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## Materiali di discussione

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### A forward-looking model for time-varying capital requirements and the New Basel Capital Accord

by

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# **A forward-looking model for time-varying capital requirements and the New Basel Capital Accord**

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## **Abstract**

This paper proposes a forward-looking model for time-varying capital requirements which finds application within the New Basel Capital Accord (NBCA) framework. The model aims at reconciling two somewhat contrasting objectives of the NBCA proposal: introducing risk-sensitive capital requirements and avoiding at the same time procyclical effects. The model rests on the relationship existing between default rates and the business cycle phases and proposes a modelisation of the default probabilities which is based on a business cycle forecast over the credit horizon. The model is applied to US data over the forecasting period 1971-2002: despite a failure in predicting the early nineties recession, the objective of raising the capital requirements in anticipation of a recessions is in general satisfied. The results obtained are interesting as they suggest that there is room for dampening procyclicality of capital requirements even within a risk-sensitive framework.

JEL: G21, G28, C32

Keywords: capital requirement, default probability, business cycle, procyclicality

## **Introduction**

In April 2003 the Basel Committee published the last proposal for the New Basel Capital Accord (NBCA), which innovates over the 1988 accord (Basel Capital Accord, BCA) and is based on the so called *three pillars*: i) Minimum capital requirements; ii) Supervisory review process; iii) Market discipline.

As for the first pillar, the main objective is to make the capital requirements more risk-sensitive, i.e. more representative of the actual banks' risk profiles. The increased risk-sensitivity of capital requirements under the NBCA has raised concerns about a possible procyclicality side effect due to the dependence of credit risk on the business cycle. Procyclicality is commonly meant as the phenomenon of business cycle amplification due to the reduction in credit availability in recession periods (and vice versa in expansion periods). Procyclicality is at some degree inherent to bank activity: if the capital requirement is risk-sensitive, it is likely to increase during recessions and decrease during expansions, hence exacerbating procyclicality.

The present paper proposes a simple model, which can be used to tackle the procyclicality issue by defining the capital requirements in a forward-looking way, so that capital requirement changes in anticipation of the business cycle rather than as a consequence. The model essentially rests on the predictability view of the business cycle and on some stylised empirical facts emerging in the business cycle literature. The paper is organised as follows. Section 1 analyses the relationship between credit risk measurement and the business cycle so as to highlight how the procyclicality issue emerges within the NBCA risk measurement framework. In Section 2, the model is set up and its theoretical and empirical underpinnings are discussed. Section 3 applies the model to US data. The last Section concludes. The Appendix reports the capital requirement formula in the Basel Capital Accords.

## **1. Credit Risk Measurement and the Procyclicality issue in the NBCA**

Credit risk is determined both by idiosyncratic risk factors related to the single obligor features and by systematic risk factors affecting the creditworthiness of all the obligors. Systematic risk, being not diversifiable, is of uttermost importance in the assessment of credit risk at a portfolio level and is generally dependent on macroeconomic conditions. The relationship between credit risk measurement and the business cycle has given rise to a wide literature (see Allen and Saunders (2003) for a survey), also fostered by the NBCA proposals.

In the following subsections, we will recall the main issues that we consider to be relevant in setting up a model for capital requirements, which is consistent with the NBCA.

### **1.1 The time dimension of risk**

The relationship between credit risk and the business cycle is supported both by the empirical evidence (e.g. Fons (1991), Wilson (1997), Nickell et al. (2000) or Bangia et al. (2002), Carey (2002)) that shows the increase in default rates during recessions and by several theoretical models of the real business cycle, which support a negative correlation between credit risk factors and output (e.g. Williamson (1987), Kvarn (2002)). The analysis of the time dimension of risk, i.e. the relationship between the credit risk and the business cycle, differs depending on whether risk is measured when it materialises or when it accumulates.

While the existence and the nature of the relationship between the real activity and the default rates (as a measure of the materialised risk) is not controversial, the debate is still open as for the relationship between risk accumulation and the economic conditions. In fact, while risk is generally considered countercyclical (i.e. higher during recessions and vice versa), some authors believe that risk may be highest at business

cycle peaks. In particular, Borio et al. (2001) maintain that the high default rates during recessions are just a materialisation of the risk that has been built up during booms, especially if a strong expansion combines with the creation of financial imbalances.

Borio et al. (2001) argue that these different views about the risk dynamics over the business cycle eventually reflect different opinions about the nature of the economic process underlying the business cycle. In fact two are the main and most distant views of the business cycle: the “*predictability view*”, i.e. the business cycle is a predictable regular sine wave and the “*random walk view*”, i.e. the business cycle is too irregular to be predicted. While in the former view, macroeconomic forecast can be considered in a credit risk model, in the latter one the current conditions are considered the best forecast for the next period.

The direct consequence of these two different views of the business cycle dynamics on risk measurement is the timing of the increase/decrease of the risk measure. According to the random walk view, the measured risk reflects the current economic conditions and hence it increases during recessions and decreases during expansions. By contrast, in the predictability view, the risk measure should increase if a recession is going to happen over the credit horizon (and vice versa) and the measured risk can increase during an expansion.

## **1.2 Capital requirements and the business cycle in the NBCA**

The NBCA aims at defining risk-sensitive capital requirements, i.e. capital requirements which vary with the riskiness of the banks’ portfolios. The risk-sensitivity of capital requirements implies that the latter vary with the business cycle as the actual risk changes. It follows that the procyclical effect of compulsory capital requirements is likely to be amplified if the same are risk-sensitive.

The NBCA, analogously to the current regulation (BCA), imposes banks to hold the capital ratio (i.e. the ratio of capital over the sum of risk-weighted assets) above the solvency coefficient of 8% against credit risk (see the Appendix). In the BCA the weights are constant over time, hence only the numerator changes over the business cycle: in periods of recession, the capital would decrease due to default losses (because of increased default rates), reducing the capital ratio and consequently forcing banks to alternatively reduce lending (i.e. risky assets) or increase capital in order to comply with the capital requirement. In the NBCA, particularly in the Internal Rating Based (IRB) Approach, as the weights are made risk-sensitive, also the denominator is likely to change over time: if the risk-weighted asset increase during recessions, this effect will enhance the effect of the numerator implying a further reduction in the capital ratio.

