An assessment of Basell II procyclicality in mortgage portfolios[*♥]

Jesús Saurina

(Banco de España)

Carlos Trucharte

(Banco de España)

July 2006

Abstract

In this paper we develop a probability of default (PD) model for mortgages, taking advantage of the Spanish Credit register, a comprehensive database about loan characteristics and credit quality. Using that model, we evaluate different rating systems based on the way the PD is calculated (PIT, point in time, TTC, through the cycle, average across the cycle, acyclical). Then, we compare capital requirements using Basel II different formulas and approaches (i.e. rating systems). We show that capital requirements under Basel II are going to be very sensitive to the risk measurement methodology. Thus, the procyclicality of Basel II is an open question, depending on the way internal ratings systems are implemented under Basel II. We focus on mortgages since it is one of the most under researched areas regarding Basel II impact and because it is one of the most important banks' portfolios.

JEL: E32, G18, G21

Key words: procyclicality, Basel II, rating systems, mortgages

---

[*] This paper is the sole responsibility of its authors and the views presented here do not necessarily reflect those of Banco de España.

[♥] Address for correspondence: Jesús Saurina; C/Alcalá 48, 28014 Madrid, Spain. Tlf: + 34 91 338 5080; e-mail: jsaurina@bde.es.

1. Introduction

How will capital requirements evolve with Basel II? This is a key question to evaluate the real impact of the change in the capital requirements framework brought about by the Basel Committee on Banking Supervision (BCBS) release in June 2004 (updated November 2005) of its International Convergence of Capital Measurement and Capital Standards, the so-called Basel II framework. Bankers, regulators, and academics have tried to answer this question during the process of discussion of Basel II (beginning in 1999) with different aims. Bankers are concerned about the impact of Pillar I credit, market and operational risk requirements in each bank capital level as well as the additional impact that Pillar 2 could have on minimum requirements stemming from Pillar I. Moreover, Pillar 3 transparency requirements regarding risk exposure have also been a concern for banks. Regulators have focused their interest on obtaining capital requirements proportional to risk in order to make sure that bank managers, and bank stakeholders have, in general, enough incentives to measure and manage risk properly. Academics and some central banks have shown concerns regarding the impact that Basel II might have on the aggregate behaviour of banks along the cycle, especially in financial stability terms.

A more targeted question focuses on the procyclicality of Basel II. A series of questions arise from it. Are capital requirements under Basel II going to be too much procyclical? How much will capital requirements vary form one period to the next? Will that put too much pressure on the soundness and stability of financial systems of different jurisdictions? Will capital requirements become binding during recessions? These questions have attracted a lot of attention from bankers, regulators, central banks, and academics[1]. The evidence provided up till now has been, in general, supportive of procyclical concerns. However, Gordy and Howells (2006) challenge this view arguing that collateral, maturity, bank behaviour and Pillar 2 and 3 might temper substantially Basel II procyclicality and they end up proposing a particular solution to it.

[1] See, among others, Borio, Furfine and Lowe (2001), Ervin and Wilde (2001), Allen and Saunders (2004), Amato and Furfine (2004), Ayuso, Pérez and Saurina (2004), Gordy and Howells (2006), Kashyap and Stein (2004), Taylor and Goodhart (2004), Catarineu-rabell, Jackson and Tsomocos (2005), White (2006).

The objective of our paper is to develop a methodology for the analysis of capital requirements under Basel II that will allow us to focus on the procyclicality issue, and to assess with real data the impact of several ways to compute probabilities of default (i.e. point-in-time, through-the-cycle, averages along the cycle, corrected of the cycle, etc.). One of the most important conclusions that different supervisors and regulators have observed in analysing simulated Basel II capital requirements is that there are important differences, wide dispersion among credit institutions, that do not correspond with identifiable differences in risk. In fact, the various methods or even the different alternatives that banks use to estimate their key credit risk parameters (i.e. the probability of default, PD), is somehow the responsible for the wide dispersion and uncertainty surrounding the internal ratings-based approach proposed by the BCBS to calculate regulatory capital.

Furthermore, if one thinks that, within the wide range of possibilities of calculation of PDs, some of them are clearly influenced by the prevailing economic conditions, nothing but important fluctuations and great variability among institutions requirements will be found as a result of Basel II. Consequently, the proposal of the paper is general and can be used to assess corporate and retail portfolios. However, here we focus on one of the most under researched area regarding Basel II which is the potential procyclicality of mortgage portfolios. The lack of research might be a consequence of the lack of data availability even though mortgages are, for retail banks and many internationally active banks, one of their largest portfolios. Moreover, the cyclicality of mortgage portfolios is also interesting because the largest contribution to the reduction in minimum regulatory capital according to the latest quantitative studies is brought about by such portfolios (BCBS, 2006).

First of all, we develop a classification system which encompasses a model that estimates a probability of default (PD) for each obligor, that is, there is a model which assigns an individual PD for each particular borrower. Secondly, we evaluate different rating systems based on the way the PD is calculated: PD estimations can be used directly (i.e. point in time), averaged across the cycle, using different criteria, or we can use the worst PDs (i.e. through the cycle)[2]. Finally, we compare capital requirements using Basel II different formulas and approaches (i.e. standardized and IRB) as well as

different rating systems. The results provided in this paper show that capital requirements under Basel II are going to be very sensitive to the risk measurement methodology. Thus, the procyclicality of Basel II is an open question, depending on the way internal ratings systems are implemented under Basel II, specifically, on how the main inputs of the Basel II formulae, basically PDs, are calculated.

We have information that covers a long period of time which allows us to evaluate the impact of Basel II capital requirements on mortgage portfolios along a full business cycle, including a house price bust. The information comes from a unique database: the Spanish Credit Register (CIR) run by Banco de España[3]. It includes information on almost the whole *population* of mortgages granted by *all* Spanish credit institutions. Therefore, we can perform a global analysis for the whole banking system.

The rest of the paper is organized as follows. In Section 2 we revise quickly the procyclicality discussion under Basel II and the literature on mortgages capital regulation. Section 3 presents the PD estimation methodology used and the database which supports it. Section 4 shows the results in terms of distributions of PDs along time. Section 5 focuses on capital requirements derived from the different inputs obtained in the previous section while Section 6 concludes.

2. Procyclicality and the mortgage market

Basel I impact on lending policies and on economic activity has been subject to intense research. Empirical papers have found evidence of a credit crunch at the beginning of the nineties in the US. Some papers consider that lending contraction due to a capital crunch can be attributed to Basel I capital requirements[4]. During the discussion of Basel II proposals, some analysts have provided concerns regarding procyclicality. The underlying argument goes as follows: Procyclicality would basically translate into lower capital requirements when favourable economic conditions prevail and into higher requirements when unfavourable ones do. This could have an undesired

[2] See Heitfield (2004) for a formal discussion of point in time and through the cycle rating systems.
[3] Jiménez and Saurina (2004), Trucharte (2004) and Jiménez, Salas and Saurina (2006) contain a detailed description of the Spanish Credit Register.
[4] See, among others, Bernanke and Lown (1991), Berger and Udell (1994), Peek and Rosengren (1995)

effect on the overall economy if banks, according to a more risk sensitive credit system, are obliged to significantly alter their lending behaviour.

