MITIGATING THE PROCYCLICALITY OF BASEL II

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Abstract

This paper compares alternative procedures to mitigate the procyclicality of the new risk-sensitive bank capital regulation (Basel II). We estimate a model of the probabilities of default (PDs) of Spanish firms during the period 1987-2008, and use the estimated PDs to compute the corresponding series of Basel II capital requirements per unit of loans. These requirements move significantly along the business cycle, ranging from 7.6% (in 2006) to 11.9% (in 1993). The comparison of the different procedures is based on the criterion of minimizing the root mean square deviations of each smoothed series with respect to the Hodrick-Prescott trend of the original series. The results show that the best procedures are either to smooth the inputs of the Basel II formula by using through-the-cycle PDs or to smooth the output with a multiplier based on GDP growth. Our discussion concludes that the latter is better in terms of simplicity, transparency, and consistency with banks' risk pricing and risk management systems. For the portfolio of Spanish commercial and industrial loans and a 45% loss given default (LGD), the multiplier would amount to a 6.5% surcharge for each standard deviation in GDP growth. The surcharge would be significantly higher with cyclically-varying LGDs.

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1. Introduction

The 1988 Basel Accord consolidated capital requirements as the cornerstone of bank regulation. It required banks to hold a minimum overall capital equal to 8% of their risk-weighted assets. As all consumer and business loans were included in the full weight category, 8% became the universal capital charge for household and corporate lending, while for mortgages the capital requirement was 4%. Following widespread criticism about the risk-insensitiveness of these requirements,[1] the Basel Committee on Banking Supervision (BCBS) approved in 2004 a reform, known as Basel II, whose primary goal is "to arrive at significantly more risk-sensitive capital requirements" (BCBS, 2006, par. 5). Basel II introduces a menu of approaches for determining capital requirements. The standardized approach contemplates the use of external ratings to refine the risk weights of the 1988 Accord (henceforth, Basel I), but leaves the capital charges for loans to unrated companies essentially unchanged. The internal ratings-based (IRB) approach allows banks to compute the capital charges for each exposure from their own estimate of the probability of default (PD) and possibly the loss given default (LGD) and the exposure at default (EAD).

As a result of this risk-sensitiveness, a widespread concern about Basel II is that it might amplify business cycle fluctuations, forcing banks to restrict their lending when the economy goes into recession. Even in the old Basel I regime of essentially flat capital requirements, bank capital regulation had the potential to be procyclical because bank profits may turn negative during recessions, impairing banks' lending capacity.[2] In fact, there is a debate in the literature on whether the implementation of Basel I capital requirements in the US might have brought about a credit crunch in the early 1990s. This credit crunch would be the result of a capital crunch as banks facing binding capital constrains and not able to raise new capital would have had no option but to sell assets or reduce the amount of credit granted, in particular, loans to households and firms.[3] Under the IRB approach of Basel II, capital requirements are an increasing function of the PD, LGD and EAD parameters estimated for each borrower, and these

[1] See, for instance, Jackson (1999).
[2] See Borio, Furfine, and Lowe (2001).

inputs are likely to rise in downturns. So concerns about Basel II are stronger than those regarding Basel I because the worsening of borrowers' creditworthiness in recessions will significantly increase the requirement of capital for banks and might lead to a severe contraction in the supply of credit.

Two conditions are necessary for this contractionary effect to occur. First, some banks must find it difficult to respond to the higher capital requirements by issuing new equity. Second, some of their borrowers must be unable to switch to other sources of finance. These conditions are very likely to hold, but they are not sufficient for the existence of significant procyclical effects, since banks may hold sizable capital buffers (capital in excess of regulatory requirements) that can be used to support lending in recessions. So the critical question is whether these buffers (that will endogenously respond to regulatory changes) will be sufficient to neutralize the procyclicality added by the new requirements. Repullo and Suarez (2008) show that banks have an incentive to hold capital buffers, but that the buffers maintained in expansions are typically insufficient to prevent a significant contraction in the supply of credit at the arrival of a recession. They also show that Basel II leads to a substantial increase in the procyclicality induced by bank capital regulation, and that some simple cyclical adjustments in the 99.9% confidence level (used to derive the Basel II capital requirements) may significantly reduce its procyclical effects. However, their analysis is based on a simple two-state Markov process of the business cycle, in which the state of the economy is publicly observable, so they do not consider how the idea of countercyclical regulation could be implemented in practice. Furthermore, other proposals to reduce the procyclical effects of bank capital regulation have been put forward, so a systematic analysis of these alternatives is warranted.

The purpose of this paper is to present, analyze, and discuss the leading alternative procedures that have been proposed to mitigate the procyclicality of the Basel II capital requirements. As a first step, we show that capital requirements under Basel II move significantly along the business cycle.

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[3] For evidence that regulatory actions contributed to the credit crunch see Bernanke and Lown (1991), Berger and Udell (1994), Hancock and Wilcox (1994), Hancock, Laing and Wilcox (1995), and Peek and Rosengren (1995a,b). Gambacorta and Mistrulli (2004) show that bank capital affects lending.

The analysis is based on the results of the estimation of a logistic model of the one-year-ahead probabilities of default (PDs) of Spanish firms during the period 1987-2008. The database includes all commercial and industrial loans granted in Spain during this period, and comes from the Credit Register of the Bank of Spain. The dependent variable is a binary variable that takes value one when a firm defaults in the course of a year on its outstanding loans at the end of the previous year, and zero otherwise. The explanatory variables comprise characteristics of the firm (industry, location, age, credit line utilization, and previous delinquencies and loan defaults), characteristics of its loans (size, collateral, and maturity), characteristics of the banks from which the firm borrows (distribution of exposures among lenders and changes in the main provider of finance), and macroeconomic controls (the rate of growth of the GDP, the rate of growth of bank credit, and the return of the stock market). The empirical model provides an estimate of the point-in-time (PIT) PDs of the loans in the portfolio of commercial and industrial loans of the Spanish banks over the sample period, so we can compute the corresponding Basel II capital requirements per unit of exposure (assuming an exogenous LGD). We find that Basel II capital requirements for the entire portfolio of corporate increase more than 50% from peak to trough, which is a very significant change compared with the flat requirements of Basel I.

After estimating the credit risk profile of the Spanish banks over the sample period using the metric of Basel II, we consider the effect of different procedures to mitigate the cyclicality of these requirements over the business cycle. According to Gordy and Howells (2006) there are two basic alternatives: One can smooth the inputs of the Basel II formula, by using some sort of through-the-cycle (TTC) adjustment of the PDs, or smooth the output by using some adjustment of the Basel II capital requirements computed from the PIT PDs. We analyze both approaches. Following the work of Saurina and Trucharte (2007) on mortgage portfolios, we first construct TTC estimates of the PDs by setting the value of the macroeconomic controls at their average level over the sample period, and then compute the corresponding Basel II capital requirements. Second, we analyze different adjustments to the PIT capital requirements based on aggregate information (the rate of growth of the GDP, the rate of growth of bank credit, and the return of the stock market) and individual bank information (the rate of growth of banks' portfolios of commercial and industrial loans). The comparison of the different procedures is based on the criterion of minimizing the root mean square deviations of each smoothed series with respect to the trend of the original series. This trend is computed by applying the Hodrick-Prescott (HP) filter, which is the procedure customarily used by macroeconomists to separate cycle from trend. Thus, our approach aims at smoothing just the cyclical component of the Basel II capital requirements.

The results show that the best procedures in terms of approaching the HP trend are to either smooth the inputs of the Basel II formula using TTC PDs or to smooth the output with simple multiplier of the PIT capital requirements that depends on the deviation of the rate of growth of the GDP with respect to its long-run average. Our discussion of the pros and cons of these two procedures concludes that the latter is better in terms of simplicity, transparency, low cost of implementation, and consistency with banks' risk pricing and risk management systems.

The paper aims to contribute to the growing policy debate, initiated by Kashyap and Stein (2004) and taken up in the recent G20 Summits, on how risk-sensitive bank capital regulation should be adjusted to mitigate its inherent procyclicality.

The structure of the paper is the following. In Section 2 we present the empirical model of probabilities of default (PDs) using data from the Credit Register of Bank of Spain on firms' loans for the period 1987-2008. In Section 3 we compute the corresponding Basel II capital requirements and its trend using the Hodrick-Prescott (HP) filter, and then compare different smoothing procedures using root mean square deviations from the HP trend. Section 4 extends the analysis to adjustments using individual bank credit data and to the case where the loss given default moves along the business cycle, and also considers the cyclical adjustment of expected losses. Section 5 contains our discussion of the results, and Section 6 concludes.

2. Empirical model of probabilities of default

2.1. The empirical model

To compute how Basel II capital requirements would evolve over the business cycle we estimate a model of default for the firms that borrowed from Spanish banks over the period 1987-2008. The model provides estimates of the probabilities of default (PDs) for each firm in each year which are used to compute the corresponding Basel II capital charges.

The procedure is obviously subject to the Lucas' critique. Had Basel II been in place, banks' decisions over lending, and consequently the pool of borrowers, might have been different. However, the dominant role of universal banks in the Spanish financial system, the limited role of securitization, as well as the tight model of supervision implemented by the Bank of Spain, suggests that this composition effect may not be very significant.

Based on direct information on firms' economic and financial conditions, banks discriminate among them and grant loans with significantly different characteristics. Some of these differential features are, directly or indirectly, contained in the information included in the Credit Register of the Bank of Spain and constitute the basis for our empirical analysis.

The Credit Register also provides information on the default status of each loan. Based on this information we construct the dependent variable for the regression model, y_{it+1}, which is a dichotomous (zero-one) variable which takes value 1 if the borrower i defaults in year $t + 1$, and 0 otherwise.[4] It should be noted that the default event is conditional, requiring that a firm defaulting in a certain year shall not have defaulted during the previous year.

The next step is to specify the explanatory variables (all dated in year t) that try to approximate the risk profile of each borrower. The statistical model selected to establish the relationship between the default variable and the explanatory variables is:

$$\Pr(y_{it+1} = 1) = F(\beta_1 BORROWER\_TYPE_{it} + \beta_2 RISK\_PROFILE_{it} + \beta_3 MACRO\_VAR_t) \quad (1)$$

where $F(\cdot)$ is the cumulative standard logistic function.

[4] A borrower is considered to have defaulted if it is 90 days overdue, failing to meet its financial obligations on a certain loan or if, with a high probability, it is considered to be unable to meet its obligations. If a borrower has several loans, failure to meet payments on any of them means that the borrower is in default. This definition is similar to that established in Basel II; see BCBS (2006, par. 452).

The *BORROWER_TYPE*$_{it}$ vector includes several variables. *COLLATERAL*$_{it}$ represents the average (weighted by the size of the exposures) of the proportion of guarantees in a firm's borrowing.[5] The empirical evidence (Berger and Udell, 1990, Jiménez, Salas and Saurina, 2006) shows that banks ask for collateral to those firms perceived as riskier.