From a macroeconomic point of view, the diffused fear (see e.g. Danielsson et al. (2001)) is that a co-movement in capital requirement and the business cycle, may induce banks to further reduce lending during recessions due to the high capital requirement to comply with. The opposite would happen in economic booms. This mechanism would eventually exacerbate the business cycle peaks and troughs. As highlighted by Leaven and Majnoni (2002), the risk of a ‘capital crunch’, i.e. a situation of simultaneous shortage of capital and contraction in the supply of new loans, can stem from the joint working of high capital requirements and economic slowdown.

This concern is particularly relevant if the ‘random walk view’ of the business cycle prevails: a risk sensitive capital requirement is in fact likely to fluctuate over the business cycle, and, especially if a ‘random walk’ view is adopted, it will be higher during recessions and lower during expansions. By contrast, if the “predictability view” is accepted, the capital requirement can be forced to increase at the peak of the business cycle in anticipation of a recession and to decrease at the trough in anticipation of an

expansion. This would smooth the business cycle sine wave turning points compared to the former situation.

### **1.3 Credit risk variables and the business cycle**

The business cycle can enter at different levels by affecting the main variables, which characterise a credit risk measurement framework, i.e. :

1. Rating;
2. Probability of Default (PD) (and Transition Matrices (TM));
3. Loss Given Default, LGD;
4. Exposure at Default, EAD;
5. Correlations among PD, LGD and EAD;
6. Correlations of PDs across borrowers.

Given the focus of the model proposed in the present paper, we restrict the attention to the first two variables<sup>1</sup>, which correspond to the two phases characterising a rating system: the *rating assignment*, which classify obligors by rating classes, and the *rating quantification*, which associates a PD to each rating class.

In order to capture the time dimension of risk, either the ratings or the corresponding PDs need to be modelled so as to account for economic conditions prevailing over the credit horizon. In line with the literature, we will refer to the PDs dependent on a particular state of the business cycle as '*conditional PDs*', as opposed to the '*unconditional PDs*' which are independent of the particular state of the business cycle.

The rating assignment and the rating quantification overlap at a certain degree since models to estimate the PD of a single obligor can be used both to assign a rating and to contribute to the definition of the PD relative to a certain rating class. In fact, the PDs can be estimated in four different ways by means of:

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<sup>1</sup> For a complete treatment of the link between the risk components listed above and the business cycle, we refer to the survey by Allen and Saunders (2003) and to the article by Lowe (2002).

- Statistical methods based on obligors' specific features (mainly accounting data);
- Structural models based on equity market data;
- Reduced form models (typically modelling the default intensity rather than the annual PD) based on credit spread market data;
- PDs implied from ratings based on historical default data.

In the first three cases, the rating assignment and quantification can overlap, in that a PD estimated for the single borrower can be used both to assign the rating and to calculate the rating class PD as an average.

Moreover, the rating systems can follow a *'point in time'* (*pit*) logic or a *'through the cycle'* (*ttc*) logic. The former assigns ratings according to the ability of the borrowers to fulfil obligations over the credit horizon and is likely to change over the business cycle; the latter considers this ability independently of the business cycle, i.e. considers a fixed scenario: the ratings assigned through the cycle are built to be stable over the business cycle, changing only with the idiosyncratic factors. The choice between these two conceptually different rating assignments depends on what type of risk the ratings are meant to represent, i.e. relative vs. absolute risk of borrowers. If only the relative riskiness is considered in the rating assignment, ratings represent an ordinal ranking of borrowers, regardless of the dimension of risk. By contrast, ratings accounting for absolute risk consider the actual level of risk and hence also its time dimension, i.e. the way it varies over the business cycle. Ratings assigned *pit* consider the absolute dimension of risk, including the time dimension, and hence they will fluctuate over the business cycle. Ratings assigned *ttc* instead are meant to neutralize the business cycle effects in order to isolate the relative riskiness of borrowers. Amato and Furfine (2003) argue that credit ratings *"are intended to distinguish the relatively risky firms (or specific bonds) from the relatively safe"* and hence ratings should be assigned *ttc*.



Crouhy et al. (2001) suggest that *ttc* ratings are preferable for investment (lending) decisions, while *pit* ratings should be used when allocating capital and defining reserves (hence capital requirements).<sup>2</sup>

As for the NBCA, the banks adopting the IRB Approach are required to use a time horizon longer than one year in assigning ratings and to assess ratings according to the “*borrower’s ability and willingness to contractually perform despite adverse economic conditions or the occurrence of unexpected events*” (BCBS (2003), par 376): in such a way the NBCA implicitly requires a *ttc* rating system. Moreover the NBCA requires PDs to be estimated as long-run averages, hence tendentially constant. These choices, which are in line with the rating agencies’ methodology, respond to the willingness of smoothing capital requirements over the different phases of the business cycle to avoid or reduce the procyclical effect, but they tend to reduce risk-sensitivity.

## **2.The proposed Model**

### **2.1 Aim and set up**

From the previous section, it emerges that the main NBCA objective of introducing risk-sensitive capital requirements is at odds with the concern about procyclicality. In fact, by essentially requiring a *ttc* logic in both risk assignment and risk quantification, risk-sensitivity is sacrificed in favour of a reduction in procyclicality.

In our opinion, a way to reconcile these two somewhat contrasting needs would be to use a *ttc* logic in the rating assignment and to account for business cycle effects with a forward-looking perspective in the rating quantification (i.e. PDs estimation). The forward-looking approach allows to smooth capital requirements over the business cycle without giving up the risk sensitivity of the very same.