To take an example, if credit models overstate default risk during recessions, capital requirements will increase in consequence. As a result, banks will respond by tightening their credit standards and, in the latest instance, by reducing their volume of lending to comply with the higher ratios of the new capital regime. Economic agents (basically households and firms) will experience serious difficulty to recover from these adverse economic conditions. This means that the most unfavourable part of the business cycle becomes more accentuated aggravating the general economic situation and magnifying the economic downturn. The opposite will occur in the benign part of the business cycle. A good summary of arguments in favour of this view, focusing on the content of Basel II, is in Taylor and Goodhart (2004). Arguments against, again focusing on Basel II proposal, appear in Gordy and Howells (2006).

In order to address procyclicality, Gordy and Howells (2006) argue that the best option for supervisors is to smooth the output (i.e. final capital requirements derived from the Basel II proposals) instead of the inputs (i.e. the probabilities of default that enter IRB formulas) or the formulas in itself (flattening of the curves). They propose an autoregressive capital requirement formula or another one directly tied to the position of the cycle. Goodhart (2005) proposes a second instrument to deal with procyclicality. Jiménez and Saurina (2006) argue for a countercyclical loan loss provision device that, in fact, could also work as a capital requirement throughout Pillar 2.

Note that even if the new capital requirements were procyclical as described above, it is necessary that several events took place, namely: that bank managers do not react to the cyclical profile of their capital buffer, additionally, that banks could not raise preference shares or subordinated debt during downturns, furthermore, that the cyclical effect were significant[5], that the capital buffer decline has a significant impact in lending policies[6], and finally, that the decline in lending were only a supply side

[5] Ayuso, Pérez and Saurina (2004) find a significant but small cyclical impact of GDP on the capital buffer hold by Spanish banks.

[6] Gambacorta and Mistrulli (2004) find evidence of the impact of capital on lending policies in a sample of Italian banks while Altumbas, Fazylow y Molineux (2002) and Ehrmann et al (2003) do not find support for the hypothesis that poorer capitalized banks suffer more under tight monetary conditions.

factor (i.e. not induced by a weak demand for loans) and that non-financial firms are not able to substitute bank funding by trade credit and/or resort to short or long term markets (i.e. commercial paper, bonds, asset backed securities, etc.).

Before getting real data based on Basel II requirements, something that will happen at the earliest in the European Union in 2007 for the more basic approaches and in 2008 for the most advanced ones, (the Basel II schedule is even more delayed for certain jurisdictions, i.e. the US), most efforts have been concentrated on trying to anticipate banks' future behaviour using past portfolio information. These attempts have focused, overwhelmingly, on the corporate (and sovereign) portfolios, those for which there is more publicly available information about their credit quality (i.e. borrowers' ratings)[7]. Some work has been done on the retail SMEs portfolio[8] while mortgages are very little explored.

Empirical work on Basel II procyclicality has usually been based on corporate portfolios and, usually, on Moodys-KMV ratings. Here, for the first time in the literature, we evaluate the potential cyclical behaviour of Basel II capital requirements in mortgage portfolios, using a prototype of rating-scoring system in the same vein as those that banks usually employ to classify their mortgage obligors when granting a loan and that in the future will be the ones utilised for qualificaton for the most advances Basel II approaches.

Mortgage markets have been widely studied. Allen (2004) surveys this literature as well as more general Basel II issues (i.e. procyclicality, incentives, securitization, and capital arbitrage). It also focuses on Basel impact on mortgage markets although the papers she surveys (where emphasis is devoted to the German market) are quite different from our paper since none of them develops a classification system in order to determine capital requirements under Basel II premises for mortgage portfolios. Similarly, our paper departs from Calem and LaCour-Little (2004) who simulate economic capital for mortgage portfolio and conclude that Basel I or Basel II

[7] See, among others, Corcóstegui et al (2003), Segoviano and Lowe (2002), Goodhart, Hofmann and Segoviano (2004), Kashyap et al.(2004) and Goodhart (2005).
[8] Among others see Dietsch and Petey (2002) and Saurina and Trucharte (2004).

standardized approaches, which offer little risk differentiation, result in significant divergence between economic and regulatory capital[9].

3. Estimation methodology and database

3.1. PD equation for borrowers

The first step consists of the developing of a PD model for mortgage borrowers. We do not have detailed information on borrowers' social and financial characteristics (marital status, type of employer, income, wealth, etc.). However, we do have information in the Credit Register that characterizes the risk profile of borrowers. To account for the business cycle, we use contemporaneous real GDP growth rates. The PD equation we estimate is the following:

$$PD_{it} = \beta_1 RISKBORR_{it} + \beta_2 LIQBORR_{it} + \beta_3 GDPG_t + \beta_4 CONTROL + \eta_{it} \qquad (1)$$

The endogenous variable is a dichotomous (zero-one) variable which takes value 1 if the borrower defaults in year t, 0 otherwise. It has to be clearly stated that the estimated PDs are a measure of the likelihood that an obligor will default in during a certain assessment horizon. This horizon is fixed to a one-year period. Under this premise, the endogenous variable is constructed, also assuming that a defaulted obligor is defined in a similar way as in Basel II: at least 90 days overdue, failure to meet its financial obligations on a certain loan. If a borrower has several mortgages, failure to meet his payments in any of them means that this borrower is in default. Based on that, we estimate a logistic transformation of equation (1) by the standard maximum likelihood maximization process.

Among the explanatory variables, RISKBORR(t) is a vector of risk profile characteristics of each borrower. In particular, we use DEFHIST(t) as a variable which informs on whether a certain borrower has defaulted in any period previous to the one used to fix the one-year assessment period for which the PD is calculated (t-2, t-3...). Additionally, this variable is weighted by the distance in time since the default of that

[9] Elizalde and Repullo (2004) show that regulatory and economic capital may differ quite significantly.

obligor took place. Thus, the more distant in time is the default, the less it counts, which seems in line with banks' credit policy practices in general.

OVERHIST(t) is another risk profile variable which accounts for the possibility that a borrower has been delinquent in previous periods (t-1, t-2...). That is, OVERHIST(t) represents borrowers being overdue on their loans that finally meet their financial obligations before the 90-day threshold, so before becoming defaulted. As for the previous variable, this one is also weighted by the distance in time a borrower committed delinquency on his loan. It has to be noted that many of the problems that are behind an overdue loan are "technical" ones, spanning only a few days as a result of mistakes or lack of monitoring of balances, casual cash shortage, holidays, etc. Nevertheless, we include this risk profile variable since a risk averse borrower will always hold a minimum buffer for unexpected events to avoid, precisely, becoming overdue.

We also include as an explanatory variable the rate of change in the latter variable (CHANOVERHIST(t)). Its inclusion intends to anticipate future declines in borrowers' ability to repay their mortgages.

Finally, the variable AGE(t) measures the age of each loan which usually coincides with the number of years each borrower is in the Credit Register, that is, it represents his age as a borrower. As will be shown later, there is a particular relationship between the age of a loan and its probability of default, showing that, in general, higher rates of default take place during the first years of a mortgage. After that period of time (three to four years), the rate of default decreases progressively with the age of the loan[10].