MATURITY$_{it}$ represents the proportion of long-term exposures (more than one year) over total exposures. The longer the maturity of a loan, the more thorough will be the screening process of the quality of the borrower. Riskier borrowers will probably be granted only short-term loans.

AGE$_{it}$ tries to approximate the age of each firm, with the idea of capturing that firms of recent creation (especially small-sized ones) are more prone to disappear than older ones. Thus, higher rates of default are expected during the first years of activity. As the relationship is not likely to be linear, we have constructed a set of dummy variables each accounting for the number of years (one, two, three, and four or more) a borrower has been reporting to the Credit Register.

We include in equation (1) the variable *NUMBER_BANKS*$_{it}$, representing the number of banks that have granted a loan to firm *i* in year *t*. We hypothesize that the more banks a firm is related to, the more constrained it may be in terms of liquidity and thus the higher its probability of default. We expect a non-linear relationship between this variable and the default event, so it enters the equation in logarithmic terms. We have also included a variable that accounts for the number of times a firm changes its main lender, *MAIN_LENDER_CHANGE*$_{it}$. It indicates the frequency with which a firm changes the bank that provides the largest amount of funding. High values of this variable imply high rates of rotation and hence possible constraints or even difficulties in securing finance, which suggest low creditworthiness.

[5] Note that the analysis is at borrower level across all banks with which it has lending relationships. Therefore, *BORROWER_TYPE* variables are weighted across all the exposures each borrower has with all its lenders. It could be argued that some of these variables (such as collateral) may be endogenous, but this is not a problem since we are interested in predicting default, not in estimating causal effects.

$FIRM\_SIZE_{it}$ stands for the total amount of bank borrowing, and proxies for the size of each firm. The variable has been deflated by the consumer price index, and enters equation (1) in logarithmic terms.

$UTILIZATION_{it}$ is the ratio between the amount of credit drawn by a borrower and the total available amount (credit line). For various reasons, firms extensively use credit line facilities where they can withdraw funds at any time. Collateral required, if any, remains pledged to the credit line. The rationale for this variable is that the more a borrower withdraws, the more liquidity constrained it may be. The empirical evidence in Jiménez, López and Saurina (2009a) shows that firms that eventually default draw down more intensely their credit lines. In fact, utilization ratios are significantly different for defaulted and non-defaulted firms well in advance of the date of default (even 4 or 5 years before).

Finally, two sets of dummies have been included among the $BORROWER\_TYPE_{it}$ variables. The first one stands for the industry in which the firm is classified according to its economic activity (NACE code). The other set refers to the Spanish province in which the firm is registered.

Among the explanatory variables included in equation (1), $RISK\_PROFILE_{it}$ is a vector that accounts for the main risk profile characteristics for which information is available for each borrower. In particular, $HISTORIC\_DELINQUENCY_{it}$ represents the borrowers' record of overdue loans that have been paid before the 90-day threshold (that is, before having defaulted) measured as the number of years in which the firm has been delinquent divided by the number of years it has been reporting to the Credit Register. The problems behind overdue loans are sometimes "technical," spanning only a few days as a result of mismatches in cash flows, but in other cases they are good predictors of future defaults. In the same way, $HISTORIC\_DEFAULT_{it}$ is another risk profile variable that captures whether a certain borrower defaulted in years $t - 1$, $t - 2$, etc.[6] As in the case of the delinquency variable, this variable is defined as the number of

[6] The dates have to be $t - 1$ or before to be consistent with the definition of default: failing to meet its financial obligations in year $t + 1$ given that it was not in default in year t.

years in which the firm has been in default divided by the number of years it has been reporting to the Credit Register.[7]

The macroeconomic controls included in equation (1) are the rate of growth of the gross domestic product, GDP_t, the rate of growth of the commercial and industrial loans in the Credit Register, $CREDIT\_GROWTH_t$, and the return of the Spanish stock market index, $STOCK\_MARKET\_Var_t$. These variables proxy macroeconomic activity factors that affect credit risk, an essential ingredient for our analysis of the cyclical implications of Basel II.

2.2. The data

The database used in the estimation of the model of PDs is the Credit Register of the Bank of Spain (CIR). This Register records monthly information on all credit operations granted by all credit institutions operating in Spain for a value of over €6,000. The data distinguishes between loans to firms and to households. CIR includes information on the characteristics of each loan, including the following: instrument (trade credit, financial credit, leasing, etc.), currency denomination, maturity, existence of guarantees or collateral, type of guarantor, coverage of the guarantee, amount drawn and undrawn of a credit commitment, and whether the loan is current in payment or past due, distinguishing in turn between delinquency and default status. CIR also includes information on the characteristics of borrowers: province of residence and, for firms, the industry in which they carry out their main economic activity.

Our analysis focuses on loans to firms. The sample period goes from 1984 to 2008, although to use explanatory variables such as age or historic delinquency and default for estimation purposes it spans from 1987 to 2008. It should be noted that this time span includes the recession of the early nineties and the subsequent upturn during the late

[7] Jiménez, Lopez and Saurina (2009a) show that these two variables are good proxies for firms' financial condition. When they replace them by balance sheet and profit and loss data there is no significant change in the fit of the empirical model. The Credit Register is a comprehensive database covering all banked firms in Spain. Incorporating balance sheet and profit and loss accounting data, would imply restricting our analysis to a much smaller sample of firms, and a sample probably biased towards firms with higher quality. Given that the purpose of the analysis is to estimate the credit risk profile of the Spanish banks over the sample period, we prefer to use the full population than to have a much smaller set of firms with not much better information.

nineties and the first years of the current decade. The database contains a vast amount of information (over 10 million observations). To facilitate the analysis we have randomly selected a 10% sample,[8] which leaves us with nearly 1 million observations. Table 1 shows some descriptive statistics of the whole population as well as those of the sample chosen. The main statistics of the sample (and in particular those referred to the default condition of borrowers) perfectly match those of the entire population.[9]

Table 1 also reveals that credit exposure increases significantly over time and that the proportion of defaults follows a cyclical pattern reaching a maximum in 1993 (recession year). Table 2 reports the mean, standard deviation, and maximum and minimum values of the regression variables for the period 1987-2008.

2.3. Results

Table 3 shows the estimated coefficients of the variables in equation (1) and their standard errors. All the variables are significant at the 99% confidence level. An indication of the goodness of fit of the model can be found in the expected signs with which all variables enter the equation and in the predictive power of the model.

The results show that firms that post collateral when granted a loan have higher probabilities of default. Lenders try to mitigate risks by requiring collateral to those firms that they consider riskier. Longer maturities are associated with lower default rates, and this is also the case for the age of the borrower. Firms that are two or three years old have, on average, lower credit quality, and as firms grow older their default rate starts to decrease.[10] The more lenders a firm has, the higher its probability of default, and this is also the case with the higher rotation of its main lender. Larger firms are safer than smaller ones, and the higher the utilization of credit lines the higher the probability of default, so liquidity constraints also seem to play a role in firms' defaults. With respect to the risk-profile variables, past overdue and past default events are a

[8] Each borrower in the Credit Register is randomly assigned a code whose second to last digit is a number (0 to 9). We have chosen all firms whose digit coincides with one particular number.

[9] Although not shown in Table 1, other statistics such as number of borrowers, number of defaults, average size loan, average size of defaulted firms, and several other size characteristics have also been compared, obtaining similar results to those in Table 1.

signal of future loan defaults. Finally, the macroeconomic controls show that firms' defaults increase during downturns, proxied by low GDP growth, credit growth, and stock market returns.

Tests of stability have been carried out by estimating the model without some of the variables, which does not change the signs and statistical significance of the remaining variables, and by omitting some years of the sample period, which leads to very small changes in the estimated coefficients.

Table 4 presents the performance of the estimated model in terms of classification power.[11] The model classifies correctly approximately 70% of the defaulted and non-defaulted firms in the sample. Alternative performance measures confirm the predictive precision of the model. In particular, the area under the ROC curve is over 76% which results in an Accuracy Ratio (AR) of 52%.[12]

Finally, we tested the predictive power of the model by using a second 10% sample of the population.[13] The parameters estimated with the original sample were used to predict defaults in the validation sample. The results show that 68% of defaulted and 71% of non-defaulted firms were correctly classified, with 76% being the value of the area under the ROC curve, and 52% that of the Accuracy Ratio.

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[10] Note that since the one-year dummy has been left out of the regression, it takes some time before firms start defaulting.

[11] Based on the PDs obtained from the model, firms are sorted in ascending order and a rough first classification is obtained. Taking as a cut-off value (threshold) the average default rate of the sample, a firm is assigned into the default category if its PD exceeds this threshold value and to the non-default category otherwise.

[12] The AR measure is obtained from the Cumulative Accuracy Profile curve, CAP, and determines the performance enhancement over the random model. Other common statistical measures for determining the discriminatory power of models are the area under the ROC (Receiver Operating Characteristic) curve. For references of performance power statistics see, among others, Sobehart, Keenan and Stein (2000), Sobehart and Keenan (2001), and Engelmann, Hayden and Tasche (2003). Our results are in line with those in the related literature; for example, Chava and Jarrow (2004) obtain an AR of 53%.

[13] We simply used a different number of the second to last digit of the code assigned to each firm.

3. Cyclical adjustment of Basel II capital requirements

3.1. Point-in-time (PIT) capital requirements

Building on the results in Section 2, we compute the point-in-time (PIT) capital requirements for each firm and each year using the Basel II formula for corporate exposures (BCBS, 2006, par. 272), the estimated PD, and assuming a loss given default (LGD) of 45% (as in the foundation IRB approach of Basel II), and a 1 year maturity.[14] We then compute the PIT capital requirements per unit of exposure for each year of the sample.

Figure 1 shows how PIT capital requirements would have evolved in Spain during the sample period had Basel II been in place, together with the Spanish GDP growth rate. Both series are highly negatively correlated, which suggests that GDP growth rates may be useful to mitigate the procyclicality of Basel II.[15]

There is a very significant cyclical variation of the Basel II capital requirements when they are calculated with PIT PDs. In 1993, at the worst point in the business cycle, they would have been 11.9%, falling to around 8% at the peak of the cycle (8.07% in 2005, 7.63% in 2006, and 8.06% in 1986, three years of strong economic expansion). The variability of 57% in Basel II capital requirements from peak to trough contrasts with the flat 8% requirements of Basel I.[16]

3.2. The Hodrick-Prescott benchmark

To identify a trend in the PIT capital requirements series we apply a Hodrick-Prescott (HP) filter with a smoothing parameter $\lambda = 100$ (annual data). Figure 2 shows the HP

[14] Section 4.2 analyses the case where LGDs vary over the business cycle.