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<sup>2</sup> Note, in fact, the the main rating agencies (e.g. Moody’s, Standard&Poor’s) follow the *ttc* logic. As for bank practice, many banks use rating system based on balance-sheet data, which are *pit* and ‘backward-

To this end the model proposed in this paper takes the predictability view of the business cycle and aims at increasing capital requirements in anticipation of a recession and to lower them in anticipation of a boom. Specifically, the model suggests measuring capital requirements in a forward-looking way by calibrating PDs on the macroeconomic conditions expected to prevail over the credit horizon.

Two are the main underpinnings of the model proposed.

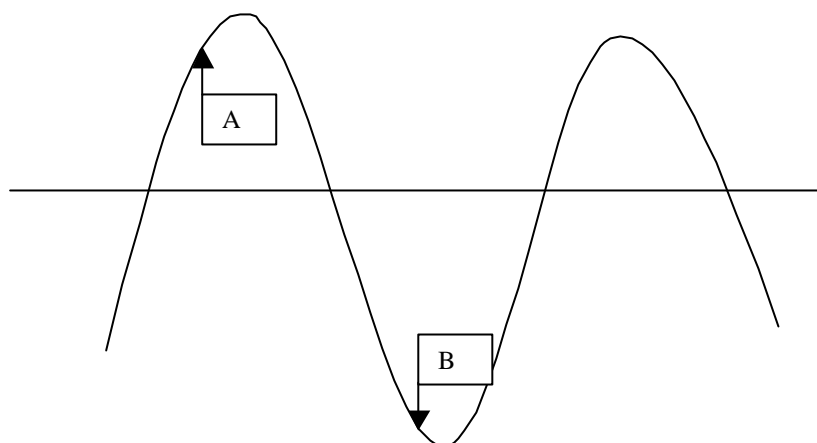
The first one, which underlies the forward-looking nature of our model, is the theoretical argument put forward by some authors that risk builds up before recessions (i.e. during expansions) and materialises during recessions. Specifically, Borio et al. (2001) and Segoviano and Lowe (2002) among others, stress that measured risk can be unduly procyclical due to a misperception of risk over the business cycle. During recessions the high default rates determine a high perceived risk, but according to Borio et al. (2001) such an increase is just a materialisation of the risk built up before the recession, i.e. during the economic boom. A risk measure should increase if a recession is going to occur over the (future) credit horizon considered, and not if the current economy is facing a recession at the time of the measurement. In the latter case, capital requirement would tend to increase when a recession has already settled, hence when not only it is too late to prevent losses but the increase in capital requirements can also exacerbate the ongoing recession.

The increase in the capital requirement in anticipation of a recession (e.g. point A in Figure 1) allows banks to adjust the level of capitalization when the economic conditions are still good. Analogously, the reduction in the capital requirement at the end of a recession (e.g. point B in Figure 1), i.e. in anticipation of an expansion, allows banks to expand lending and hence helps the economic recovery.

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looking' by nature. See BCBS (2000) for a survey of the most diffused bank practice.

Figure 1 Business Cycle: the timing of capital requirements changes



The second underpinning of our model, which underlies the PDs modelisation, is represented by the empirical evidence of regimes in the PDs over the business cycle.

In fact, some recent literature has presented evidence of regimes existing in the PDs (and transition probabilities) corresponding to the business cycle regimes. Bangia et al. (2002) analyse the US Standard&Poor's default and transition data and they estimate an expansion matrix and a recession matrix according to the NBER chronology on quarterly rating/default data. They find clear evidence of the existence of two regimes, with the recession matrix presenting higher default and downgrading probabilities. Nickell et al. (2000) present similar evidence on Moody's data, but they define three regimes: peaks, troughs and normal times. Both Bangia et al. (2002) and Nickell et al. (2000) stress that the PDs are especially sensitive to the business cycle compared to the other transition probabilities: this is important since the 'default class' is the only one that is not affected by the rating agency subjectivity<sup>3</sup>.

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<sup>3</sup> In fact, even if the rating are assigned *ttc*, they are likely to embed some residual procyclicality (as shown for example by Amato and Furfine (2003)) and anyway depend on the rating agency judgement, while the default class is objective since it is based just on historical default data.

Supported by this evidence, the default rates are modelled as dependent on two discrete states of the business cycle, namely expansion and recession.<sup>4</sup>

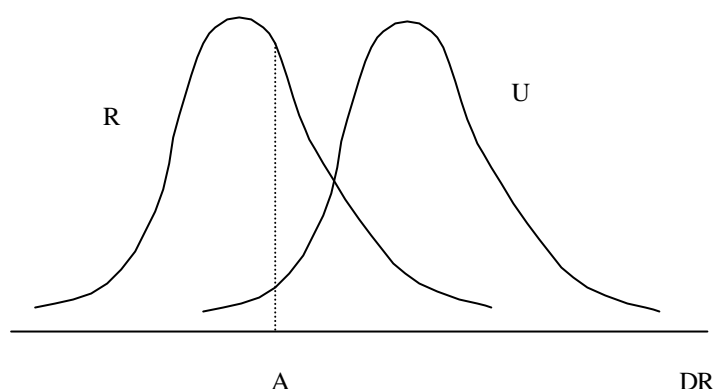
When the PD for a given rating class is estimated as a long-run average of realised default rates (as in the NBCA and in the rating agencies' practice), the implicit underlying assumption is that the default rate DR is a stochastic variable with stable probability distribution  $f(DR)$  and expected value  $E(DR)=PD$ .