Taking for granted the previous statement, Chart 1 shows important differences in the PD behaviour depending on the cohort we are focusing on. In particular, the PD during the first year of the loan is strongly tightened to the business cycle. During the recession year that PD is above 5% while it decreases almost monotonically from 1994

[10] A similar behaviour, an inverted U-shaped curve between the age of a loan and its probability of default, is found on credit cards delinquencies by Gross and Souleles (2002).

onwards, as the economy recovers. The same happens with the maximum PD for each cohort. For loans granted in 1990 the maximum is reached in the period 1993-1994 as well as for those granted in 1991 and 1992. Loans granted from 1994 to 1996 show the highest PD in their first year, still a reminiscence of the recession while for those granted at the end of the nineties a normal shape of defaults by cohort reappears. Thus, although age has an impact on the PD, the cyclical position of the economy seems to be, certainly, a determinant of default. That enhances the interest of analyzing the procyclicality of capital requirements for mortgages in the new framework.

[Insert Chart 1 about here]

We also include in equation (1) a vector of variables that proxy for the liquidity constrains that a borrower may face (LIQBORR(t)). Variable UTIL(t) is the quotient between the drawn amount of credit used by a borrower and the total available amount (credit line). Some mortgages are sold as a credit line facility where the borrower can withdraw money at any time over the already repaid amounts. The collateral (i.e. the house that was the object of the mortgage) remains pledged to the credit line. The more the borrower withdraws, the more liquidity constrained might be. The second liquidity variable is NUMBANKS(t), the number of banks with which the borrower has lending relationships (number of banks a borrower applies for getting a mortgage loan). Note that we focus on individual borrowers, not banks. As result, we hypothesize that the higher the amount of banks a borrower is related to, the more liquidity constrained is.

The above mentioned risk profile and liquidity variables are only a subset of the total amount of variables we have used. Apart from levels or first differences, we have tried continuous and discrete specifications. Given that many of these variables are highly correlated, we previously run univariate regressions (borrower mortgage default as a function of a variable at a time). From those regressions we took the variables with the highest explanatory power. Later on, we run equation (1) using combinations of the selected variables. Based on forecasting capacity[11], the main guide for banks when they develop their scoring systems, we have, finally, set the variables included in the final regressions as the ones with the highest explanatory power.

[11] This predicting capacity has to be understood in terms of accurate classification of defaulted and non-defaulted borrowers.

Note that banks, in developing their internal models for mortgage defaults, will have much more detailed information of each borrower (basically, income and social information). We are hypothesizing here that the past experience of the borrower both in terms of defaults and overdue loans as well as their age as borrowers are a sufficient statistic for that information. Thus, the main difference between our benchmark model and those of banks lies in the accuracy of default forecasts (i.e. the percentage of defaulted and non-defaulted borrowers properly classified as such). Note that this is less relevant in our paper since we focus on the behaviour of PD along the cycle and the different ways they are calculated and the dispersion they can create in determining regulatory capital and there is no reason to think that our sufficient statistics performs differently in upturns and downturns.

Our cyclical variable is the real GDP growth rate (GDPG(t)). Among the CONTROL variables, we have included a dummy that accounts for the region where the borrower is granted the loan. We also control for the type of mortgage lender: commercial bank, savings bank, credit cooperative or credit finance establishments. Savings banks (not-for-profit banks) hold half of the market share in mortgages. Moreover, the risk profile might change according to the ownership structure of the bank[12]. We also include a dummy variable (REG99) that takes the value of 1 from 1999 onwards and 0 otherwise, in order to reflect the change in the report of defaulted loans in the database. After 1999, any defaulted amount is reported while before that year only defaults above 6,000 euros were reported. The expected sign of the dummy variable is positive. Finally, we include a constant. η_{it} is the error term.

3.2. Database

The database used for this study is the Credit Register of the Bank of Spain (CIR). The Spanish CIR records monthly information on all credit operations granted by credit institutions (banks, savings banks, credit cooperatives and specialised credit institutions) in Spain for a value of over €6,000. The CIR's data structure distinguishes

[12] See, Esty (1997a, b), Gorton and Rosen (1995), and Delgado, Salas and Saurina (2006) for the Spanish case.

between credits given to firms and those to individuals[13]. Among the latter it is possible to identify those engaging in business activities (individual businesspersons). The CIR includes information on the characteristics of each loan, including the following: instrument (trade credit, financial credit, leasing, etc.), currency denomination, maturity, existence or not of guarantees or collateral, type of guarantor (government or credit institution), the coverage of the guarantee, the amount drawn and undrawn of a credit commitment and, finally but very importantly, whether the loan is current in payment or past due (distinguishing between delinquency and default status). The CIR also includes information relating to the characteristics of borrowers: province of residence and, for firms and businesspersons, the industry in which they operate. There is no information regarding the interest rate of the loan.

Here, we focus on mortgages to individuals. Those are collateralized loans with a maturity over five years. The time period covered goes from 1990 to 2004, which covers a whole business cycle in Spain, with a deep recession around 1993 and the corresponding upturn, even boom, during the nineties and the first years of the current decade. Given the very low threshold for a loan to be included within the CIR, we reassure ourselves with regard to the entire population of mortgages in Spain. That means dealing with a vast amount of information (over 30 million loans) which makes it almost impossible to run any regression. So, we have cut down the population into another tractable one by choosing only a certain amount of borrowers . A sampling procedure based on a very simple rule and that produces a stratified sample that perfectly matches with the main characteristics of the entire population was carried out. After sampling the population of loans we are still left with over 3 million mortgages. We are not aware of any paper that uses such an amount of information for modelling default probabilities of mortgages.

Table 1 shows some descriptive statistics for several years regarding the objective of this paper of the whole population of mortgages as well as that of the sample chosen. Note that the even though the default ratios (proportion of defaulted

[13] There is a clear separation between the characteristics of loans to companies (mainly in terms of the size of the loan, maturity, collateral and default rates) and those loans granted to individuals, making it appropriate to treat each of the two groups separately.

borrowers) are quite low (even below 1%), given the amount of observations we have, that does not presupposes a problem at all for the estimation of equation (1).

[Insert Table 1 about here]

The number of borrowers as well as the amounts lent increase along time significantly while the increase in the average size of the loan less than doubles. The problem loan ratio as well as the proportion of defaults (i.e. the PD rough calculation from the population and the sample) follow a cyclical patter with their maximum around 1993 (the recession year) while current levels show the strength of the business cycle in Spain and/or the change in bank credit risk policies. There is an almost perfect matching between the whole population and the sample we have taken from it.

3.3. Results

Table 2a,column 1, shows the results of the estimation of (1). All the variables have the expected signs. The higher the risk profile of a borrower, the higher his probability of default. Consequently, overdue loans (OVERHIST(t) and CHANOVERHIST(t)) can be considered as a signal of future default (both in levels and rates of growth). Regarding other variables, the older a loan, the lower its probability of default[14] (positive sign in the age variable). –Taking into account liquidity issues, the higher the use of bank funds and the more lenders an individual resorts to, the higher the probability of default (positive sign in variable UTIL(t) and NUMBANKS(t)). Thus, liquidity constrains also seem to play a role in mortgage defaults.

Commercial banks (omitted dummy variable of ownership type) are the least risky regarding mortgages, whereas credit finance establishments show the highest probability of default (positive and highest coefficient for the type of lender dummies). The latter credit institutions hold a small market share (around 1%) but they concentrate riskier borrowers, maybe those that do not receive a mortgage in deposit institutions.

