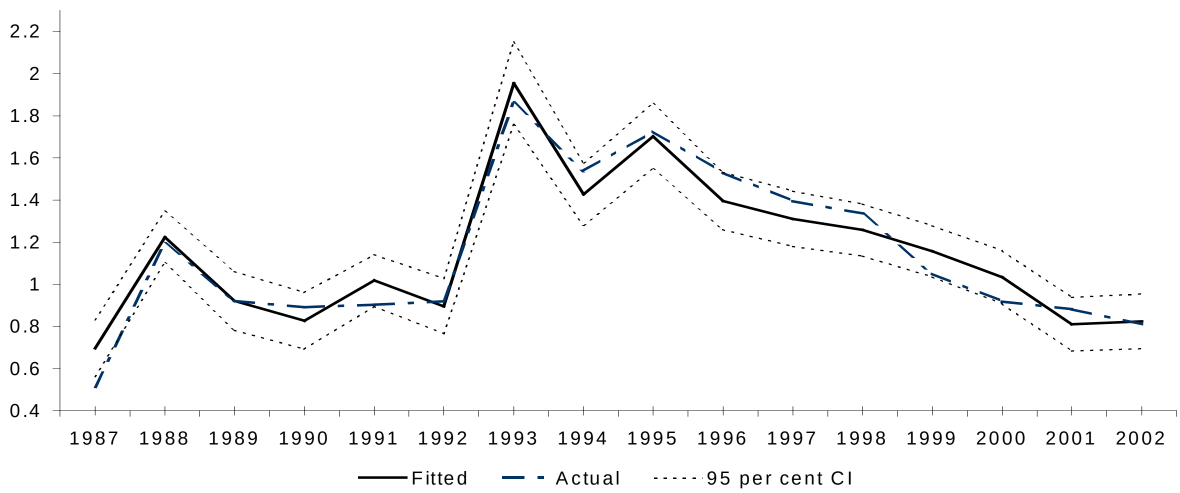

FIG. 3 - LLP - DYNAMIC MODEL
Actual and fitted values
(averaged across banks)