In the present model the one period default rate DR for each rating class is modelled as a stochastic variable with a probability distribution dependent on the state of the business cycle: the probability distribution of DR over a given period is  $f_E(DR)$  if the period is of expansion and  $f_R(DR)$  if the period is of recession. The modelling of the DR conditional on the state of the business cycle implies a different interpretation of the observed (realised) default rates. If a unique distribution is assumed to represent the DR over the business cycle, the actual default rates observed on different periods are interpreted as random draws from the stable distribution: high and low values of the default rate, which likely cluster over different general economic conditions, are just bad and good realisations of the same distribution. Alternatively, if two distinct distributions are assumed to hold over expansion and recession periods, low and high observed default rates can be seen as realizations of these two distributions. Figure 2 represents the assumption considered: point A, an observed default rate, could be an extreme (very rare) realisation of an unconditional distribution  $f(DR)$  or it could be a 'normal' realisation of a recession distribution  $f_R(DR)$ .

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<sup>4</sup> The proprietary model CreditPortfolioView (CPV), for example, models dependence of the PDs on the business cycle by using macroeconomic variables as explanatory ones. This essentially implies dependence on an infinite number of states.

Fig. 2 Conditional and unconditional default rate distribution



'R' stands for recession distribution  $f_R(DR)$ : 'U' stands for unconditional distribution  $f(DR)$

While the application of the two-regime model would be straightforward if the business cycle state over the time horizon considered were known, this is clearly not the case, and the probabilities of each state need to be considered. Bangia et al. (2002) propose to use constant regime switching probabilities from the Hamilton (1989) model.

By contrast, in the present model we propose to use time-varying forward-looking regimes probabilities estimated within an econometric binary choice model. While the constant regime probabilities aim at representing the dynamics of the business cycle state in the long-run, the time-varying probabilities account for a forecast of the state prevailing over the time horizon of interest. The introduction of this forward-looking element is central to our modelling of the default rate over a future horizon, since it allows to address the procyclicality issue.

## 2.2 A formal representation

The model is based on the following assumptions.

A1. The model is a one-period model and the period length is equal to the credit horizon.

A2. The business cycle state  $S$  over the period is a binomial variable:

$$S = \begin{cases} E & P(E) \\ R & P(R) \end{cases} \quad (1)$$

where:

E = expansion;

R = recession;

P(E) = probability of an expansion over one period;

P(R)=1-P(E) = probability of a recession over one period.

A3. The probability of the two states P(E) and P(R) are time-varying and predictable.

Given the current information  $I_t$  available in t, the recession probability in period t+k is defined as

$$P_t(S_{t+k} = R) = P(S_{t+k} = R | I_t) = f(\mathbf{b}'x_t) \quad (2)$$

where:

$x_t$  = explanatory variables for the business cycle regime;

$\mathbf{b}$  = coefficients of the explanatory variables;

$f(\mathbf{b}'x_t)$  = probit/logit function.

$P_t(S_{t+k} = R)$  represents the probability of a recession occurring in t+k given the information available in t. The expansion probability is just its complement to one.

A4. The rating are assigned through the cycle and the default rate DR for each rating class is a stochastic variable with state-dependent distribution:

$$f(DR | S) = \begin{cases} f_E(DR) & \text{if } S = E \\ f_R(DR) & \text{if } S = R \end{cases} \quad (3)$$

By combining the hypotheses A2 and A4, the prior (hence unconditional) distribution of the DR over one period can be modelled as a mixture of the two conditional distributions:

$$f(DR) = P(E) \times f_E(DR) + P(R) \times f_R(DR) \quad (4)$$

By defining the PDs as the means of the two conditional distributions

$$\begin{cases} PD_E = E_E(DR) = \int DRf_E(DR)dDR \\ PD_R = E_R(DR) = \int DRf_R(DR)dDR \end{cases} \quad (5)$$

the unconditional PD can be obtained as

$$PD = E(DR) = \int DRf(DR)dDR = P(E) \times PD_E + P(R) \times PD_R \quad (6)$$

It has to be noted that the definition of the unconditional PD in (6) is also consistent with the NBCA definition (long-run average) if the regime probabilities  $P(E)$ ,  $P(R)$  are estimated as sample proportions of realised expansions and recessions respectively<sup>5</sup>. However, by considering *A3*, the regime probabilities are forward-looking, i.e. clearly different from the sample proportions.

The prior distribution of the default rate over the horizon  $t+k$  given the information in  $t$  is a mixture of two distributions defined as

$$f_t(DR) = P_{t+k}(E) \times f_E(DR) + P_{t+k}(R) \times f_R(DR) \quad (7)$$

where

$$P_{t+k}(E) = P(S_{t+k} = E | I_t) \text{ and } P_{t+k}(R) = P(S_{t+k} = R | I_t).$$

While the business cycle states defines only two possible conditional distributions, the ex-ante distribution varies over time with the time-varying regime probabilities.

The associated time-varying PD, estimated in  $t$  for the horizon  $t+k$ , is

$$PD_t = E_t(DR_{t+k}) = P_{t+k}(E) \times PD_E + P_{t+k}(R) \times PD_R \quad (8)$$

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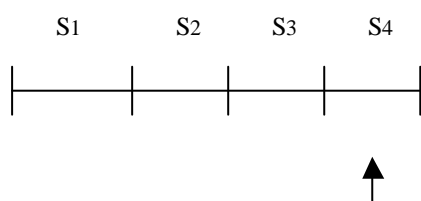
<sup>5</sup> If the conditional PDs in (5) are estimated as averages of expansion and recession default rates respectively, their combination by the sample proportion of expansions and recessions gives the long-run unconditional average.

The PD in (8) is unconditional from a statistical point of view. Even if it depends on the currently available information, its classification as unconditional is consistent with the definition of conditional and unconditional PDs given in Gordy (2002)<sup>6</sup>.

If the regime probabilities are correctly forecast, the capital requirement (*ceteris paribus*) increases when a recession is going to occur over the credit horizon and vice versa.

When applying the model defined by (1)-(8) to estimate the PDs as input to credit risk models, an issue to be solved is the time inconsistency between the credit horizon, that is typically one year, and a sensible period length for business cycle measurement, that is one month or at most one quarter. Figure 3 shows a typical situation: the business cycle state is represented by four binary variables, one on each quarter, while the PD needs to be defined over a one-year horizon.