[14] This is in line with firm defaults, where young firms have a higher mortality.

The sign of the cyclical variable included in the regression, GDP growth rate is negative and significant, as expected. During downturns and recessions, mortgage defaults increase, declining in upturns. Therefore, PDs move along the cycle. The next section analyses how much they vary depending on the way they are calculated directly obtained from a borrowers' classification system.

[Insert Table 2a about here]

Columns 2 to 4 show that the former results are robust, both in terms of sign and significance, to changes in control variables. Column 2 shows the results without type of lender dummies. Column 3 excludes regional dummies and, finally, column 4 excludes both dummies.

In addition, we have performed several robustness analysis to Table 2a results (not shown here to save space). We have included an interest rate variable, both in nominal and real terms. It is positive and significant in both cases but the accuracy of the model does not improve significantly. We have also excluded GDPG and included the interest rate with similar qualitative results. We probably could also include other business cycle variables but, then, we would lose clarity in modelling changes in the cycle. That is why we stick to only GDPG for the measurement of cyclical effects. More importantly, either the average level of PD or their profile along time according to different rating methodologies do not change too much depending on the macro variables we use.

Once the variables that determine an individual's possibility of defaulting have been established and their coefficients and signs within the multivariate model are known, it is convenient to establish certain performing measures for the estimated regression model to evaluate its classification power. Table 2b also shows the classification table of the final model. It can be observed in the main diagonal that the model classifies approximately 77% of the borrowers included in the sample. In terms of alternative performing measures, the area under the ROC curve roughly reaches 78%

which results in an Accuracy Ratio (AR) near to 60%[15]. the PS ratio measures the performing power that a model possesses.

[Insert Table 2b about here]

The previous classification power is obtained for the training sample. In order to test the consistency of the model, a validation sample should be constructed using external data (2005 data). The validation process simply consists of calculating the score of every borrower and of comparing it with its observed default status. The results are pretty close to those of the training sample (77% of individuals were correctly classified) indicating a satisfactory classification power of the estimated model.

4. Probabilities of default along the cycle and rating methodologies

Once equation (1) has been estimated and its performance power has been established, each borrower in the sample is assigned an individual PD based on loan particular characteristics (idiosyncratic factor) and on a macro variable (cyclical factor). This allows us to rank each borrower regarding his PD as well as to calculate alternative values for average PDs for the entire sample to evaluate their main properties, their appropriateness for calculating regulatory capital measures and, finally, their procyclical implications.

The first PD obtained is the simplest one (the point-in-time (PIT) PD). For that we can use the actual PD (that is, the ratio between the number of mortgage borrowers that default in year t, not having defaulted in the previous period, over total number of borrowers with a mortgage) or the estimated one (using the model estimated and the predictions extracted from it). Given the two options available, we focus on the first one in order to use the most accurate possible information. In any case, the average PD in both approaches is very similar (1.1% and 1.2%, respectively) as well as their risk profile along time.

[15] The AR measure determines the performance enhancement over the random model of the model under evaluation (equation (1)) with respect to the ideal model. More details related to accuracy ratios and model-performing measures can be found in Sobehart et al. (2000).

[Insert Table 3 about here]

Table 3, column 1 shows the PIT values. There is substantial variation in PT along time. Around the recession, Spanish banks experienced relatively high default rates. On the other hand, at the end of the last decade and at the beginning of the current one, when a protracted period of growth combines with a significant increase in the number of borrowers that receive mortgages, the observed PDs are quite low. It should be noted that the Spanish economy experienced during the period analysed a structural change leading to the entrance in the European Monetary Union in 1999. As a consequence of that change it might be quite possible that in the next recession the levels of PD will increase but not as far as those of 1993[16].

The second type of PD calculated is a through-the-cycle one (TTC). According to Heitfield (2005), that PD is computed using the trough of the business cycle. That means that we use the value that the GDP growth rate took in year 1993, the worst year in the sample. In fact, that year was the worst recession that Spain has suffered in the last 40 years or so. Thus, we keep constant the GDPG(t) variable while allowing for changes in the other significant variables in (1). We obtain an average PD for each year, as the result of substituting the average value of each explanatory variable in (1), keeping the value of GDPG at the 1993 level. Table 3, second column, shows, as expected, that the average PD TTC is almost 80% higher than the PIT PD. However, taking into account how both PDs have been calculated, the profile along time ot the TTC PD is much smoother than that of the PIT one.

The third column in Table 3 contains another smoothing type of PD (a long-run average PD). This is a cumulative average, where the PD attributed to each year is the simple average of the PD up till that year. Its average is not too far away from the average of the TTC. That is mainly by construction since we start with high levels of PD that remain along the cycle. A partial answer to that problem is to use a rolling average, with the drawback of not being able to use the first years of the period that, in our case, are those of the recession. The rolling average results show a less volatile PD along time.

[16] Delgado and Saurina (2004) provide evidence supporting this view.

The last three columns in Table 3 show different variations of a rating system based on cyclical corrections in the PD. The fourth column shows the PD estimates when the value of the GDP growth rate variable in equation (1) is substituted by its average during the sampling period. Volatility, measured by the standard deviation declines dramatically in comparison with PIT or even TTC estimates. However, the average PD across the period is almost equal to that of the PIT PD. The coefficient of variation, that is, the dispersion measure that controls for the level of the mean, shows roughly similar dispersion for the TTC PDs and the cycle-corrected ones, while the levels are much higher for the former than for the latter.

Columns 5 and 6 of Table 3, show what we could call acyclical PDs. These are ratings based on the prediction model (1), excluding the cycle variable (GDPG(t)). That is, we reestimate model (1) excluding GDPG(t) and, subsequently, predict the PD. The difference between column 5 and 6 is whether the model contains regional dummies or not. The difference is almost negligible. The average PD is very similar to the PIT one since we have smoothed away the large PDs that took place during the recession. Nevertheless, the variability across PDs is higher for the PIT one since as a result of the relatively high values recorded in the early nineties. The volatility of the acyclical PDs is extremely low as the coefficient of variation compared to that of TTC one and a bit higher than the PIT one.

Chart 1 shows the outcome of the six different rating systems. There are significant differences across the various approaches that produce significantly distinct Basel II capital requirements for mortgages. The next section analyses those requirements.

[Insert Chart 1 about here]

5. Capital requirements and procyclicality

5.1. Basel II and rating systems

In order to measure capital requirements under the IRB approach for mortgages it is necessary to make a hypothesis regarding the LGD. 15% is a reasonable number, given our supervisory experience in the quantitative impact studies. In any case, as LGD enters lineally in Basel II capital requirements formulas, so wherever it is fixed to a certain value it is only a matter of level but not of the shape along time unless the way LGDs are calculated are also dependent on the business cycle and different approaches were used for their estimation regarding different periods of time.

Table 4, first column shows the capital requirements associated with a PIT PD. The fluctuation in capital figures is quite evident showing a substantial decline along the cycle. Compared with the new standardized approach, in recession, the requirements are slightly larger and in upturns can be very well below. It is important to remember that the Spanish credit market as changed significantly the last decade and banks have improved significantly risk management. In any case, even acknowledging the structural shift in the Spanish economy and the improvement in credit risk management, PIT capital requirements will change significantly along the cycle. As argued by the extant literature and by most regulators across the world, capital calculated using a PD totally dependent on the prevailing economic conditions will provoke an enormous volatility in banks' solvency with the undesired consequences that this effect implies.