[15] With the capital requirements series it is possible to carry out additional robustness tests of the model in Section 2. In particular, we ran a cross-section regression for each year of the sample (thus excluding the macroeconomic controls) and computed the PDs and the corresponding Basel II capital requirements per unit of exposure. The cyclical profile of these capital requirements compared to those obtained from the panel model is very similar, with a correlation coefficient between both series of 0.94.

[16] It can be argued that this result is only for a specific portfolio (of loans to firms). However, Saurina and Trucharte (2007), using a very similar approach, show that PIT capital requirements also fluctuate significantly for mortgage portfolios in Spain. Loans to firms and mortgages represent close to 90% of total loan portfolios of Spanish banks.

trend in dashed lines. As expected, the trend filters out the cyclical movements in the capital requirement series, being below the series in bad times and above the series in good times. The purpose of computing this trend is to provide a benchmark for the comparison of different alternatives proposed in the literature to mitigate the cyclicality of the Basel II requirements. Note that the HP filter produces capital requirements which are risk-sensitive along time (i.e. they increase in downturns and decline in upturns).

3.3. Adjusting the inputs of the Basel II formula: TTC capital requirements

The first procedure that we analyze is to smooth the PD input of the Basel II formula by using through-the-cycle (TTC) PDs. To estimate these PDs we follow the idea in Saurina and Trucharte (2007) of replacing the current values of the macroeconomic controls (the rate of growth of the GDP, the rate of growth of bank credit, and the return of the stock market) by their average values over the sample period. We then compute the capital requirements for each firm and each year using the Basel II formula for corporate exposures, the estimated TTC PDs, an LGD of 45%, and a maturity of 1 year. Figure 3 shows the TTC capital requirements per unit of exposure for each year of the sample.

In comparison with the PIT capital requirements, the cyclical variability of the TTC capital requirements series declines significantly. The maximum is reached in 1991, two years before the recession, at the level of 10.8%, while the minimum is 8.8% in 2005. The change in capital requirements from peak to trough reduces to 25%, which is less than half of the 57% figure obtained for the PIT series. Alternatively, the standard deviation of the TTC series is 0.62, while for the PIT series was 1.27.

Figure 3 also shows that TTC PDs would have produced capital levels above those coming from PIT PDs during the boom period 2003-2007, with a very significant increase in 2005 and 2006.

3.4. Adjusting the output of the Basel II formula

The second procedure to smooth the Basel II capital requirements that we analyze is to apply to the PIT series a business cycle multiplier of the form:

$$\hat{k}_t = \mu_t k_t \tag{2}$$

where k_t is the original PIT capital requirements series and $\hat{k}_t$ is the smoothed series. A convenient functional form for the multiplier μ_t is:

$$\mu_t = \mu(g_t, \alpha) = 2\Phi\left(\frac{\alpha(g_t - \overline{g})}{\sigma_g}\right) \tag{3}$$

where g_t is the growth rate of some indicator variable of the business cycle, $\overline{g}$ its long-run average, σ_g its long-run standard deviation, $\Phi(\cdot)$ is the standard normal cumulative distribution function, and α is a positive parameter. The multiplier is increasing in g_t and it is equal to 1 when $g_t = \overline{g}$.

Two issues related to the proposed adjustment have to be addressed. First, what is the variable that should be chosen as indicator of the business cycle? Second, how does one choose parameter α? With respect to the first issue, we consider the three macroeconomic controls used in the empirical model in Section 2, namely the rate of growth of the GDP, the rate of growth of bank credit, and the return of the stock market. With respect to the second, we propose as criterion for the choice of α (for each proxy for the business cycle) to minimize the root mean square deviations (RMSD) of the adjusted series with respect to the HP trend. In other words, we choose the value of α that is best in terms of smoothing the cyclical component of the PIT capital requirements series.

The results obtained are as follows. When the variable selected as indicator of the business cycle is the rate of growth of the GDP we get α(GDP) = 0.081; when the variable is the rate of growth of bank credit we get α(credit) = 0.075; and when the variable is the return of the stock market we get α(stock market) = 0.038.

Figures 4, 5 and 6 show the adjustment of the PIT capital requirements series for the three indicators of the business cycle and the optimally chosen values of parameter α, together with the HP trend. It can be readily seen that the stock market indicator does very poorly in terms of approaching the HP benchmark, while the other two are much better.

An alternative procedure to smooth the output of the Basel II formula is to follow the proposal of Gordy and Howells (2006) to use an autoregressive filter of the form:

$$\hat{k}_t = \hat{k}_{t-1} + \phi(k_t - \hat{k}_{t-1}) \tag{4}$$

where k_t is the original PIT capital requirements series, $\hat{k}_t$ is the smoothed series, and ϕ is a positive parameter. As in the case of parameter α, we propose as criterion for the choice of parameter ϕ to minimize the RMSD of the adjusted series with respect to the HP trend, which gives $\phi = 0.306$.

Figure 7 shows the autoregressive adjustment of the PIT capital requirements for the optimally chosen value of parameter ϕ, together with the HP trend. As expected, this adjustment follows the original series with a lag. The results in Repullo and Suarez (2008) suggest that this is a significant shortcoming, especially in downturns, when capital requirements should be brought down in order to reduce the likelihood of a credit crunch. Another disadvantage of the autoregressive adjustment, noted by Gordy and Howells (2006, p. 415), is that "it assumes that the bank's lending strategy is stationary. A weak bank would have the incentive to rump up portfolio risk rapidly, because required capital would catch up only slowly."

3.5. Comparing the different smoothing procedures

In line with the proposed HP benchmark, we compare the different smoothing procedures by computing the root mean square deviations (RMSD) of the adjusted series with respect to the HP trend. Table 5 shows the results. Two procedures are clearly dominated according to this criterion, namely smoothing the output of the Basel II formula with a credit growth multiplier and with a stock market returns multiplier. The other three procedures are very similar in terms of RMSD. We have argued that there are good reasons to discard the autoregressive adjustment, so the final choice is between smoothing the inputs of the Basel II formula with TTC PDs and smoothing the output with a GDP growth multiplier. The discussion of the pros and cons of these two procedures is contained in Section 5 below.

Given the functional form (3) of the multiplier μ_t, the value α(GDP) = 0.081 implies that capital requirements should be increased in expansions (or reduced in recessions) by approximately 6.5% (since $2\Phi(0.081) = 1.065$) for each standard deviation in GDP growth. The value α(GDP) = 0.081 also implies that multiplier is almost linear for reasonable values of GDP growth.

It should be noted that the methodology presented in this paper may be used to assess other proposals on how to mitigate the procyclicality of Basel II. For instance, it could be argued that one should focus on proxies for the business cycle that are more closely related to banks' business activity, such as loan losses or profitability. However, in both cases the results are disappointing. The RMSD corresponding to a multiplier based on the ratio of loan loss provisions to total loans is 0.0077, [17] while the RMSD corresponding to the multipliers based on ROA (return on assets) and ROE (return on equity) are 0.0075 and 0.0070, which are much higher than the figures in Table 5 for the GDP growth multiplier. At any rate, we would be rather sceptical about making regulation contingent on a variable that may be easily manipulated by the regulated.[18]

Alternatively, some may argue that the adjustment could be done using credit markets variables such as corporate credit spreads. These spreads could be based on CDS indices or corporate bond spreads. However, for the Spanish market, it is not possible to find such credit market variables for the whole period under analysis. Even for the last years, there is only a small number of non-financial companies with CDS prices available and no information on the liquidity of those contracts (to figure out how reliable those prices are). A similar remark applies to corporate bond spreads.

[17] We are using specific loan loss provisions, that is, provisions that cover individually identified losses.
[18] Earnings management, sometimes through loan loss provisions, seems to be a widespread phenomenon; see, among others, Moyer (1990), Scholes, Wilson and Wolfson (1990), Beatty, Chamberlain and Magliolo (1995), Kim and Kross (1998), Ahmed, Takeda and Thomas (1999), and Pérez, Salas-Fumás and Saurina (2008).

4. Extensions

4.1. Adjustments using individual bank data

The results obtained so far are based on an adjustment for the entire banking system, but they would be applied to individual banks. Therefore it is important to check the performance of the different procedures with individual bank data. In addition, this extension allows us to assess the performance of adjustments based on disaggregated data such as the credit growth of each bank.

In particular, we have chosen five Spanish banks that have opted for the IRB approach of Basel II, and that are currently calculating their minimum capital requirements using the IRB formulas. We compute the point-in-time (PIT) capital requirements per unit of exposure for each of these five banks and for each year of the sample, using the model in Section 2 to estimate the probability of default (PD) of each of their borrowers and the Basel II formula for corporate exposures, with a loss given default (LGD) of 45% and a 1 year maturity.

The results show that there is significant heterogeneity across our sample of five banks. The average value over the sample period of their Basel II capital requirements ranges from 4.5% to 8.2%, and the range of variation from peak to trough is between two and three times higher than the 57% figure obtained for the aggregate data. The significant heterogeneity among these banks makes the comparison of the different smoothing procedures much more interesting.

The analysis is carried out with the PIT capital requirements series data of the five selected banks plus a sixth fictitious bank which comprises all the other banks in the system. To provide a benchmark for the comparison of the different procedures, we compute for each of these six banks the Hodrick-Prescott trend of each capital requirements series.

Following the steps in Section 3, we first consider smoothing the PD input of the Basel II formula by using through-the-cycle (TTC) PDs estimated by replacing in (1) the current values of the macroeconomic controls by their average values over the sample period. In this way we get the TTC capital requirements for each of the six banks. Second, we apply to the PIT series of each bank the business cycle multiplier (3), where the value of parameter α (for each proxy for the business cycle) is chosen to minimize the sum for the six banks of the root mean square deviations (RMSD) of the adjusted series with respect to the HP trends.[19] As proxies for the business cycle, we use the rate of growth of the GDP, the rate of growth of the credit of each bank, and the return of the stock market. Finally, we also compute for each bank the autoregressive adjustment (4), where the value of parameter ϕ is chosen to minimize the sum for the six banks of the RMSDs of the adjusted series with respect to the HP trends.

In line with this approach, we compare the different smoothing procedures in terms of the sum for the six banks of the RMSDs of the adjusted series with respect to the HP trends. Table 6 shows the results, together with the estimated values of parameters α and ϕ. The best procedure is now to smooth the inputs of the Basel II formula with TTC PDs, with the procedure based on a GDP growth multiplier coming second, and the autoregressive procedure coming third. The other two procedures are clearly dominated, including the one based on individual credit growth. In fact, comparing Tables 5 and 6 we conclude that the relative performance of the credit growth multiplier worsens when moving from aggregate to disaggregated data. Thus, our results raise doubts about the proposal of Goodhart and Persaud (2008) to adjust Basel II capital requirements "by a ratio linked to the growth of the value of bank assets, bank by bank."

The values of parameters α and ϕ in Table 6 are broadly in line with those in Table 5, although interestingly α(GDP) jumps from 0.081 to 0.124. This implies an increase in the corresponding multiplier from 6.5% to 9.8% (since $2\Phi(0.124) = 1.098$) for each standard deviation in GDP growth.