*Fig. 3 Different periods' length*



The regime probabilities should in principle be estimated for each quarter and then combined to define the unconditional yearly PD. In the application presented, however, the choice is to estimate only the regime probability over the fourth quarter, i.e. to model  $S_4$ : the reason lies in the final purpose of the model, that is to estimate PDs in a

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<sup>6</sup> “An obligor’s unconditional default probability, also known as its PD or expected default frequency, is the probability of default before some horizon given all information currently observable. The conditional default probability is the PD we would assign the obligor if we also knew what the realized value of the systematic risk factors at the horizon would be. The unconditional PD is the average value of the conditional default probability across all possible realizations of the systematic risk factors. ”, Gordy (2002).



forward-looking way in order to anticipate the business cycle and hence smooth the procyclicality effect when estimating the capital requirements.

### **3. Application to US data**

In this Section the model presented in Section 2 is applied to a simple artificial portfolio of US obligors. The application of the model consists in three phases, detailed in the following subsections:

1. Identification of the expansion and recession regimes in the default rates and estimation of regimes PDs ( $PD_E$  and  $PD_R$ ) for each rating class;
2. Business cycle forecast: estimation of the recession probability for each period according to equation (2) of the model;
3. Estimation of the time-varying PDs according to equation (8) of the model and calculation of the capital requirements through the NBCA formula for the IRB approach.

#### **3.1 Expansion and recession PDs**

As for the estimation of  $PD_E$  and  $PD_R$ , the results by Bangia et al. (2002) are exploited. Bangia et al. (2002) deal with full transition matrices: in the application presented in this paper, consistently with the NBCA requirements, only the PDs, i.e. the last column of the transition matrix, are considered.

Bangia et al. (2002) use Standard & Poor's default data<sup>7</sup> over the period 1981-1998 to compute both conditional and unconditional quarterly transition matrices. The two

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<sup>7</sup> Bangia et al. (2002) use a CreditPro database containing issuer credit ratings history for 7328 companies from January 1981 to December 1998. While the database contain obligors from several countries, the 88% on average of the obligors are from US. Bangia et al. (2002) focus on US obligors when dealing with the business cycle. The model proposed in this paper applies to banks dealing with obligors belonging to the same country or to countries obeying to the same business cycle (e.g. possibly European Union). If foreign obligors are considered, clearly different business cycles chronology and forecasting need to be considered.

conditional matrices, shown in Tables 1.a and 1.b, are estimated as averages over expansion and recession sub-periods according to the NBER classification<sup>8</sup>.

*Table 1a US Expansion quarterly transition matrix*

	AAA	AA	A	BBB	BB	B	CCC	D
AAA	0.9821	0.0166	0.0011	0.0002	0.0002	0.0000	0.0000	0.0000
AA	0.0015	<b>0.9808</b>	<b>0.0161</b>	0.0012	<b>0.0001</b>	0.0003	0.0001	0.0000
A	0.0002	<b>0.0053</b>	<b>0.9806</b>	<b>0.0121</b>	0.0011	0.0006	0.0000	0.0000
BBB	0.0001	0.0007	0.0147	0.9694	<b>0.0125</b>	0.0022	0.0002	<b>0.0002</b>
BB	0.0001	0.0003	0.0019	0.0193	0.9531	0.0225	<b>0.0016</b>	<b>0.0012</b>
B	0.0000	0.0002	0.0007	0.0010	<b>0.0170</b>	0.9591	<b>0.0131</b>	<b>0.0088</b>
CCC	0.0005	0.0000	0.0019	0.0023	0.0047	0.0357	0.8732	<b>0.0817</b>
D	0	0	0	0	0	0	0	1

Source: Bangia et al (2002)

*Table 1b US Recession quarterly transition matrix*

	AAA	AA	A	BBB	BB	B	CCC	D
AAA	0.9799	0.0176	0.0025	0.0000	0.0000	0.0000	0.0000	0.0000
AA	0.0018	<b>0.9689</b>	<b>0.0279</b>	0.0005	<b>0.0009</b>	0.0000	0.0000	0.0000
A	0.0002	<b>0.0088</b>	<b>0.9644</b>	<b>0.0259</b>	0.0007	0.0000	0.0000	0.0000
BBB	0.0004	0.0004	0.0111	0.9631	<b>0.0233</b>	0.0007	0.0000	<b>0.0011</b>
BB	0.0000	0.0006	0.0006	0.0139	0.9498	0.0272	<b>0.0042</b>	<b>0.0036</b>
B	0.0000	0.0006	0.0006	0.0011	<b>0.0072</b>	0.9502	<b>0.0272</b>	<b>0.0177</b>
CCC	0.0000	0.0000	0.0000	0.0000	0.0000	0.0120	0.8560	<b>0.1320</b>
D	0	0	0	0	0	0	0	1

Source: Bangia et al (2002)

Bangia et al. (2002) prove that the elements in the grey cells are significantly different at the 5% level from the unconditional matrix. Moreover the volatility of each element is strongly reduced in the two conditional matrices compared to the unconditional one.

This evidence is stronger for the recession matrix, indicating that transition probabilities

<sup>8</sup> The NBER classification is monthly. Bangia et al. (2002) label each quarter as expansion or recession according to the NBER definitions.

are more stable during recessions. The default probabilities display most clearly the existence of the two regimes: they increase strongly during recessions and their coefficients of variation decrease more than the other elements of the transition matrix (by at least 40%).

According to the NBCA, the reference credit horizon is one year: hence we have converted the quarterly matrices into annual ones. Assuming that the credit migration/default process is a time-homogeneous Markov chain, the annual matrix can be obtained by taking the fourth power of the quarterly matrix<sup>9</sup>.