It is important to note that if the capital figure of 2004 (1,04%) is compared to the current figure for mortgage loans (around 4%), one can have a rough idea of where the important reductions in requirements, anticipated by exercises such as the Quantitative Impact Studies (QIS) carried out by the BCBS, can be found. Average requirements along the cycle, coincide with the capital that the standardized approach of Basel II demands and they are still quite far from the current ones. The main conclusion from the use of such PDs is that supervisors via Pillar 1 or 2 would have to perform or articulate some measure to try to reduce the dispersion showed and to maintain an acceptable level of one of the most important elements that determines the soundness and stability of banks' financial condition.

TTC PDs have several important properties as one can see in Table 4. In first place, a great extent of the dispersion that PIT PDs incorporate disappears. That is the result of how TTC PDs are calculated, The inclusion of the worst record of the business

cycle in the PD equation assures that for the worst period of the business cycle the amount of capital will cover totally the losses that the Basel II formulae assign at the 99,9% percentile (excess over the expected losses in principle covered by provisions). At the same time, the worst GDP growth rate record partly compensates in the PD equation the improvement that the rest of the explanatory variables experiment as the cycle moves towards its most benign part.

This partial balance provokes a fewer reduction in capital required and as a result in less associated volatility. A similar case will take place if the cycle moves into a new recession, the progressive deterioration of the rest of the variables will increase gradually the capital required as prevailing conditions deteriorate with no important variations from one period to the next. It can also be seen that the current credit requirements for the most advanced approach of Basel II will approximate to the ones coming from the standardized approach requirements (1.84% versus 2,3%), more than half of those coming from the current capital regime.

In a similar vein, a PD based on a long run average, in principle, the one proposed by the BCBS to be used as the input for the credit capital requirement formulae would produce similar results to the TTC PD described above. However this measure will never exactly reproduce the requirements needed to cover the unexpected losses at the 99,9% percentile at the trough of the business cycle, as a mere consequence of the way it is calculated. On the other hand, the requirements for the boom periods will be lower than those of the TTC, as the longer the distance from the trough the more similar the estimates to the PIT PDs. This translates into a higher variation over the business cycle. The current IRB capital figure that would derive from this method of calculation will be, somehow, lower than the figure from the standardized approach (30% lower) and would be more than half the current regime figure.

Finally, the PDs corrected by the cycle or those defined as acyclical produce pretty similar results. It seems that when the variable representing the business cycle is set to its average value, the effect on the estimated PDs is similar to the one that would take place when the cycle is obviated. The variability observed for these approaches is much lower than that in any other forms in which PDs can be calculated. However, at the trough of the business cycle these methods are the ones which fall much shorter to

cover the part of the unexpected losses associated with the 99.9 % percentile. On the other hand, for the most favourable part of the cycle, the estimated PDs are much similar to the real ones (PIT ones). As just said the dispersion of this approach is the lowest, however, the omission of the cycle prevents from covering an important part of the losses that could take place and that could provoke solvency problems in case of severe problems.

Chart 2 shows the different capital requirements.

[Insert Chart 2 about here]

5.2. Discussion on procyclicality

The former sections have shown that PDs and, consequently, capital requirements under Basel II for mortgages will change significantly depending on the method used by banks for calculating their credit risk parameters, namely, their PDs. That is, depending on the rating system used by the banks. The first lesson to be learned is that variability may be an important caveat as observed in the mortgage portfolio for the entire system and that the reduction in capital figures, considering possible estimates of measures of risk, could rise up to 75% with respect to the current capital regime. The use of PIT PDs is the extreme case, with significant variations across the business cycle.

The second important idea that can be obtained from the previous results is the wide dispersion that can exist among banks when producing regulatory capital measures regarding Basel II and that that may not correspond to real differences in borrowers' risk profiles. Supervisors must be sure of the accuracy, reliability and application of the inputs that banks may use to determine IRB capital requirements. The previous section contained a very illustrative example of this situation: if capital is calculated using a PIT PD the resulting figure is 45% lower than the one obtained if a TTC PD was used (a similar reduction is observed if a long-run average was used instead). This enormous diffusion over different possibilities of calculating measures of risk (all of them related, in one way or another, to the prevailing conditions of the economic cycle) must pose a question of which of them, if any, should be the most appropriate to determine capital figures.

PIT PDs have important properties and are basically the ones that banks work with when applying their scoring systems either for pricing or making the decision whether or not granting a loan to a possible customer. Additionally, they allow for a cross comparison among banks of their credit risk profiles and, as a result, produce accurate and homogenous assessments of the risk incurred by each bank. However, it seems highly unlikely that supervisors will be prepared to accept such a measure for computing capital, basically for the variability it contains which mirrors in capital requirements under the Basel II formulae.

Several options are open to try to work out this caveat: for example, those pointed out in Gordy and Howells (2004) by means of smoothing the final output through a countercyclical capital requirement formula in Pillar 2. Jiménez and Saurina (2006) argue for a countercyclical loan loss provision. However, the same mechanism or a similar one could be used for capital requirements in Pillar 2. That countercyclical mechanism would be transparent and, thus, not hampering Pillar 3 market discipline, which seems to be one of the main worries in Gordy and Howells (2004) who postulate the smoothing of the output but not of the inputs.

TTC PDs may not be the answer to the previous question either, since the level of requirements is quite above any other measure, especially for the benign part of the business cycle. Banks could be asked for high level of capital when clearly this is not required regarding the level of actual risk. However, this measure assures that in the trough of the cycle, losses will be covered (under the Basel II framework) with a 99.9% probability. A trade-off comes up in this situation, high probability of covering losses when most needed against requiring banks to maintain a buffer of excess of capital over their real needs.

Although counterintuitive, this type of risk measure also discriminates between the degree of risk each bank incurs. If PIT PDs reflect both current economic and obligor-specific conditions whereas TTC ones only reflect the latter, as all banks share in the PD equation the same value which the cycle variable takes (whether the current one or the worst in the sampling period), both measures incorporate valid information to classify each obligor in terms of the inherent risk that its profile presupposes.

Finally, it is also important to take into account the asymmetry in requirements that this measure produces. As said before, using a TTC PD, supervisors can be sure that for recession capital required will be in line with the real needs that the economic situation implies, on the other hand, the inadequacy of capital only comes during upturns, and could be consider as a price for a lower level of volatility in capital figures anticipating possible future bad times when raising capital could be much harder to obtain, an in any case, far more expensive than maintaining a higher amount in good times.

Long run averages, share most of the properties of TTC PDs as commented above. Based on the particular way they are constructed, they are less demanding for banks, as for upturns they will be more similar to PIT PDs and consequently, the capital figures will much lower than those calculated using TTC PDs. Their main drawback arises in downturns when the amount of capital will not assure with a 99.9% probability that losses will covered. From a supervisory perspective long run averages fall short of the most important advantage of TTC PDs without significantly improving its main caveat. Other things equal, TTC PDs, as presented in this paper, seem superior to long-run averages.