4.2. Cyclically varying LGDs

We have assumed so far a constant LGD fixed at the 45% level specified in the foundation IRB approach of Basel II. However, banks in the advanced IRB approach

[19] Although parameter α could be estimated for each bank, we restrict attention to multipliers that are the same for all banks.

must input their estimated LGDs, which clearly vary over the business cycle (they are typically higher in recessions when asset prices are depressed than in expansions).[20] This means that for those banks there is further cyclicality of the PIT capital requirements.

A problem to assess the impact of cyclically varying LGDs on the procedures to smooth the Basel II capital requirements is that we do not have data on the LGDs of the loans in our sample. For this reason, in what follows we simply postulate a linear relationship between LGD_t and PD_t with the same slope as in Altman et al. (2005) and with an intercept such that when the PD is at its average level over the sample period then the LGD equals the reference value of 45%,[21] that is:

$$\mathrm{LGD}_t = 0.45 + 2.61(\mathrm{PD}_t - \overline{\mathrm{PD}}) \qquad (5)$$

where PD_t is the weighted average PD in year t (with weights equal to the borrowers' exposures), and $\overline{\mathrm{PD}}$ is the average of PD_t over the sample period. Figure 8 represents the values of weighted average PDs and cyclically varying LGDs. The fluctuation in LGDs ranges between 40% and 55%.

Figure 9 shows PIT capital requirements when LGDs vary over time and PIT capital requirements calculated using a fixed 45% LGD. Clearly, the cyclicality of capital requirements increases significantly. From peak to trough, PIT capital requirements range from almost 7% to more than 14%, which is twice the variation that we had before.

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[20] For example, Altman et al. (2005) show that that there is a positive relationship between PDs and LGDs. In particular, they regress average bond recovery rates (1 – LGD) on average bond default rates (PD), obtaining a slope coefficient of –2.61.

[21] There is not much justification in the literature for this assumption. Araten, Jacobs and Varshney (2004), using JPMorgan internal data, estimate LGDs in the interval between 39.8% and 50.5%, while for Gupton (2000), using corporate loans data, estimates that LGDs may fluctuate between 30.5% and 47.9%. Frye (2000) finds similar results for senior secured corporate loans. Data collected during the calibration processes leading to Basel II (the so-called Quantitative Impact Assessment, QIS, exercises) do not settle the question because those exercises were carried out under benign economic conditions. Therefore, it seems reasonable to take the 45% focal point set by the Basel Committee for the IRB foundation approach as the average reference LGD value.

With this data we proceed to perform the same analysis as in Section 3, comparing the different smoothing procedures by computing the root mean square deviations (RMSD) of the adjusted series with respect to the HP trend. The results in Table 7 show that the best procedures are either to smooth the inputs of the Basel II formula with TTC PDs or to smooth the output with a GDP growth multiplier.[22] The performance of the autoregressive adjustment worsens relative to the case with a fixed 45% LGD, while as before the other two procedures are clearly dominated.

Thus, the introduction of cyclically varying LGDs does not affect the relative performance of the different procedures to smooth the Basel II capital requirements. However the value of the multipliers is higher. In particular, α(GDP) jumps from 0.081 to 0.133. This implies an increase in the corresponding multiplier from 6.5% to 10.6% (since $2\Phi(0.133)=1.106$) for each standard deviation in GDP growth.

Obviously, these results should be taken with care, since they are based on the ad hoc linear relationship between LGDs and PDs postulated in (5). On the other hand, there is an additional factor that increases the sensitivity of PIT capital requirements to the business cycle, namely that exposures at default (EADs) also move in parallel with PDs; see, for example, the evidence in Jiménez, Lopez and Saurina (2009b). It is not easy to simulate the impact of EADs on capital requirements, so we will not pursue this here. But the fact that LGDs and EADs vary over the business cycle makes the cyclical adjustment of capital requirements even more compelling.

4.3. A flat benchmark

It could be argued that our results are highly dependent on the filtering procedure used. We believe that the HP filter is a standard procedure to separate cycle from trend. However, to check the robustness of our results, we use another benchmark to compare the different adjustment procedures.

The alternative benchmark is a constant requirement at the average of the estimated PIT requirements over the sample period.[23] Therefore, for each procedure we calculate the

[22] Note that TTC means here that we still use the 45% LGD.

RMSD of the adjusted series with respect to a flat line at the level of 9.37%. One way to rationalize this filter is to think of it as Basel I-type benchmark.

For this benchmark the best adjustment is obtained with the autoregressive procedure, because starting at the 9.37% level and setting the autoregressive parameter ϕ equal to zero we get a zero RMSD. Thus, risk-sensitivity is eliminated by making the capital requirement equal to the flat benchmark. This is another reason which supports the arguments against the use of this adjusting procedure. As for the other procedures, smoothing the inputs of the Basel II formula with TTC PDs dominates the adjustment based on GDP growth (RMSDs = 0.0066 and 0.0074, respectively), which in turn is better than the adjustments based on credit growth and stock market returns (RMSDs = 0.0085 and 0.012, respectively). The main conclusion from this exercise is that the performance of the different procedures does not seem to depend on the selected benchmark, but on their ability to smooth cyclical patterns in the original PIT capital requirements series.

4.4. Adjustment of expected losses

Regulatory capital under Basel II is set aside to cover unexpected losses, while expected losses must be covered with loan loss provisions. Assuming an LGD of 45%, our empirical model allows us to compute the expected losses for each firm and each year of our sample. From here we may obtain an estimation of the expected losses per unit of exposure for each year of the sample. Figure 10 shows expected losses and capital requirements per unit of exposure over the sample period. Both series exhibit a very similar pattern, driven by the cyclical behaviour of PDs. It is also worth noting that the average level of expected losses (2%) is significantly lower than the average level of capital requirements (9%). This means that in order to mitigate the procyclical effects of regulation, acting on the capital requirements front is much more important than acting on the expected losses front.

As a response to the current financial crisis, there is a growing consensus among academics and policy makers about the need to build buffers of resources in good times

[23] Charles Goodhart and Michael Gordy independently suggested using a flat benchmark.

that can be drawn down when conditions deteriorate.[24] One way to build up those buffers would be to implement an explicit cyclical adjustment of loan loss provisions similar to the adjustment of capital requirements discussed above. For example, a multiplier of expected losses based on GDP growth could be designed to smooth the provisioning requirements over the business cycle. Thus, during expansion phases, when expected losses are below their cyclically adjusted value, the buffer would be built up, while in recessions, when the opposite obtains, the buffer would be drawn down. This "economy cycle reserve" (to use the terminology of the Turner Review, 2009), could be implemented by either adjusting the P&L figures (as in the case of the Spanish dynamic provisioning system[25]) or by restricting distributable profits. The choice between these two alternatives would have to be based on an agreement between prudential and accounting regulators.

5. Discussion

Our previous results show that the best procedures for mitigating the procyclicality of the Basel II capital requirements are either to smooth the inputs of the IRB formula by using through-the-cycle (TTC) PDs or to smooth the output with a multiplier based on GDP growth.

The use of TTC PDs has been criticized by Gordy and Howells (2006, pp. 415-416) on the grounds that "changes in a bank's capital requirements over time would be only weakly correlated with changes in its economic capital, and there would be no means to infer economic capital from regulatory capital." They also point out that "through-the-cycle ratings are less sensitive to market conditions than point-in-time ratings, (so) they are less useful for active portfolio management and as inputs to ratings-based pricing models." Finally, they also note that "despite the ubiquity of the term 'trough-the-cycle'

[24] See, for example, Brunnermeier et al. (2009) and the G20 Leaders' Declaration on Strengthening the Financial System of 2 April 2009.
[25] Jiménez and Saurina (2006) explain the rationale for a dynamic or anti-cyclical provision. Such a provision has been applied in Spain since mid-2000 and further adjusted when IFRS came into effect in 2005.

in descriptions of rating methods, there seems to be no consensus on precisely what is meant."

As noted in Financial Services Authority (2009, p. 89) adjusting PDs so that they reflect "an average experience across the cycle" involves a very significant challenge, since it requires "the ability to differentiate changes in default experience that are due entirely to the economic cycle from those that are due to a changing level of non-cyclical risk in the portfolio." As a result, they note that "in general firms have not developed TTC ratings systems whose technical challenges are typically greater than those of PIT approaches." The UK Financial Services Authority has been working with the industry to develop a so-called "quasi-TTC" rating approach, based on adjusting the PIT PDs by a cyclical scaling factor. However, calibrating such factor seems a difficult task. From this perspective, doing the scaling with the output of the Basel II formula, along the lines that we have proposed above, seems much easier.

The difficulty in making precise the notion of TTC ratings implies that this smoothing procedure would be implemented very differently across banks in a single jurisdiction, and especially across banks in different jurisdictions, so level-playing field issues may emerge. These issues would be particularly difficult to resolve because of the lack of transparency of the procedure. From this perspective, it also seems better do the adjustment with a single (and fully transparent) macro multiplier.

Finally, it has been argued that using one-year-ahead PDs is not appropriate for loans with longer maturities, and that for this reason a TTC procedure would be more appropriate. The reply to this objection is three-fold. First, the share of long term loans in non-mortgage portfolios is likely to be small.[26] Second, even for longer-term loans, a correct assessment of their risk should be done conditional on the state of the economy, not in an unconditional manner. Doing the latter, which is in the spirit of TTC ratings, contradicts the Basel II requirement of using "all relevant and material information in assigning ratings" (BCBS, 2006, par. 426). Third, one should remember that the Basel II formula incorporates a maturity adjustment factor that is supposed to take care of possible downgrades during the life of the loan.

[26] For example, the proportion of loans in our sample with an initial maturity over one year is only 28%.

The distinction between conditional and unconditional assessments of risk deserves a further discussion. To make it more precise, consider an economy with two aggregate states, expansion (denoted by h) and recession (denoted by l). Let p_h and p_l denote the representative PDs in the two states, with $p_h < p_l$, and let q_{ij} denote the transition probability from state i to state j. From the transition probabilities one can derive the unconditional probabilities, q_h and q_l, of being in each state, which gives the unconditional PD $\bar{p} = q_h p_h + q_l p_l$. Now suppose that the economy is in an expansion state, and that we want to price a one-year loan. Clearly we should use the PIT p_h rather than the TTC $\bar{p}$. Similarly, for a two-year loan we should use p_h for the first year, and (if the loan does not default during the first year) $q_{hh} p_h + q_{hl} p_l$ for the second year. If q_{hh} is sufficiently high, i.e. if expansions have a long duration, then this PD will be close to p_h, so using the (conditional on the state) one-year-ahead PD would be approximately correct for pricing purposes. And so on for longer maturity loans. The conclusion is that cyclically smoothing the PDs produces a distortion in the correct measurement of risk that makes them rather useless for risk pricing and risk management purposes.