### 3.2 Recession forecast

In order to have a recession forecast, equation (2) of the model has to be estimated. In the present application we do that within a probit model<sup>10</sup>, i.e.

$$P(S_{t+k} = R \mid I_t) = P_t(R_{t+k} = 1) = \Phi(\mathbf{b}'x_t) \quad (9)$$

where:

$x_t$  = explanatory variables, including the constant;

$\mathbf{b}$  = coefficients on the explanatory variables;

$\Phi$  = cumulative normal distribution function;

$R_{t+k}$  = recession indicator k-periods ahead defined as

$$R_t = \begin{cases} 1 & \text{if } t = \text{recession} \\ 0 & \text{otherwise} \end{cases}$$

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<sup>9</sup> The transition matrices estimated by rating agencies as historical averages rely on a time-homogeneous Markov chain assumption: such a property allows to collect data over different years to obtain estimators for the transition probabilities. Under the time-homogeneity hypothesis transition probabilities over multiple horizons can be derived as  $P(0,T) = (P(0,1))^T$  with  $P(0,1) = P(1,2) \dots = P(T-1,T)$ . While in estimating the unconditional matrix the migration process is assumed to be a time-homogeneous Markov chain over the entire sample, the hypothesis restricts to the two recession/expansion sub-sample when estimating the conditional matrices.

<sup>10</sup> In line with most of the literature on recession probability forecast, a probit model is chosen. Moreover, a logit model (as used e.g. in Artis et al. (2002)) has been estimated on the same data set and the results are very similar.

We set  $k$  equal to four quarters to obtain a four quarters ahead forecast. We take the realized value of  $R_t$  to be defined by the NBER quarterly classification. The NBER turning points on the period of interest (1951-2002) are listed in Table 2.

*Table 2 NBER classification*<sup>11</sup>

<b>Peaks</b>	<b>Troughs</b>
Jul-53	May-54
Aug-57	Apr-58
Apr-60	Feb-61
Dec-69	Nov-70
Nov-73	Mar-75
Jan-80	Jul-80
Jul-81	Nov-82
Jul-90	Mar-91
Mar-01	Nov-01

As for the explanatory variables, in the present paper we consider the term spread between the ten years treasury bond and the three months treasury bill rate and the Standard&Poor's equity price index.

Many economic and financial variables have been tested in the literature on business cycle forecasting. Financial variables are appealing for forecasting purposes since they contain predictive information and are immediately available, while macroeconomic variables are generally available with some delay. Specifically, there is a consensus on the usefulness of the interest rate term spreads and equity prices in predicting the

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<sup>11</sup> The conversion from the monthly chronology to the quarterly one is performed according to the following criterion:

- if the turning point occurs in the first month of the quarter → the quarter is classified according to the regime prevailing at the end of the quarter;
- if the turning point occurs in the third month of the quarter → the quarter is classified according to the regime prevailing at the beginning of the quarter;

business cycle<sup>12</sup>. The forecasting power of stock prices is related to their interpretation as expected present values of future dividend streams. Moreover, it could be argued that agents in financial markets have access to additional private information, which provides them with a forecasting power eventually embedded in equity prices. The spread is related to a forward interest rate and can be decomposed into a real and an inflation component. While the expected real rate embeds expectations on monetary policy, the expected inflation component is related to future real growth, since inflation tends to be positively related to real activity<sup>13</sup>.

The choice of these two financial variables is supported by empirical evidence. In particular, Estrella and Mishkin (1998), analyse the US business cycle from 1959 to 1995 by means of a probit model considering many macroeconomic and financial variables and find that the term spread is the best predictor at least from two quarters ahead onwards. Moreover the equity index price gives good results when combined with the term spread, particularly for horizons longer than two quarters<sup>14</sup>.

The series for the explanatory variables considered in this paper have been downloaded from *DataStream*. The estimation over the full sample (1951-2002) gives coefficients which reflect the expected theoretical relation: a negative relationship between the recession probability and the equity index, suggests a positive relation between the latter

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•if the turning point occurs in the second month (i.e. in the middle) of the quarter → the quarter is classified according to the regime prevailing at the beginning of the quarter.

<sup>12</sup> There is a wide econometric literature on business cycle forecasting based on financial variables, in particular on the interest rate term spread, as predictors. While most of it use linear regression-based techniques to forecast the output growth rate, some authors (e.g. Estrella and Hardouvelis (1991), Estrella and Mishkin (1997), (1998)) estimate instead the likelihood of future recessions by means of binary choice models.

<sup>13</sup> Rendu de Lint ad Stolín (2003) present a theoretical model to explain the predictive power of the term spread for output. Estrella et al. (2000) briefly present several possible explanations for the positive empirical relationship between the slope of the yield curve and real activity.

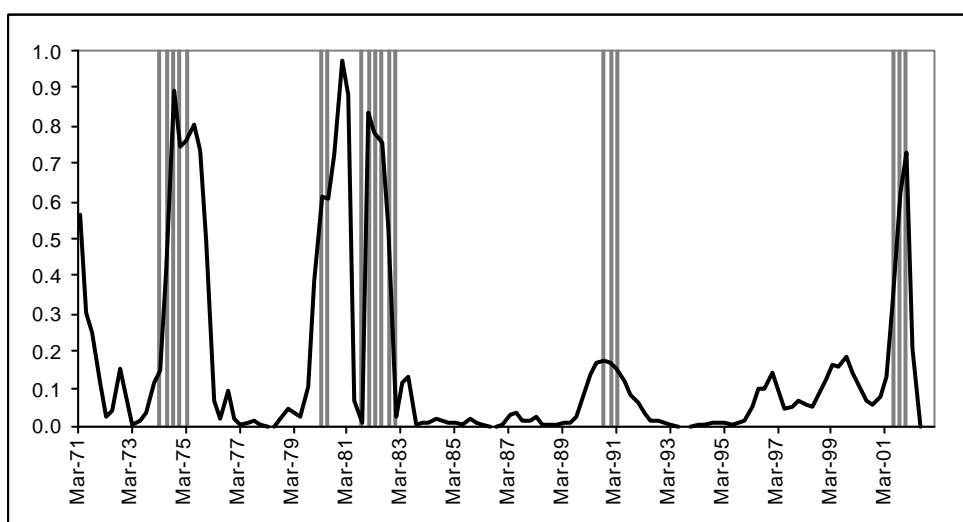
<sup>14</sup> In the in-sample analysis Estrella and Mishkin (1998) find that there are several variables with good explanatory power, that are the ten years bond – three months bill spread, the stock index (NYSE or S&P500), the real monetary base and the Stock-Watson leading index. While the spread outperforms all the other variables at least from the third quarter ahead, both the two real variables perform better than the stock index over most of the horizons. However, if the two economic variables are combined with the