In principle, acyclical PDs should be the most preferred measure whenever the model that produces them precisely puts apart the cyclical effect without ignoring it. If one could get rid of the fluctuations that the cycle incorporates but maintaining the its pattern in the risk profile of obligors, via their idiosyncratic features particularised by the specific moment of the business cycle, this could avoid extreme swings in required capital and may constitute the solution regulators are looking for. Thus, these measures seem to work the best, still allowing for much more variability in capital requirements that the standardized approach but without the huge swings that PIT ratings seem to produce.

A half way compromise could be to use a through-the-cycle approach but based not on the worst position in the cycle but in a somehow less extreme approach. That might produce significantly higher capital requirements in boom periods while still

producing enough capital in recessions but without the high level in average terms that a pure TTC approach requires.

6. Conclusions

This paper provides a simple methodology for banks and bank supervisors to analyze procyclicality of Basel II capital requirements. We focus on mortgages, one of the most under researched areas of Basel II, even despite the fact that for many banks, they are one of the largest subsets in credit portfolios. We take advantage of the Spanish Credit Register, a comprehensive database that contains loan and borrower information (including credit risk performance) for the last twenty years (i.e. almost two business cycles).

We estimate a probability of default (PD) model for mortgages, using information of roughly 3 million borrowers. This equation model includes several risk profile variables (liquidity constraints and default and delinquency past history of each borrower) and a macro variable (GDP growth rate) and allows to assign to each individual a single probability of default. Based on those probabilities and on different approaches to depending on the nature of the measure to be calculated we obtain distinct averages that allow us to study their properties and adequacy for regulatory capital.

In short, we compare point-in-time (PIT), through-the-cycle (TTC), long-term averages and acyclical PDs. The comparison of these approximations to measure credit risk, provides us with evidence which translates into a highly significant variability of PIT PDs along the cycle with huge changes in capital requirements from peek (expansion) to trough (recession). That variability raises a serious concern for supervisors that aim to apply the most advanced approaches included in Basel II.

TTC measures show much less variability although the average level of capital requirements is relatively high. Acyclical ratings produce stable and relatively low requirements. Thus, a reasonable compromise could be the use of TTC ratings but not using the worst point in the cycle to compute them. An alternative compromise may well be the use of acyclical PD measures which share most of their properties with TTC

PDs with the advantage of being more benign, in terms of required capital, during upturns.

All in all, we show that Basel II procyclicaity is an open issue that deserves a careful scrutiny for mortgage portfolios and, by extension, for corporate and retail ones. In any case, Basel II framework has in itself the mechanism to deal with this issue (i.e. rating system properties and supervisory implementation).

References

Allen, L.; (2004). “The Basel capital accords and International mortgage markets: A survey of the literature”. Financial Markets, Institutions & Instruments, V. 13, Nº 2, May 2004.

Allen, L.; Saunders, A.; (2004). “Incorporating systemic influences into risk measurements: a survey of the literature”. Journal of Financial Services Research 26:2, 161-192.

Altumbas, Y., Fazylow, O.; Molineux, P.; (2002): “Evidence on the bank lending channel in Europe”. Journal of Banking and Finance, 26, 2093-2110.

Amato, J. D. and C. H. Furfine; (2004): “Are credit ratings procyclical”. BIS Working Paper.

Ayuso, J.; Pérez, D.; Saurina, J.; (2004): “Are capital buffers procyclical? Evidence from Spanish panel data”. Journal of Financial Intermediation, 13, pp. 249-264.

Basel Committee on Banking Supervision (2006): “Results of the fifth quantitative impact study (QIS 5)”. June, BIS.

Berger, A.N.; Udell, G.F.; (1994). “Did risk-based capital allocate bank credit and cause a “credit crunch” in the United States? ” Journal of Money, Credit and Banking, Vol. 26, Nº 3, Part. 2. (Aug. 1994), pp. 585-628.

Bernanke, B.S.; Lown, C.; (1991). “The credit crunch”. Brookings papers on Economic Activity, 2.

Borio, C.; Furfine, C.; Lowe, P.; (2001). “Procyclicality of the financial system and financial stability: issues and policy options”. Bank for International Settlements.

Calem, P.S.; LaCour-Little, M.; (2004). “Risk-based capital requirements for mortgage loans”. Journal of Banking & Finance 28, pp. 647-672.

Catarineu-Rabell, E., Jackson, P. and Tsomocos, D. (2005): “Procyclicality and the new Basel Accord-banks’ choice of loan rating system. Economic Theory 26, 537-557.

Corcóstegui, C., L. González-Mosquera, A. Marcelo and C. Trucharte (2003). "Analysis of procyclical effects on capital requirements derived from a rating system". Basel Committee Workshop: Banking and Financial Stability: A Workshop on Applied Banking Research, Banca d’Italia, Rome.

Delgado, J. and J. Saurina (2004) “Análisis del riesgo de crédito. Una perspectiva macroeconómica” Moneda y Crédito 219, pp. 11-41, 2004.

Dietsch, M. and J. Petey (2002). "The credit risk in SME loans portfolios: Modelling issues, pricing and capital requirements", *Journal of Banking and Finance*, Vol. 24 (2002).

Elizalde, A. and Repullo, R. (2004): “Capital regulatorio y capital económico: un análisis de sus determinantes”. Estabilidad Financiera, Nº 7, Noviembre.

Ehrmann, M.; Gambacorta, L; Martínez, J.; Sevestre, P; (2003): “Financial systems and the role of banks in monetary policy transmission in the euro area”. In Angeloni, I.; A. Kashyap y B. Mojon (Eds.), Monetary Policy Transmission in the Euro Area. Cambridge Univ. Press, Cambridge, pp. 235-269.

Ervin, W.; Wilde, T.; (2001). “Pro-cyclicality in the new Basel Accord”. Credit Risk. Risk October 2001.

Esty, B.C.; (1997a). “Organizational form and risk taking in the savings and loan industry” Journal of Financial Economics, 44, 25-55.

Esty, B.C.; (1997b). “A case study of organizational form and risk shifting in the savings and loan industry”. Journal of Financial Economics, 44, 57-76.

Gambacorta, L.; Mistrulli, P.E.; (2004): “Does bank capital affect lending behaviour?” Journal of Financial Intermediation, 13, pp. 436-457.

Goodhart, C.; (2005). “Financial regulation, credit risk and financial stability”. National Institute Economic Review, Nº 192. April 2005.

Goodhart, Ch.; Hofmann, B.; Segoviano, M.; (2004). “Bank regulation and macroeconomic fluctuations”. Oxford Review of Economic Policy, Vol. 20, Nº 4.

Gordy, M.B., Howells, B.; (2006) “Procyclicality in Basel II: Can we treat the disease without killing the patient? Journal of Financial Intermediation, Vol. 15, 3, 395-417.

Gorton, G., Rosen, R.; (1995). “Corporate control, portfolio choice, and the decline of banking”. The Journal of Finance 50, 1377-1420.

Gross, D. B., Souleles, N. S. (2002). “Am empirical analysis of personal bankruptcy and delinquency”. The Review of Financial Studies Spring Vol. 15, Nº 1, 319-347.

Heitfield, E.; (2005). “Draft on the role of internal rating systems in credit-risk management”. Federal Reserve Board.

Jiménez, G., Saurina, J.; (2004). “Collateral, type of lender and relationship banking as determinants of credit risk”. Journal of Banking and Finance, 28, pp. 2191-2212.

Jiménez, G., Saurina, J.; (2006). “Credit cycles, credit risk and prudential regulation”. Forthcoming International Journal of Central Banking.