This is especially relevant in the light of the requirements on the use of internal ratings specified by the BCBS (2006, par. 444): "Internal ratings and default and loss estimates must play an essential role in the credit approval, risk management, internal capital allocations, and corporate governance functions of banks using the IRB approach."

The preceding arguments suggest that smoothing the inputs of the IRB formula by using through-the-cycle (TTC) PDs has many shortcomings. The alternative procedure, to smooth the output with a multiplier based on GDP growth, is much better in terms of simplicity, transparency, low cost of implementation, consistency with banks' risk pricing and risk management systems, and even consistency with the idea of a single aggregate risk factor that underlies the capital requirements of Basel II.

The proposed multiplier could be adjusted in several ways. For example, the range of μ_t in (2) goes from 0 (when $g_t \to -\infty$) to 2 (when $g_t \to \infty$), but one could easily introduce alternative lower and an upper bounds so that $1 - \Delta \leq \mu_t \leq 1 + \Delta$. This could be done by setting

$$\mu_t = \begin{cases} 1-\Delta, & \text{if } \mu(g_t,\alpha) \le 1-\Delta \\ \mu(g_t,\alpha), & \text{if } 1-\Delta \le \mu(g_t,\alpha) \le 1+\Delta \\ 1+\Delta, & \text{if } \mu(g_t,\alpha) \ge 1+\Delta \end{cases}$$

or by defining

$$\mu_t = 1+\Delta\left[2\Phi\left(\frac{\alpha(g_t-\bar{g})}{\sigma_g}\right)-1\right]$$

where parameter α would have to be reestimated for the desired value of Δ.

Alternatively, and in line with the idea of building capital buffers in good times, the multiplier could be redefined so that

$$\mu_t = 2\Phi\left(\frac{\alpha(g_t-g_{\min})}{\sigma_g}\right)$$

where $g_{\min}$ is the lowest value of GDP growth in the sample. In this way, the multiplier would be shifted upwards so that it would be equal to 1 at the lowest point of the business cycle. Using this formula it would be possible to generate a positive buffer of regulatory capital, so minimum capital requirements would be adjusted with the business cycle but would never be below the level specified by the Basel II formulas with point-in-time PDs.

The procedure of smoothing the Basel II capital requirements with a multiplier based on GDP growth would be applied in each national jurisdiction, possibly with different multipliers for different portfolios, and only for banks that are under the IRB approach of Basel II, on the grounds that the standardized approach is only minimally risk-sensitive. It would imply to accept different capital requirements for different jurisdictions, but this is an inevitable feature of any procedure designed to correct the effect of the business cycle on risk-sensitive capital requirements.[27] The procedure would involve some complexity in its application to international banks, especially those that have significant cross-border lending activities. In such cases, a possible approach would be to use the jurisdiction of the borrower. At any rate, dealing with these important practical issues is beyond the scope of this paper.

Finally, given the fact that credit growth at each bank level is an easily available variable and taking into account that lending cycles are very closely related to business cycles and to the risk profile of banks and, thus, to their Basel II capital requirements, we have carried out some detailed additional analysis regarding this variable. It is important to note that during the second half of 1989 and the entire 1990 there were binding credit growth limits in Spain. Those limits were an extraordinary measure to complement conventional monetary policy tools at a period were inflation was hard to tame. In order to avoid any potential bias in our results against the credit growth multiplier, we have rerun the whole exercise from 1991 onwards. RMSDs show almost no change. GDP growth is still better than credit growth, although now the TTC PDs adjustment is slightly better than the GDP adjustment.

6. Conclusion

This paper provides clear evidence that Basel II capital requirements based on point in time (PIT) probabilities of default (PDs) move significantly along the business cycle. According to our results, from peak to trough capital requirements for loans to firms may vary by more than 50%, a figure that could reach 100% with cyclically-varying losses given default (LGDs). Therefore, a very important policy question that is in the front line of current discussions among policy makers is: How should the procyclical effects of risk-sensitive bank capital regulation à la Basel II be mitigated? To the best of our knowledge this is the first paper that presents an analytical framework to address this issue.

We propose a benchmark for comparing different procedures and apply it to the smoothing of the estimated Basel II capital requirements for commercial and industrial loans in Spain over the period 1987-2008. The comparison is based on the minimization

[27] Besides, with the increasing correlation in international business cycles the differences should not be very significant.

of the root mean square deviations of each smoothed series with respect to the trend of the original series computed by applying the Hodrick-Prescott (HP) filter.

The results show smoothing the output of the Basel II formula with a credit growth multiplier (based on aggregate or bank-specific data) or with a stock market returns multiplier is suboptimal in terms of the proposed criterion, as it is also the case when using a multiplier based on variables such as profits (e.g. ROA and ROE) or specific provisions. The autoregressive adjustment performs better, but we argue that its lagged response is an important shortcoming, especially in downturns. Consequently, the final choice is between smoothing the inputs of the Basel II formula by using through-the-cycle (TTC) PDs or smoothing the output with a multiplier based on GDP growth. Our discussion of the pros and cons of these two procedures concludes that the latter is better in terms of simplicity, transparency, low cost of implementation, and consistency with banks' risk pricing and risk management systems.

Our results also show that for the portfolio of commercial and industrial loans the multiplier would amount to a 6.5% surcharge for each standard deviation in GDP growth for banks using the foundation IRB approach (with an LGD set at 45%). The surcharge would be significantly higher for banks using cyclically-varying LGDs. Applying these results to the current crisis, where GDP growth in many countries is at least 3 standard deviations below its long-run average, would imply a reduction in capital requirements of the order of at least 20%.

The analytical framework presented in the paper could also be applied to expected losses, so it can be used to calibrate economic cycle reserves or dynamic provisions.

To conclude, it is important to stress that the proposed adjustment maintains the risk-sensitivity of the Basel II capital requirements in the cross-section, so riskier loans (and hence banks with riskier portfolios) would bear a higher capital charge, but a cyclically-varying scaling factor would be introduced to increase capital requirements in good times and to reduce them in bad times. Such changes should contribute to reducing the incidence and magnitude of both credit bubbles and credit crunches.

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Table 1. DESCRIPTIVE STATISTICS OF THE POPULATION AND SAMPLE

This table reports the volume of total exposures and the default rate for the whole population of loans to firms and for the selected sample.

	Total Exposure (€ Million)			Default Rate		
Year	Population	Sample	Sample/Population	Population	Sample	|Sample – Population|
1987	72,900	8,540	11.71%	0.050	0.050	0.000
1988	82,800	9,740	11.76%	0.055	0.057	0.002
1989	110,000	12,500	11.36%	0.063	0.062	0.001
1990	125,000	13,600	10.88%	0.062	0.062	0.000
1991	143,000	15,100	10.56%	0.075	0.075	0.001
1992	149,000	15,700	10.54%	0.089	0.089	0.000
1993	119,000	10,800	9.08%	0.131	0.127	0.004
1994	144,000	13,300	9.24%	0.103	0.105	0.002
1995	161,000	14,600	9.07%	0.061	0.062	0.001
1996	169,000	15,900	9.41%	0.062	0.064	0.002
1997	190,000	17,600	9.26%	0.036	0.037	0.001
1998	219,000	22,700	10.37%	0.027	0.028	0.000
1999	260,000	26,400	10.15%	0.033	0.034	0.001
2000	314,000	33,600	10.70%	0.025	0.027	0.001
2001	347,000	35,700	10.29%	0.026	0.027	0.001
2002	391,000	40,600	10.38%	0.026	0.026	0.000
2003	440,000	44,100	10.02%	0.022	0.021	0.001
2004	526,000	49,300	9.37%	0.018	0.018	0.000
2005	659,000	59,500	9.03%	0.021	0.021	0.000
2006	865,000	77,100	8.91%	0.019	0.019	0.000
2007	996,000	94,000	9.44%	0.023	0.023	0.000
2008	1,040,000	99,600	9.58%	0.054	0.053	0.001

Table 2. DESCRIPTIVE STATISTICS OF DEFAULT DETERMINANTS

This table presents the mean, standard deviation, minimum and maximum values of the variables used to explain the default event of loans to firms. The statistics are provided for the sample period, 1987-2008.

	Units	Description	Mean	Std.Dev.	Min	Max
Dependent Variable (t+1)						
Default	0/1	=1 If a borrower defaults in period t+1	0.038	0.192	0.000	1.000
Borower_Type_Variable (t)						
COLLATERAL	%	Average proportion of guarantees in firms' borrowing	0.232	0.378	0.000	1.000
MATURITY	%	Proportion of long-term exposures over total exposures	0.282	0.373	0.000	1.000
AGE_dum_1	0/1	=1 If borrower reporting for 1 year to CIR	0.154	0.361	0.000	1.000
AGE_dum_2	0/1	=1 If borrower reporting for 2 years to CIR	0.136	0.343	0.000	1.000
AGE_dum_3	0/1	=1 If borrower reporting for 3 years to CIR	0.114	0.317	0.000	1.000
AGE_dum_4	0/1	=1 If borrower reporting for 4 or more years to CIR	0.597	0.491	0.000	1.000
NUMBER_BANKS		Log of number of lending relationships	0.489	0.619	0.000	5.252
MAIN_LENDER_CHANGE	%	Frequency of changes in main lender	0.145	0.190	0.000	0.917
SIZE		Log of loan size (deflated by general price index)	4.475	1.971	-2.834	15.370
UTILIZATION	%	Proportion of utilization of credit lines	0.831	0.275	0.000	1.000
Risk_Profile_Variables (t)						
HISTORIC_DELINQUENCY	%	Proportion of years in which firm has been delinquent	0.170	0.245	0.000	0.958
HISTORIC_DEFAULT	%	Proportion of years in which firm has been in default	0.012	0.056	0.000	0.882
Macro_Variables (t)						
GDP	%	Rate of change of GDP	0.035	0.011	-0.010	0.055
CREDIT_GROWTH	%	Rate of growth rate of total credit exposures	0.159	0.082	-0.020	0.329
STOCK_EXCHANGE_Var	%	Rate of change of Spanish stock market index	0.152	0.229	-0.248	1.083
Control Variables (t)						
Regional dummies	0/1	=1 If a borrower belongs to a certain region				
Industry dummies	0/1	=1 If a borrower belongs to a certain industry				

Table 3. ESTIMATION RESULTS

This table reports the estimation of the logistic model of firms' default. *COLLATERAL*$_{it}$ represents average (weighted by the size of exposures) of the proportion of guarantees in a firm's borrowing. *MATURITY*$_{it}$ represents the proportion of long-term exposures (over one year) over total exposures. *AGE*$_{it}$ accounts for the number of years a borrower has been reporting to the Credit Register. *NUMBER_BANKS*$_{it}$ is the number of banks with which a firm has lending relationships. *MAIN_LENDER_CHANGE*$_{it}$ indicates the frequency with which firms change the bank which provides them with the largest amount of financial support. *FIRM_SIZE*$_{it}$ is the log of a firm's borrowing deflated by the general price index. *UTILIZATION*$_{it}$ is the ratio between the amount of credit drawn by a borrower and the total available amount (credit line). *HISTORIC_DELINQUENCY*$_{it}$ is the number of years in which a firm has been delinquent divided by the number of years it has been reporting to the Credit Register. *HISTORIC_DEFAULT*$_{it}$ is the number of years in which a firm has been in default divided by the number of years it has been reporting to the Credit Register. *GDP*$_{t}$ is the growth rate of the gross domestic product, *CREDIT_GROWTH*$_{t}$ is the growth rate of the commercial and industrial loans in the Credit Register, and *STOCK_MARKET_Var*$_{t}$ is the rate of change of the Spanish stock market index.