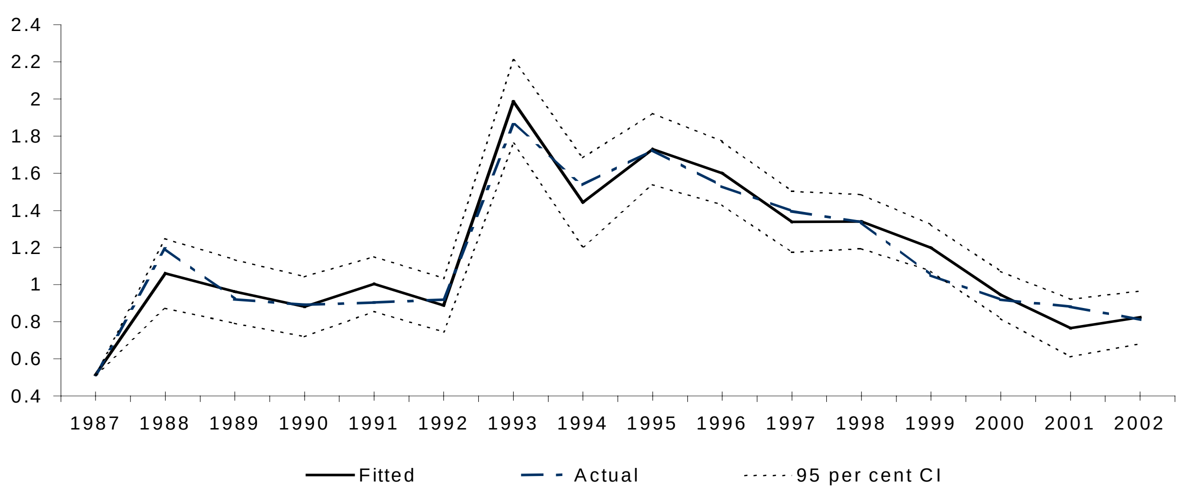

FIG. 4 - NEW BAD DEBTS OVER THE BUSINESS CYCLE

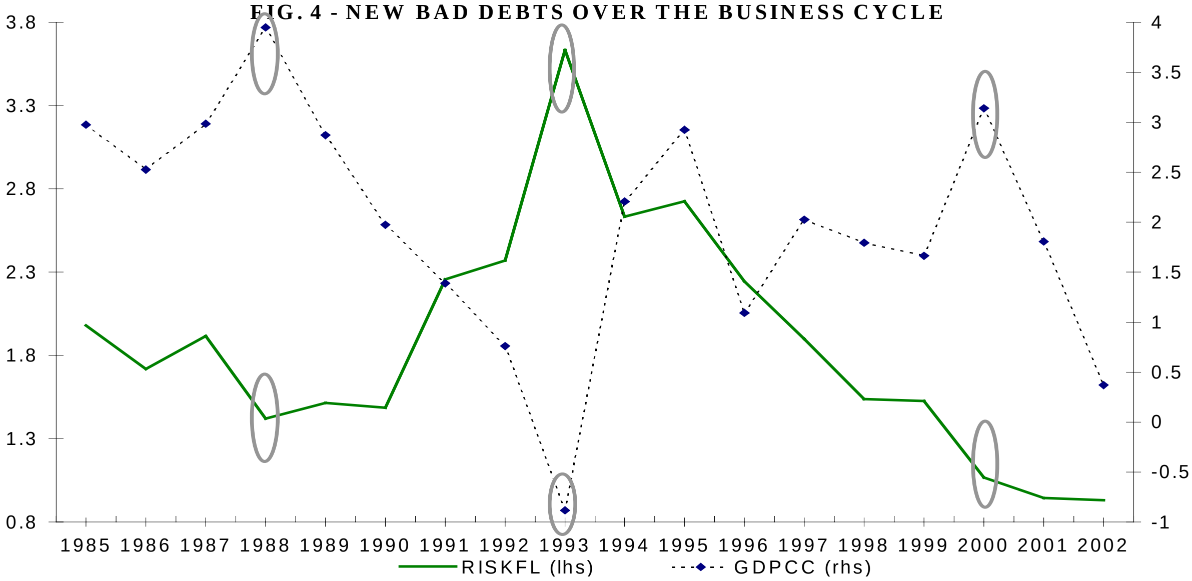

FIG. 5 - NEW BAD DEBTS - STATIC MODEL
Actual and fitted values
(averaged across banks)

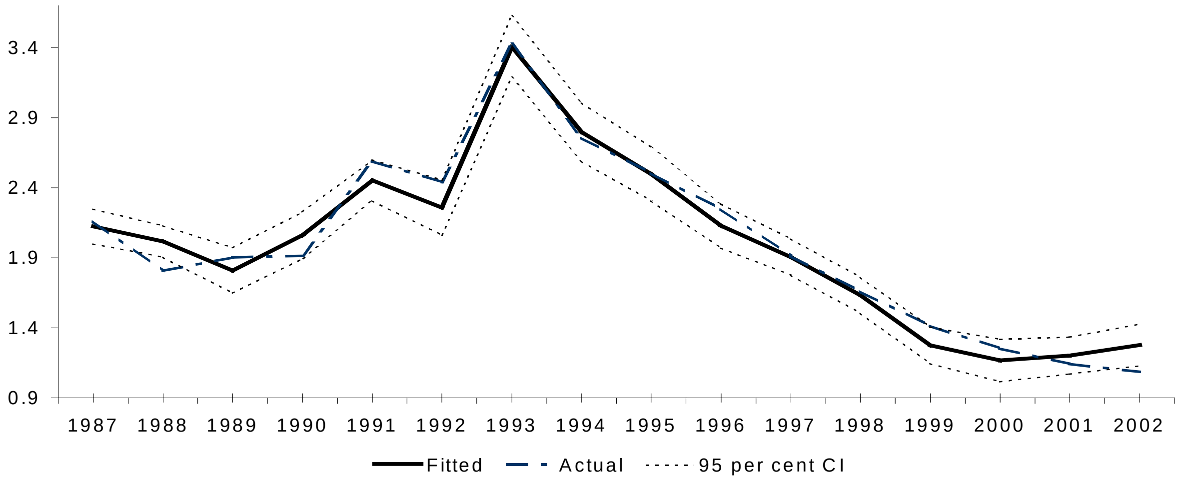

FIG. 6 - NEW BAD DEBTS - DYNAMIC MODEL
Actual and fitted values
(averaged across banks)