Jiménez, G., Salas, V., Saurina, J.; (2006). ”Determinants of collateral”. Forthcoming Journal of Financial Economics.

Kashyap, A.K.; Stein, J.C.; (2004). “Cyclical implications of the Basel II capital standards”. 1Q/2004, Economic Perspectives. Federal Reserve Board of Chicago.

Peek, J.; Rosengren, E.; (1995). “The capital crunch: neither a borrower nor a lender be”. Journal of Money, Credit and Banking, Vol. 27, Nº 3; Aug.; pp. 625-638.

Saurina, J.; Trucharte, C.; (2004): “The small and medium-sized enterprises in the Spanish credit system and their treatment according to Basel II” Journal of Financial Services Research, Vol. 26, no 2, pp. 121-144, 2004.

Segoviano, M.A.; Lowe, P.; (2002). “Internal ratings, the business cycle and capital requirements: some evidence from an emerging market economy”. Draft.

Sobehart, J., Keenan, S. and Stein, R.; (2000). "Benchmarking quantitative default risk models: a validation methodology", Risk Management Services. Moody's Investors Service. Rating Methodology, March 2000.

Taylor, A.; Goodhart, Ch., (2004). “Procyclicality and volatility in the financial system: The implementation of Basel II and IAS 29”. Preliminary draft.

Trucharte, C.; (2004): “A review of Credit Registers and their use for Basel II”. Financial Stability Institute. BIS. September.

White, W.R.; (2006). “Procyclicality in the financial system: do we need a new macrofinancial stabilisation framework? – BIS Working Papers, Nº 193.

Table 1. Descriptive features of the main characteristics of the population and the sample used in the paper.

Year	Total Operations	Exposure (thousand €)	Average loan (thousand €)	90th Percentile (thousand €)	Problem loans ratio	Proportion of defaults
1990	1,095,881	17,900,000	16.4	30.0	4.0%	3.4%
1990 sample	109,803	1,800,348	16.4	30.0	4.0%	3.3%
1993	1,792,216	33,100,000	18.5	36.0	4.2%	3.6%
1993 sample	179,814	3,328,174	18.5	36.0	4.2%	3.6%
1997	3,967,016	82,100,000	20.7	42.0	0.9%	0.9%
1997 sample	396,034	8,220,267	20.8	42.0	0.9%	0.9%
2001	5,787,661	162,000,000	28.0	55.0	0.4%	0.7%
2001 sample	578,260	16,200,000	28.0	55.0	0.4%	0.7%

Table 2a. Estimation of the logit model (1) by maximum likelihood.

$$PD_{it} = \beta_1 RISKBORR_{it} + \beta_2 LIQBORR_{it} + \beta_3 GDPG_t + \beta_4 CONTROL + \eta_{it}$$

	Coefficient	Coefficient	Coefficient	Coefficient
GDP growth rate	-0,15	-0,147	-0,146	-0,144
	(0,005)	(0,005)	(0,005)	(0,005)
Dumreg_99	0,13	0,09	0,13	0,093
	(0,014)	(0,014)	(0,014)	(0,014)
UTIL	2,30	2,03	2,44	2,18
	(0,14)	(0,14)	(0,15)	(0,144)
NUMBANKS	0,74	0,876	0,76	0,88
	(0,02)	(0,02)	(0,02)	(0,019)
AGE	-1,89	-1,84	-1,91	-1,85
	(0,043)	(0,043)	(0,043)	(0,043)
OVERHIST	1,31	1,20	1,23	1,14
	(0,022)	(0,021)	(0,021)	(0,021)
CHANOVERHIST	0,49	0,53	0,48	0,52
	(0,03)	(0,03)	(0,029)	(0,03)
DEFHIST	3,61	3,65	3,66	3,69
	(0,016)	(0,016)	(0,016)	(0,016)
Type of lender Dummies	yes	no	yes	no
Regional Dummies	yes	yes	no	no

Observations: 2,936,193. Sampling period:1990-2004. In parentheses the standard error of the coefficient. All variables are significant at the 99% confidence level.

Table 2b Logit Model Performance.

CLASSIFICATION TABLE. EQUATION MODEL

	Observed Defaults	Observed non-defaults	Total
Predicted defaults	19,009 **64.50%**	681,114 23.00%	700,123
Predicted non-defaults	10,477 35.5%	2,280,,541 **77.00%**	2,291,018
Total	29,486	2,961,655	2,991,141

Cut-off: 0,09% . An individual is assigned to the default category if the predicted probability exceeds this value.

Area under ROC curve = 0.78

Table 3. Probabilities of default (PDs) along the cycle. Different methodologies.

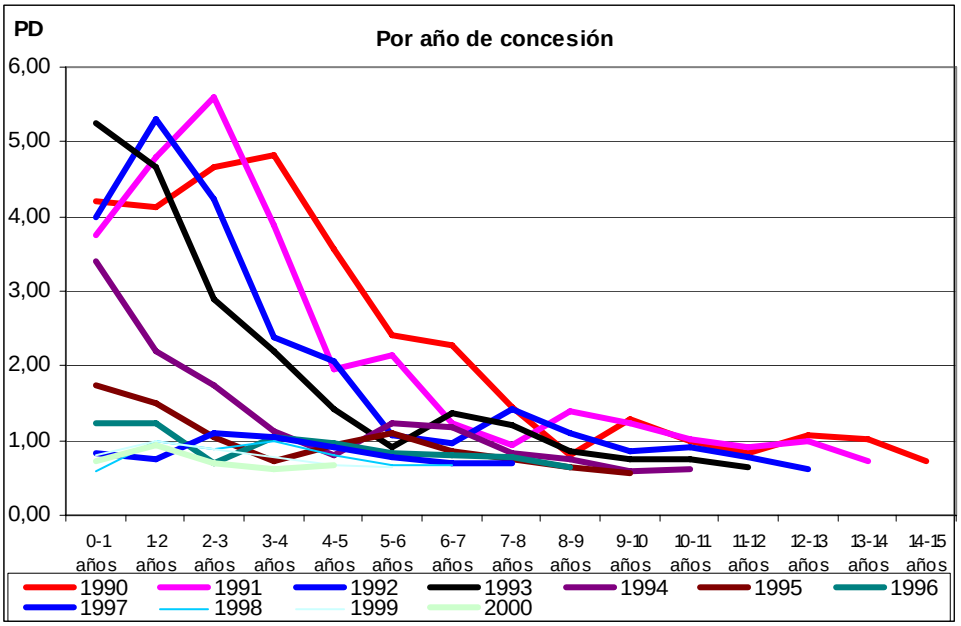
Year	PD PIT	PD TTC	PD Long-run average	PD Cyclically corrected	PD Acyclical	PD Acyclical
1991	2,27%	2,49%	2,41%	1,55%	1,62%	1,61%
1992	2,55%	2,80%	2,55%	1,77%	1,85%	1,86%
1993	2,91%	2,56%	2,73%	1,61%	1,68%	1,73%
1994	2,18%	2,33%	2,55%	1,46%	1,51%	1,51%
1995	1,24%	2,30%	2,22%	1,44%	1,49%	1,48%
1996	0,96%	2,04%	1,97%	1,25%	1,29%	1,27%
1997	0,61%	1,87%	1,74%	1,13%	1,17%	1,14%
1998	0,41%	1,60%	1,55%	0,95%	0,98%	0,99%
1999	0,49%	1,61%	1,49%	0,95%	0,92%	0,92%
2000	0,66%	1,58%	1,43%	0,93%	0,90%	0,90%
2001	0,59%	1,54%	1,37%	0,92%	0,88%	0,87%
2002	0,54%	1,49%	1,32%	0,88%	0,85%	0,84%
2003	0,44%	1,41%	1,27%	0,84%	0,81%	0,82%
2004	0,58%	1,36%	1,22%	0,80%	0,77%	0,77%

PIT: point in time; TTC: through the cycle.