Dependent variable (0/1): Borrowers default in t+1	Coefficient***	S.E.	t-value
Borrower_Type Variables (t)			
COLLATERAL	0.169	0.017	10.080
MATURITY	-0.251	0.016	-15.910
AGE_dum_2	0.868	0.023	37.270
AGE_dum_3	0.756	0.024	31.250
AGE_dum_4	-0.100	0.023	-4.350
NUMBER_BANKS	0.488	0.013	38.520
MAIN_LENDER_CHANGE	0.660	0.029	22.600
SIZE	-0.254	0.005	-52.220
UTILIZATION	2.655	0.034	77.240
Risk_Profile_Variables (t)			
HISTORIC_DELINQUENCY	2.133	0.024	90.660
HISTORIC_DEFAULT	2.858	0.058	49.380
Macro_Variables (t)			
GDP	-0.148	0.005	-27.340
CREDIT_GROWTH	-1.596	0.087	-18.400
STOCK_EXCHANGE_Var	-0.248	0.023	-10.860
Control_Variables (t)			
Regional_dummies	Yes		
Industry_dummies	Yes		
Constant	-4.829	0.046	-104.170
Number of observations	996,885		
Period (Annual)	1987-2008		
Pseudo R2	10.28%		
Log pseudolikelihood	-145,548.960		
LR chi2(47)	33,349.380		
Prob > chi2	0.000		

***All coefficients are statistically significant at the 99% level

Table 4. MODEL PERFORMANCE

This table reports the performance of the estimated logistic model regression for an in-sample and an out-of-sample set of observations in terms of observed and predicted defaults, areas under the ROC curve, and accuracy ratios.

Classification Power	Classification Table In-sample model (1987-2008)		Classification Table Out-of-sample model	
	Predicted Defaults	Predicted Non-Defaults	Predicted Defaults	Predicted Non-Defaults
Observed defaults	68.01%	30.27%	68.05%	29.54%
Observed non-defaults	31.99%	69.73%	31.95%	70.46%
	Area under ROC curve = 0.76		Area under ROC curve = 0.76	
	Accuracy ratio = 52%		Accuracy ratio = 52%	

Table 5. ROOT MEAN SQUARE DEVIATIONS FROM HODRICK-PRESCOTT TREND FOR DIFFERENT SMOOTHING PROCEDURES

This table compares the performance in terms of root mean square deviations (RMSD) from the Hodrick-Prescott trend of the following smoothing procedures: Through-the-cycle (TTC) PDs, multipliers based on GDP growth, credit growth, and stock market returns, and autoregressive adjustment. It also shows the value of the multiplier α for GDP growth, credit growth and stock market return, and of parameter ϕ for the autoregressive adjustment.

Type of adjustment	α/ϕ	RMSD
TTC PDs		0.0055
GDP growth	0.0810	0.0054
Credit_growth	0.0745	0.0066
Stock market return	0.0382	0.0081
Autoregressive	0.3062	0.0054

Table 6. ROOT MEAN SQUARE DEVIATIONS FROM HODRICK-PRESCOTT TREND FOR DIFFERENT SMOOTHING PROCEDURES USING INDIVIDUAL BANK DATA

This table compares the performance of the smoothing procedures in terms of the sum for six banks (five banks that have opted for the IRB approach of Basel II plus a sixth fictitious bank which is the aggregate of all the other banks in the system) of the root mean square deviations (RMSD) from the Hodrick-Prescott trend of each bank's series. It also shows the value of the multiplier α for GDP growth, credit growth and stock market return, and of parameter ϕ for the autoregressive adjustment.

Type of adjustment	α/ϕ	RMSD
TTC PDs		0.0048
GDP growth	0.1237	0.0066
Credit growth	0.0796	0.0091
Stock market return	0.0239	0.0098
Autoregressive	0.3654	0.0070

Table 7. ROOT MEAN SQUARE DEVIATIONS FROM HODRICK-PRESCOTT TREND FOR DIFFERENT SMOOTHING PROCEDURES USING CYCLICALLY-VARYING LGDs

This table compares the performance in terms of root mean square deviations (RMSD) from the Hodrick-Prescott trend of the smoothing procedures when LGDs are a linear function of weighted average PDs according to equation (5) in the text. It also shows the value of the multiplier α for GDP growth, credit growth and stock market return, and of parameter ϕ for the autoregressive adjustment.

Type of adjustment	α/ϕ	RMSD
TTC PDs		0.0086
GDP growth	0.1330	0.0084
Credit growth	0.1329	0.0108
Stock market return	0.0489	0.0146
Autoregressive	0.2984	0.0095