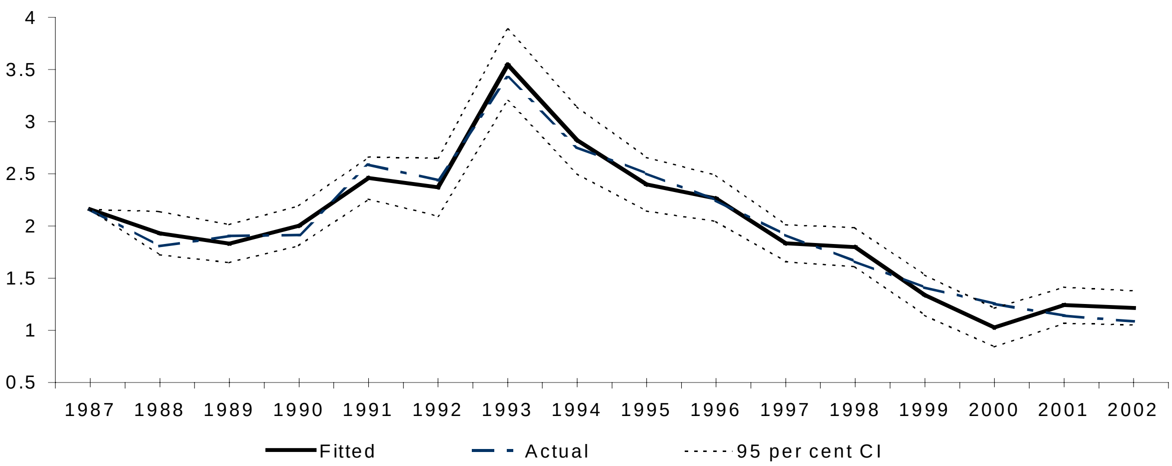

FIG. 7 - RETURN ON ASSETS OVER THE BUSINESS CYCLE

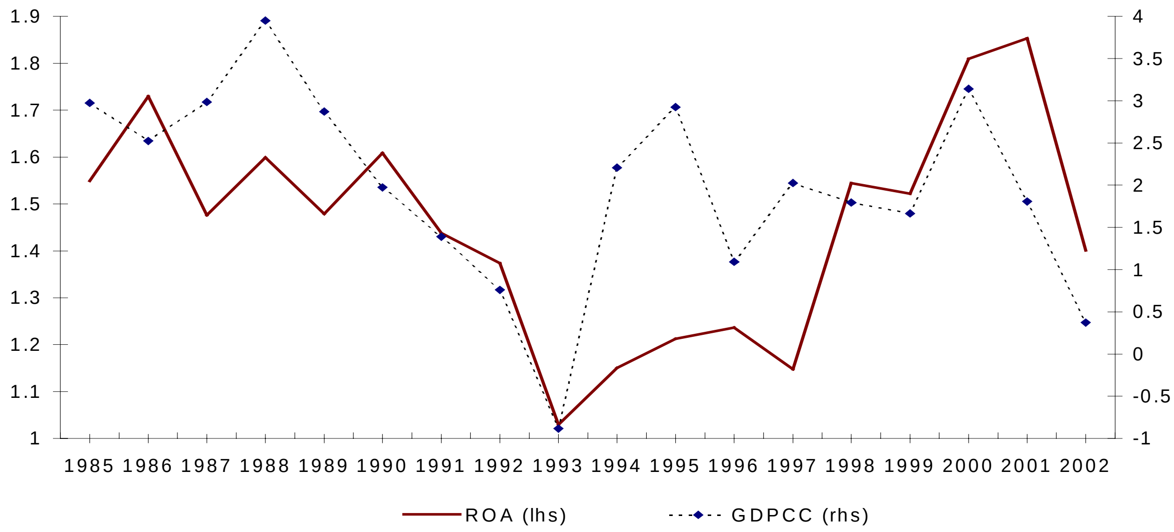

FIG. 8 - ROA - STATIC MODEL
Actual and fitted values
(averaged across banks)