Table 4. Basel II capital requirements

Year	PD PIT	PD TTC	PD Long-run average	PD Cyclically corrected	PD Acyclical	PD Acyclical
1991	2,53%	2,68%	2,63%	2,00%	2,06%	2,05%
1992	2,72%	2,87%	2,72%	2,17%	2,24%	2,24%
1993	2,93%	2,72%	2,83%	2,05%	2,11%	2,14%
1994	2,47%	2,57%	2,71%	1,93%	1,97%	1,97%
1995	1,73%	2,55%	2,50%	1,91%	1,95%	1,94%
1996	1,46%	2,37%	2,32%	1,74%	1,78%	1,76%
1997	1,07%	2,25%	2,15%	1,63%	1,66%	1,64%
1998	0,81%	2,04%	2,00%	1,46%	1,48%	1,50%
1999	0,92%	2,05%	1,95%	1,45%	1,42%	1,42%
2000	1,14%	2,02%	1,90%	1,44%	1,40%	1,40%
2001	1,06%	1,99%	1,85%	1,42%	1,38%	1,37%
2002	0,99%	1,95%	1,80%	1,38%	1,35%	1,34%
2003	0,85%	1,89%	1,76%	1,34%	1,30%	1,31%
2004	1,04%	1,84%	1,71%	1,30%	1,26%	1,27%

Chart 1. Probabilities of default (PD) by cohort



Note: By cohort we mean those loans granted the same year and followed along time.

Chart 2. PDs and GDP growth rate

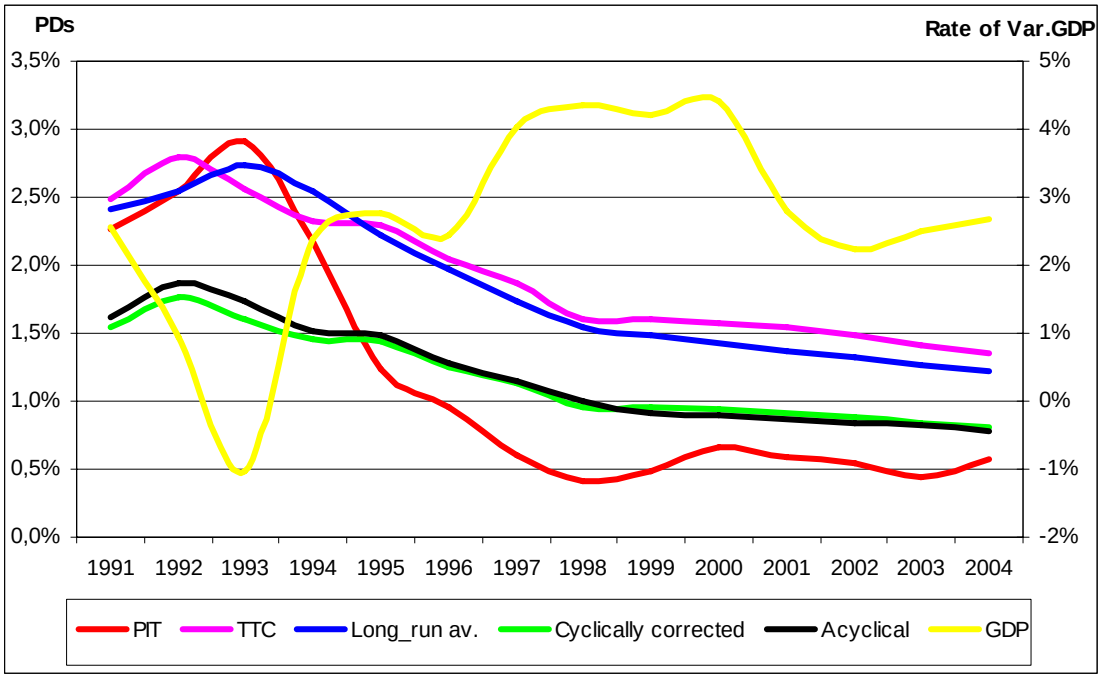
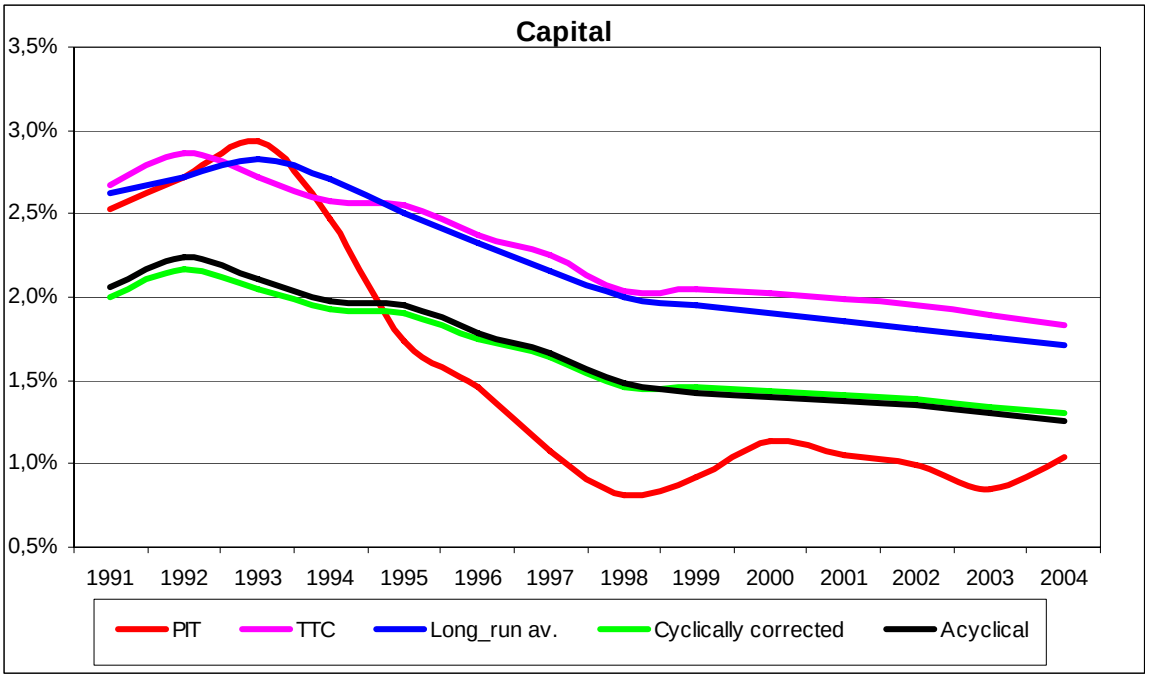



Chart 3. Capital requirements for different rating systems