Figure 1. PIT CAPITAL REQUIREMENTS AND GDP GROWTH

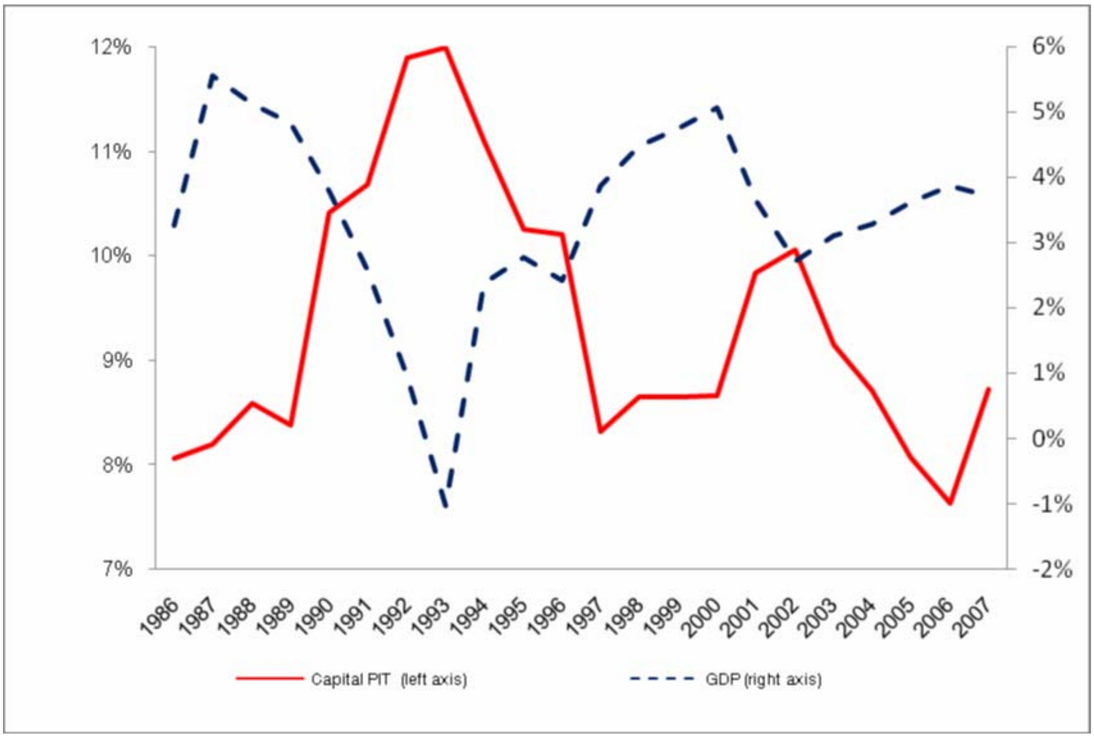


Figure 2. PIT CAPITAL REQUIREMENTS AND HP TREND

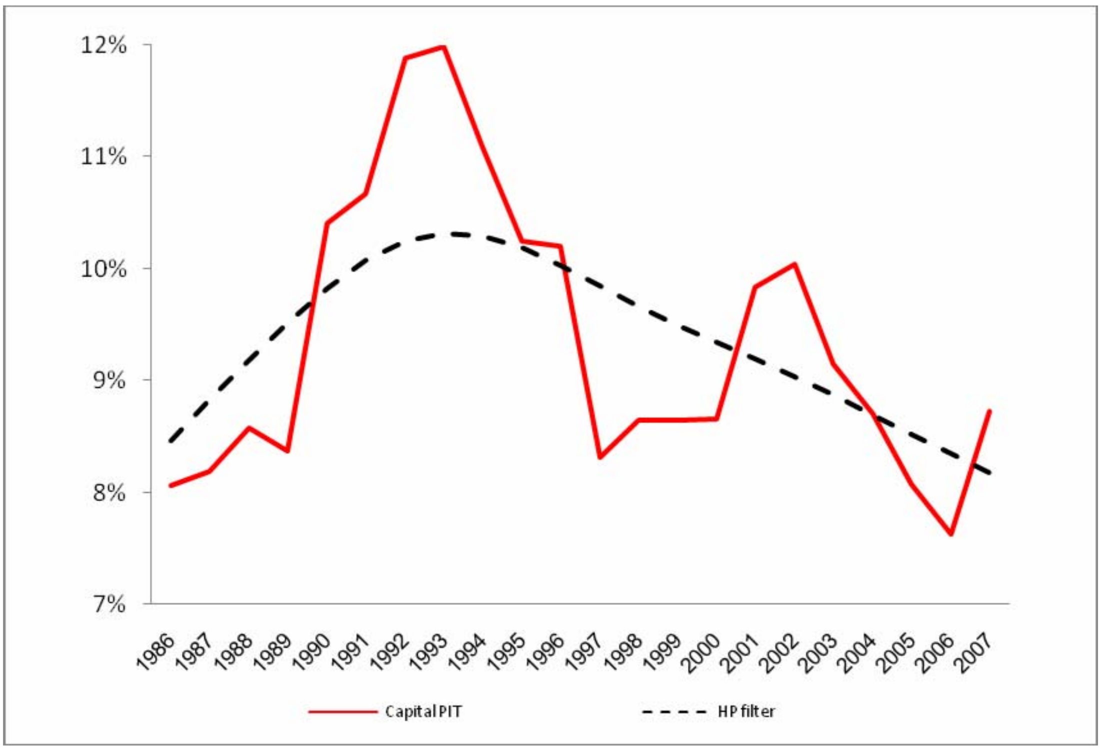


Figure 3. PIT and TTC CAPITAL REQUIREMENTS AND HP TREND

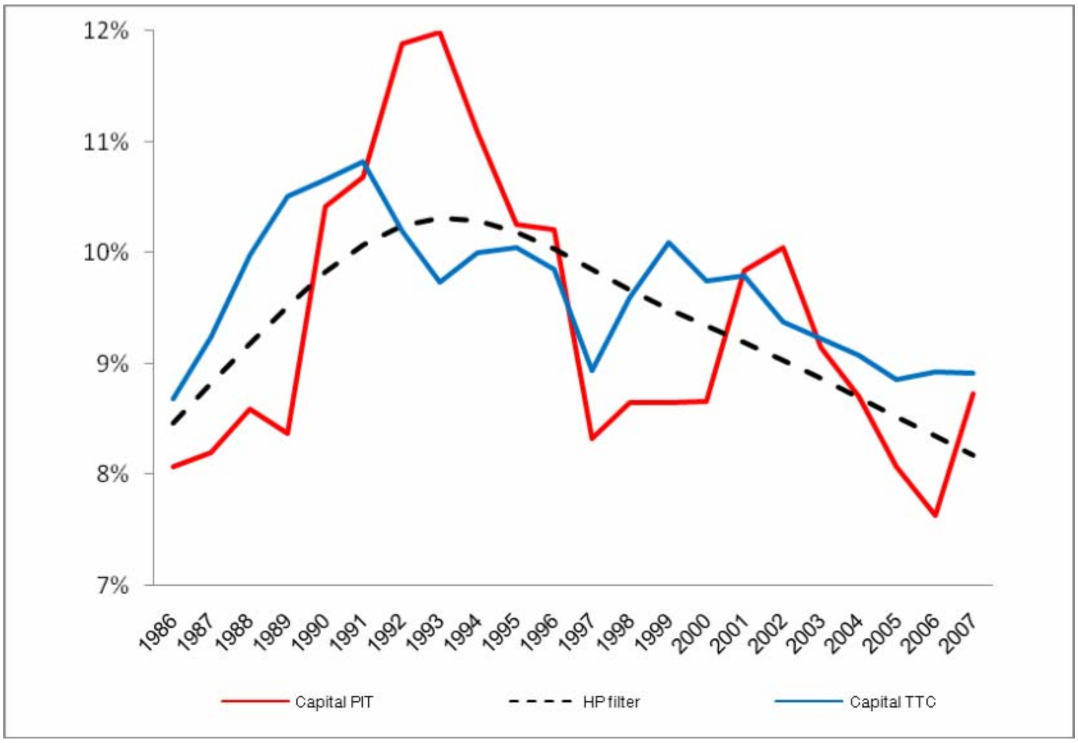


Figure 4. PIT CAPITAL REQUIREMENTS, GDP ADJUSTMENT, AND HP TREND

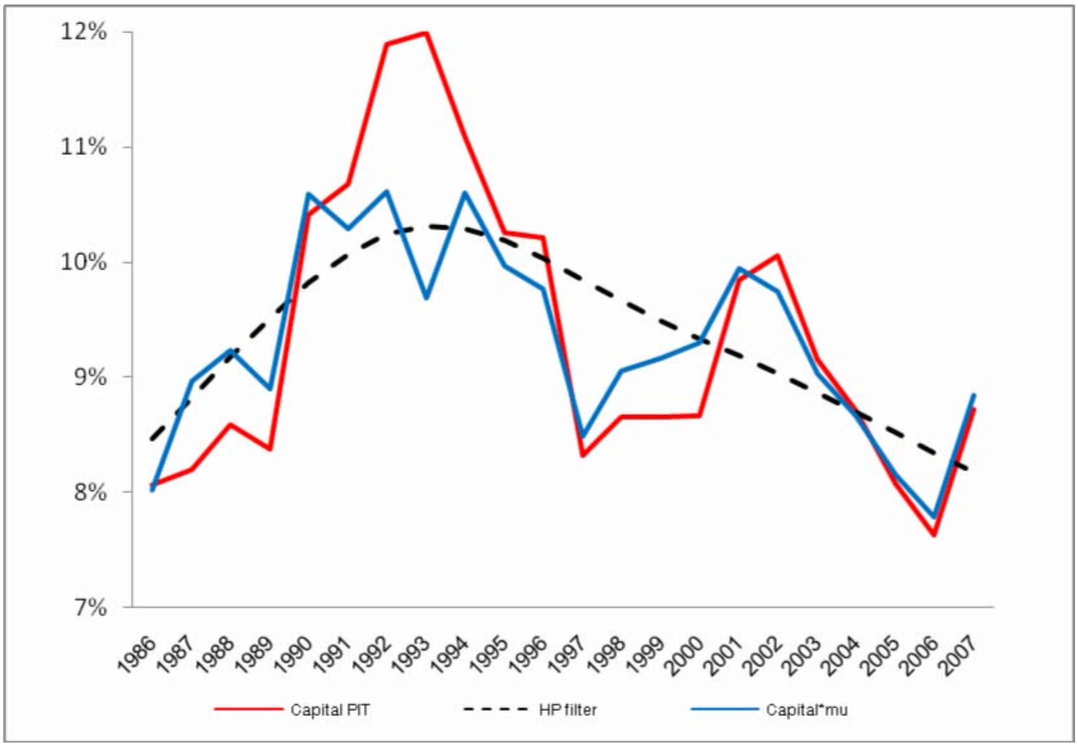


Figure 5. PIT CAPITAL REQUIREMENTS, CREDIT ADJUSTMENT, AND HP TREND

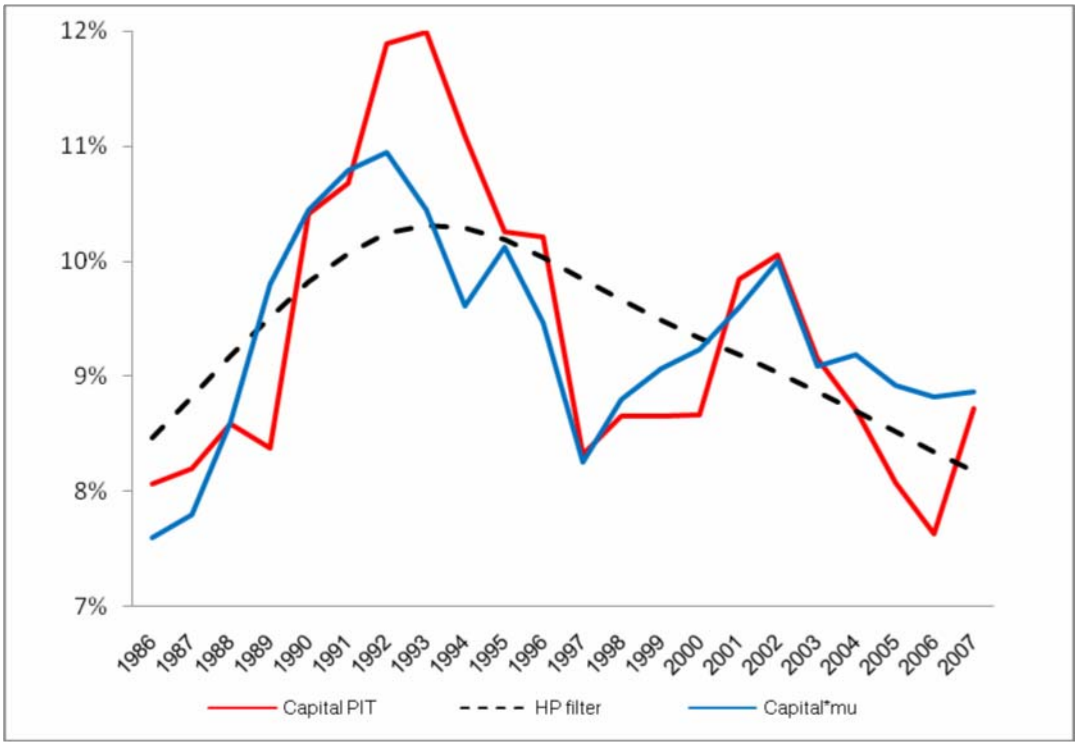


Figure 6. PIT CAPITAL REQUIREMENTS, STOCK MARKET ADJUSTMENT, AND HP TREND