and real activity. Analogously, the negative relationship between the recession probability and the term spread, suggests a positive correlation between the latter and real activity. However, an analysis based on the McFadden  $R^2$  and on the Schwartz Information Criterion suggests to drop the S&P from the regression<sup>15</sup>. Hence we used the spread as the unique predictor.

The period 1951-1970 is considered as the initial estimation period, while 1971-2002 is the forecasting period. Over the forecasting sample the parameters are estimated by updating the sample year by year<sup>16</sup>.

Figure 4 shows the out-of-sample quarterly forecast recession probability as a series from 1971 to 2002.

*Fig. 4 Quarterly Recession Probability Forecast*



*The black line is the recession probability predicted four quarters ahead. The grey bars represent the actual recessions.*

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spread, they lose their significance beyond the first quarter. On the other hand, the equity index remains significant on several horizons. This result is confirmed in the out-of-sample analysis.

<sup>15</sup> The results of the estimation are available upon request.

<sup>16</sup> Ideally the estimation window should be updated every quarter, while in this work it is updated only yearly. The reason is that, since the credit horizon requires a one-year horizon, the parameters are updated following the credit horizon. A 19 years rolling estimation window is used in this work. Estrella and Mishkin (1998) use instead an incremental window. Chauvet and Potter (2002) individuate a structural break in the first half of the eighties. The use of a rolling window makes the problem of structural breaks less stringent: for example, Chauvet and Potter (2002) stress how the recession probability over the 2001 recession changes when accounting or not for the structural break: in our case, the length of the moving window is such that the parameters estimated for the 2001 recession forecast are almost entirely based on data after the structural break.

The recession probability profile is very similar to the one obtained in Estrella and Mishkin (1998) for the common period of estimation, i.e. 1971-1995. Figure 4 shows that the recession probability forecast is high over recession periods, as it is desirable<sup>17</sup>. However, it has to be noted that the 1990/91 recession forecast is very weak: Estrella and Mishkin (1998), who find a similar result, justify it by saying that this recession was widely unpredictable since it was strictly related to the invasion of Kuwait. Over the period not covered in Estrella and Mishkin (1998), the recession probability correctly increases with the 2001 recession. There are some irregular increases in the recession probability around 1996-97 and 1999: they may be linked to specific episodes, namely the Asiatic crisis and Russian debt crisis.

### 3.3 Time-varying PDs and capital requirements

Based on the estimation results of the previous sections, the time-varying PDs are calculated for each rating class as in equation (8). A simplified portfolio with a constant exposure on each rating class from BBB to CCC is considered<sup>18</sup>: the exposures are defined approximately according to the average ratings distribution of the S&P database<sup>19</sup>.

The capital requirements are calculated by applying the NBCA formula for the IRB approach (BCBS (2003), par. 239-241). The time-varying capital requirement is calculated by using the model PDs as input<sup>20</sup>; this can be compared to the constant

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<sup>17</sup> Beyond the visual evidence, a formal measure of the goodness of fit can be computed by comparing the predictions from the estimated model with the predictions obtained by using the constant as the unique regressor (coefficients of the explanatory variables constrained to zero). The goodness-of-fit measure, henceforth *gof*, on the prediction sample is  $gof = 0.263$ , which is largely positive, even if far from one, meaning that the forecasting model is preferable to the simple sample proportion criterion.

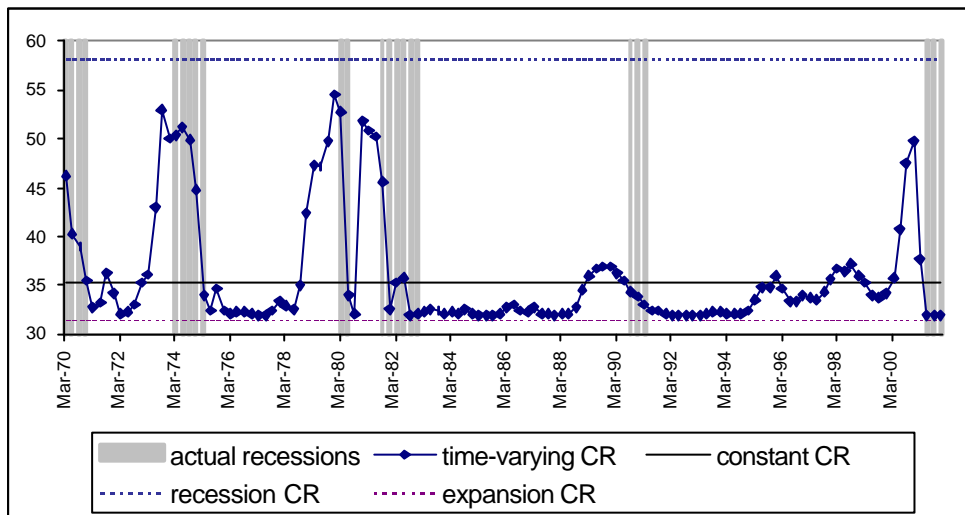
<sup>18</sup> Since the PDs for ratings above A are generally very close to zero and since the NBCA imposes a minimum PD of 0.0003 for every rating, here only rating classes from BBB downward are considered.