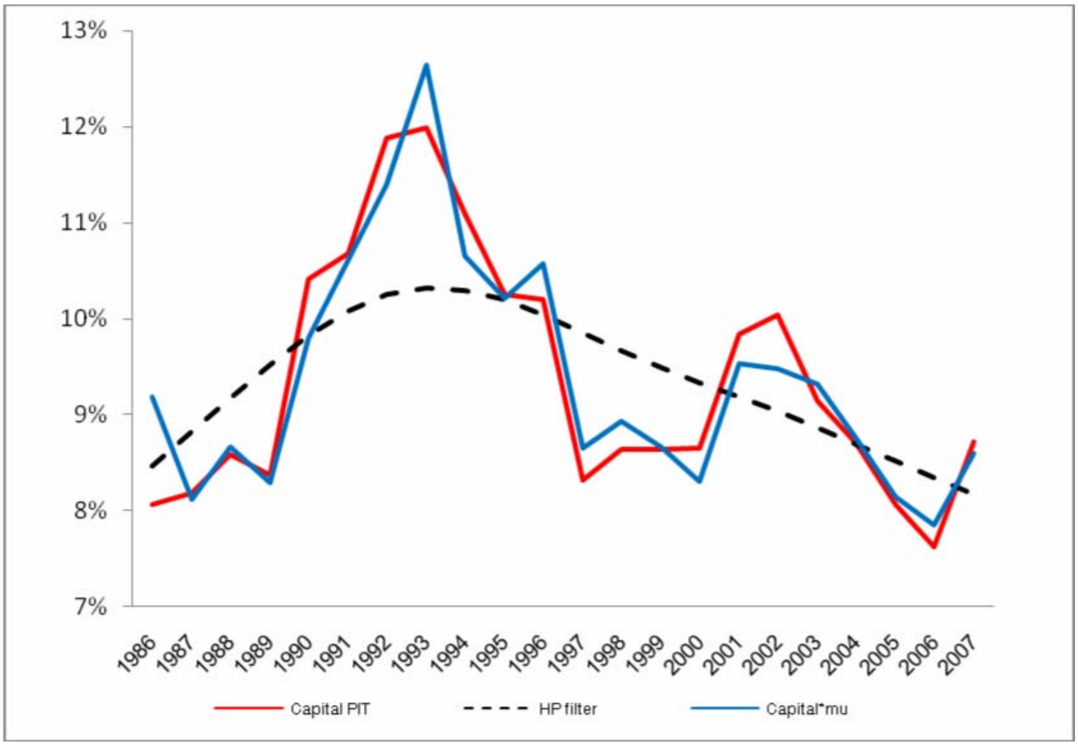


Figure 7. PIT CAPITAL REQUIREMENTS, AUTOREGRESSIVE ADJUSTMENT, AND HP TREND

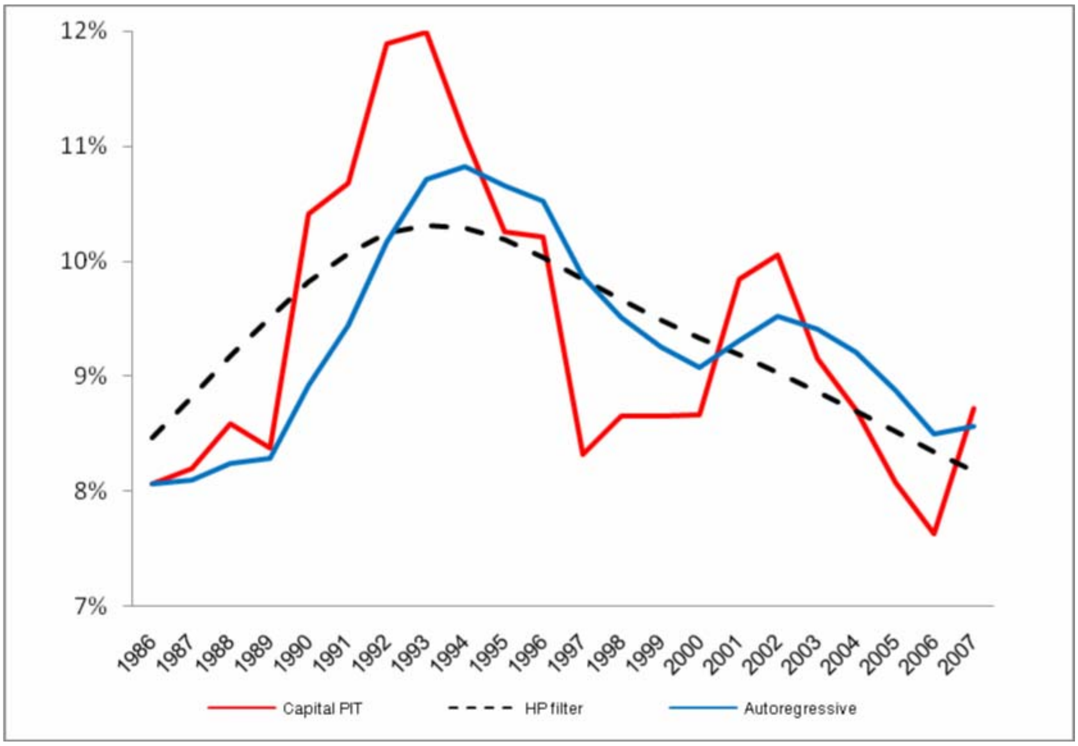


Figure 8. WEIGHTED AVERAGE PDs AND CYCLICALLY-VARYING LGDs

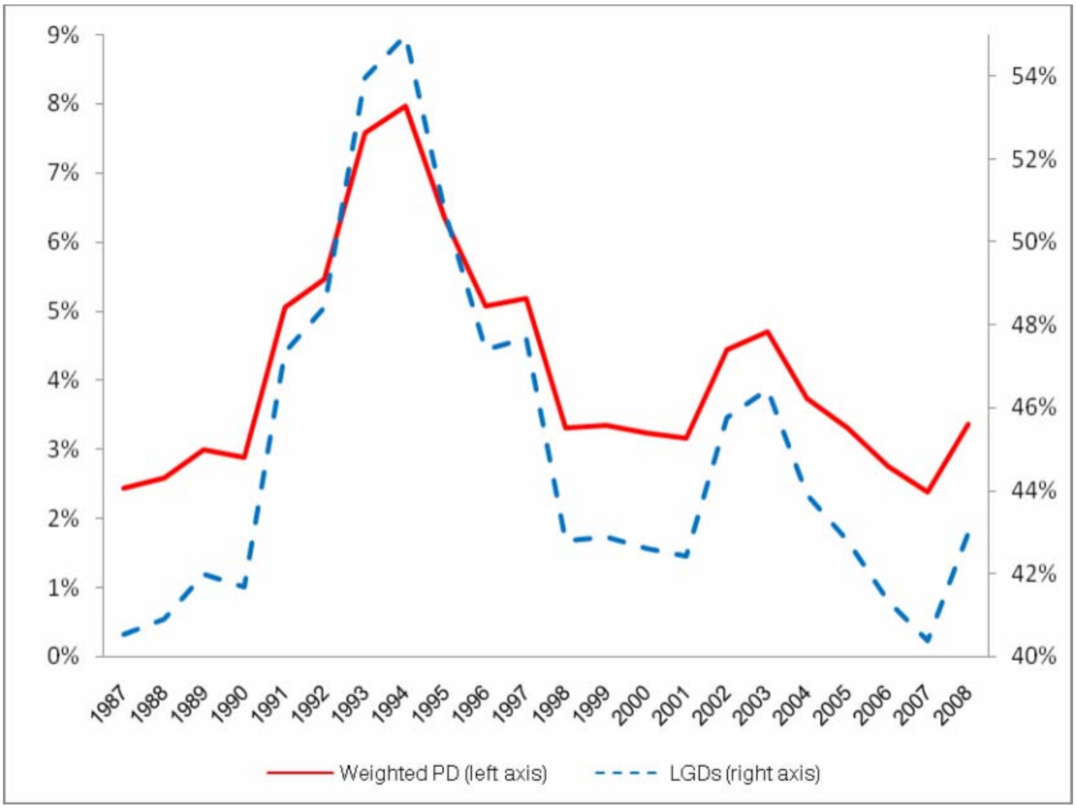


Figure 9. PIT CAPITAL REQUIREMENTS WITH AND WITHOUT VARIABLE LGDS

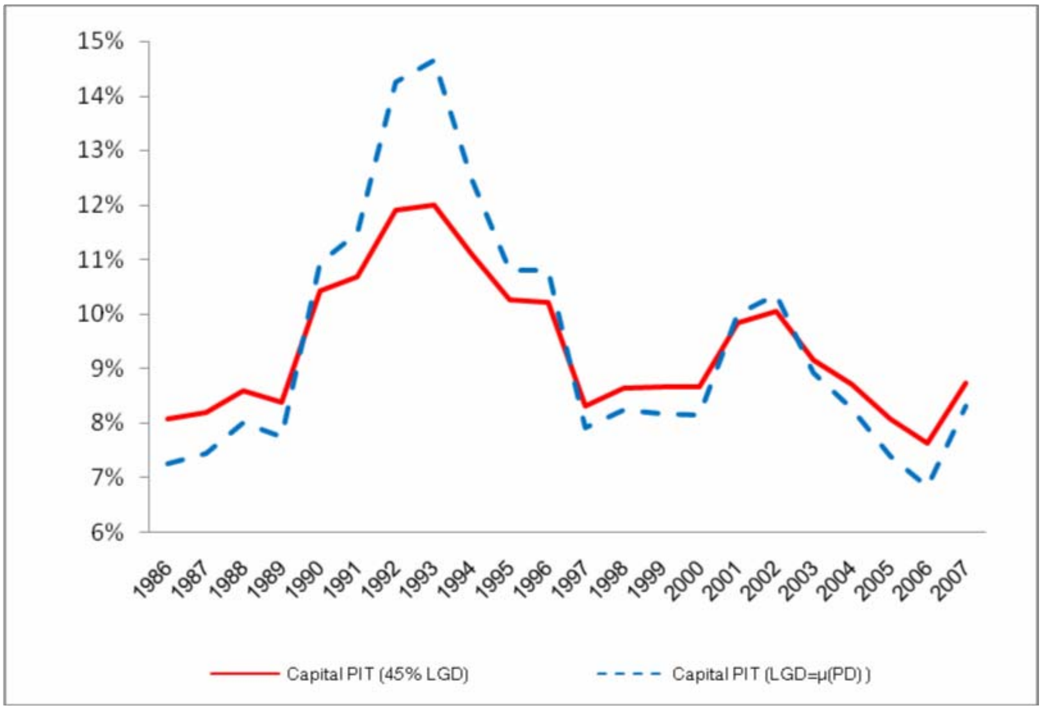
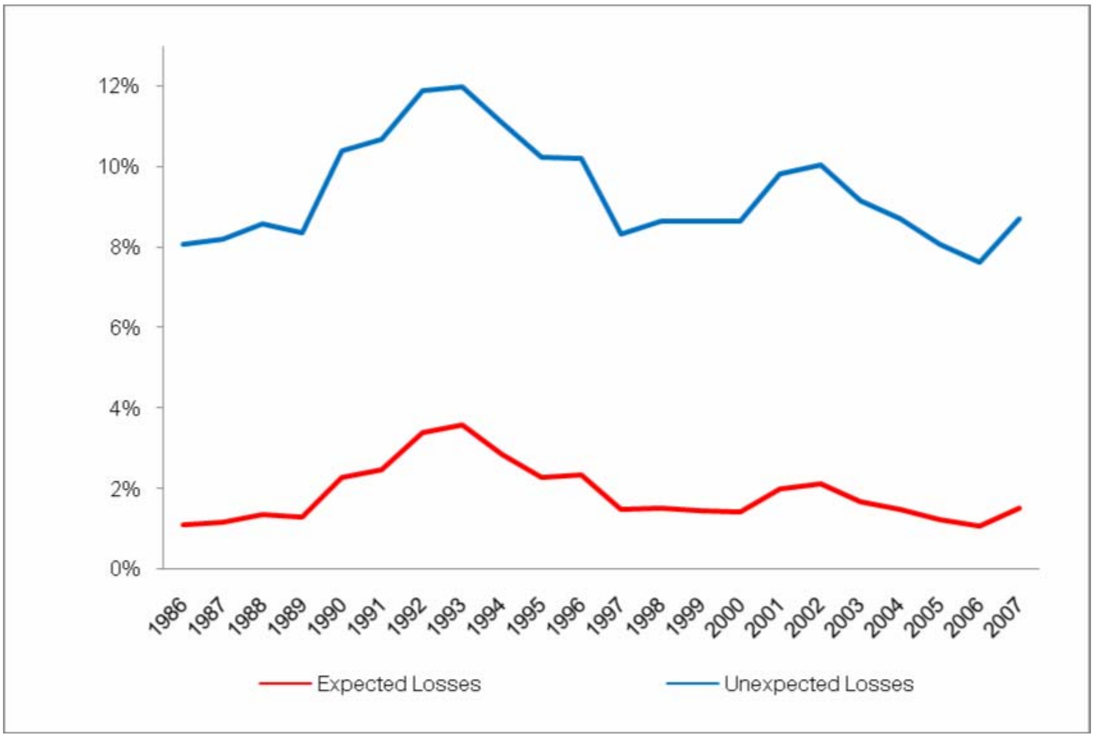


Figure 10. PIT EXPECTED AND UNEXPECTED LOSSES AND GDP GROWTH



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