<sup>19</sup> From the database used in Bangia et al. (2002), the relative percentage of the ratings BBB, BB, B, CCC is approximately derived: the resulting portfolio has exposures of 156, 118, 118 and 8 respectively on the four ratings over a total exposure of 400. Actually the composition of the portfolio is not very relevant in this context: however, this rough approximation aims at representing a realistic portfolio.

<sup>20</sup> The LGD is fixed at 50% and the maturity M at 2.5. As in the current NBCA the PDs tend to be constant over time, the correlation formula just discriminates among different rating classes. In order to fulfil this purpose and not to mix the results of the time-varying PDs with a time-varying correlation, the

capital requirement obtained with the constant (long-run averages) PDs as input. Figure 5 compares the time-varying (quarterly revised) capital requirement and the constant standard one and displays the capital requirements conditional on expansion and recession (i.e. calculated with expansion and recession PDs), which define a lower and upper bound respectively.

*Figure 5 Capital Requirements (CR)*



Clearly the time-varying capital requirement increases when the probability of a recession over the next year increases. In particular, since the constant PDs are estimated as averages over the period 1981-1998, the time-varying capital requirement is higher than the constant one when the forecast recession probability is higher than the sample proportion of recession (12.5%). In general the time-varying capital requirement behaves well in anticipating the business cycle. However, Figure 5 shows that in the case of the 1990-91 recession, the capital requirement changes only slightly, as the recession was just slightly signalled by the probability forecast (Figure 4), due to the specific features of this recession. Even if the regime prediction model did not produce a strong forecast, the time-varying estimates of the PDs produce anyway a higher capital

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correlations are calculated in the same way as the standard NBCA formula, i.e. as a function of constant PDs. (See the Appendix for details on the capital requirement formula).



requirement than the one obtained from the standard constant PDs in the period before the recession.

These results contribute to the debate on procyclicality. Clearly the capital requirement calculated by means of the model proposed changes with the business cycle, leaving space to procyclical effects. However, since the increases/decreases in capital requirement generally anticipate the business cycle, peaks and troughs can be smoothed.

## **Conclusions**

The NBCA, in innovating on the current regulation, aims at making the capital requirement more risk-sensitive, i.e. more representative of the actual risk faced by banks. As for credit risk, given the link between the latter and the business cycle, it may well be that risk-sensitive capital requirements produce procyclical effects, which in turn are likely to exacerbate recessions. In order to avoid these by-effects, the NBCA requires banks adopting the IRB approach to follow a ‘through the cycle’ logic in assigning and quantifying ratings so as to neutralise the business cycle effects. Since the business cycle affects the systematic component of risk, by neutralizing it an important risk factor is neglected.

In sum, two important objectives inherent in the NBCA, the risk-sensitivity of capital requirements on one side and the reduction of procyclicality on the other, appear somehow contrasting.

The aim of this paper is to propose a model, which, by considering the business cycle effects in a forward-looking perspective, partly reconciles the two above mentioned objectives. The model proposed defines forward-looking capital requirements by modelling the PDs as time-varying according to a business cycle forecast. The default rate is defined as a stochastic variable, whose probability distribution is a mixture of an

expansion and a recession distribution. In line with a vast literature on business cycle forecasting, the expansion and recession probabilities are estimated using financial variables as predictors.

The model is applied to quarterly US data over the forecasting period 1971-2002, whereby the NBER chronology is adopted to date the business cycle phases. The expansion and recession PDs, based on a Standard&Poor's database, are combined with business cycle states probabilities estimated within a probit model with the interest rate term spread as the only predictor. The capital requirement is then calculated according to the NBCA formula. Since the objective of the model is that of producing a capital requirement which varies in anticipation of the business cycle, its performance is clearly related to the predictive ability of the business cycle forecasting model adopted. Despite the nineties recession is only slightly signalled by the recession probability forecast, the results over the whole period are encouraging since the capital requirement generally increases/decreases in anticipation of the recessions/expansions, with a possible smoothing effect on the business cycle turning points.

The validity of the model proposed can be further evaluated both from a micro- and a macro-economic point of view. At a micro level, the effects of the capital requirement on an individual bank performance can be assessed. Specifically, the effects of the time-varying capital requirement vs. the constant one can be gauged with respect to the bank portfolio composition. This analysis could allow to evaluate the ability of the model to limit default losses. At a macro level, the issue is to evaluate the effects of the proposed forward-looking capital requirements on the economy as a whole. The macroeconomic consequences are quite difficult to assess, since they depend on the relationship between output and lending. These two issues, which require a separate study, are left for future research.

### ***Appendix: Capital requirement in the Basel Accords***

The capital requirement in both the BCA and the NBCA is defined by a minimum level for the capital ratio:

$$\frac{RC}{\sum_i A_i W_i} \geq 8\% \quad (\text{A.1})$$

$RC$  = regulatory capital;

$A_i$  = risky activities;

$W_i$  = risk weights.

The denominator in (A.1) is the sum of the risk-weighted assets, which is made more risk-sensitive in the NBCA, in particular within the IRB approach. With reference to corporate exposures, the computation of the risk weight for each activity is defined as follows:

$$W = 12.5 \times LGD \times N \left( \frac{1}{\sqrt{1-r}} \times N^{-1}(PD) + \sqrt{\frac{r}{1-r}} \times N^{-1}(0.999) \right) \times \frac{1 + (M - 2.5) \times b(PD)}{1 - 1.5 \times b(PD)} \quad (\text{A.2})$$

where:

$LGD$  = Loss Given Default;

$PD$  = Probability of Default;

$M$  = Maturity;

$b(PD) = (0.08451 - 0.05898 \times \ln(PD))^2$  Maturity Adjustment ;

$$r = 0.12 \times \left( \frac{1 - \exp(-50 PD)}{1 - \exp(-50)} \right) + 0.24 \times \left( 1 - \frac{1 - \exp(-50 PD)}{1 - \exp(-50)} \right) \text{ Asset Correlation .}$$

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