Do banks adjust their capital ratios?

Evidence from Germany

Christoph Memmel[1] Peter Raupach

Deutsche Bundesbank

Abstract

We analyze the dynamics of banks' capital ratios. Using monthly data of regulatory capital ratios for large German banks, we estimate the target level and the adjustment speed of the capital ratio for each bank separately. There exists a target level for a substantial percentage of banks. Private banks and banks with liquid assets are more likely to adjust their capital ratio tightly. Banks with a target capital ratio compensate for low target ratios with low asset volatilities and high adjustment speeds. They seem to care mainly for the resulting probability to comply with the regulatory minimum.

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[1] Deutsche Bundesbank, Wilhelm-Epstein-Strasse 14, 60431 Frankfurt, Germany, Tel.: +49 69 9566 8531, Fax: +49 69 9566 4275. Email: christoph.memmel@bundesbank.de. The opinions expressed in this paper are those of the authors and need not be the ones of Deutsche Bundesbank.

1 Introduction

Banks' capital ratios have received much attention because the ratios—being a natural indicator of soundness—are by far lower than those of industrials, and a failure of a systemically relevant bank may threaten to derail the economy as a whole.

Banks face a trade-off when choosing the appropriate level of their capital ratio. On the one hand, regulatory authorities and rating agencies force the banks to maintain a minimum capital ratio. The regulatory lower limit for the total-capital ratio is 8 percent, while rating agencies and other market participants insist that a bank holds a certain ratio of Tier 1 capital if it wants to obtain a certain rating. On the other hand, banks try to maximize their return on capital to satisfy their investors; in contradiction to Modigliani/Miller's irrelevance theorem (1958), it is believed that banks can increase their performance by substituting capital with debt. This view, however, is not the result of ignoring the risk impact of leverage. The economic literature provides a number of theoretical arguments why a high leverage is desirable for banks. Given the above reasons for the existence of a target leverage, the trivial fact that shocks change the leverage implies that the bank management has to adjust it from time to time.

We pose the following three research questions: (1) Do banks adjust their capital ratios to a predefined target level or does the capital ratio fluctuate randomly, driven only by stochastic shocks without tendency to a mean? (2) Which bank characteristics determine whether banks adjust their capital ratio? (3) In our setting, the probability of failing to meet the regulatory requirements depends on three strategic parameters: the target capital ratio, the adjustment rate, and the asset volatility. Is there a compensating relationship between these three parameters, for instance do we find that banks with a high capital cushion have volatile assets and low adjustment speeds?

Our contribution to the literature is twofold. First, we are the first to estimate a partial adjustment model for the capital ratio that determines the adjustment rate for each bank separately. Using monthly (instead of yearly or at best quarterly) data, we can apply the tools of time series analysis, especially those of stationarity analysis. Second, we provide insights into the strategic behavior of the capital management of German banks.

Our results can be summarized in four statements: (1) For a significant percentage of the banks investigated, we can reject the hypothesis of capital ratios fluctuating randomly; i.e., there seems to be a certain capital ratio that management seeks to obtain. (2) We observe that the adjustment rates vary across banks and show that private banks and banks with liquid assets are more likely to adjust the capital ratio tightly. (3) Banks with a high target capital ratio tend to have a high asset volatility and/or a high adjustment speed to maintain a certain probability of meeting the regulatory requirements. (4) Assuming perfect compensation among the three strategic parameters cited above, we can explain the interaction of asset volatility, target capital ratio, and adjustment speed with high power. The—idealized—compensation between the parameters is derived from the assumption that the long-term probability of not falling below a certain critical capital ratio be the same for all banks. We get the best fit to the data when we assume a critical capital ratio of just above the regulatory minimum of 8%.

When analyzing the adjustment of capital ratios, most of the empirical studies use a panel of firm data. Fama and French (1999) analyze a large panel of annual accounting and market data on non-financial firms. They conduct panel regressions of the change of one-year-ahead book and market leverage on the mismatch between a target leverage and the current leverage. They find a much lower adjustment rate than we do, but the difference is not surprising, for several reasons. First, banks typically have more liquid assets than non-financials, allowing them to adjust leverage more quickly. Second, Fama and French's target leverage is dynamic since it is specified as a firm-specific forecast, as opposed to the fixed target in our model. As such, mean reversion towards a *moving* target specifies the behavior in a much broader sense than that which we are testing for. Shyam-Sunder and Myers (1999) find similar results for a smaller sample of industrials.

Flannery and Rangan (2006) analyze a sample of US firms to answer the questions of whether a target capital level for firms exists and how quickly firms close the gap between the current and the target debt ratio. They find that there does exist a target level and that the firms close approximately one third of the gap in one year. Lööf (2003) compares the adjustment rate in the USA, the UK and Sweden. He concludes that the speed of adjustment is higher in the equity-based economies (USA, UK) than in Sweden.

Shrieves and Dahl (1992) and Heid et al. (2004) analyze the banks' capital and the banks' risk in a panel regression with data of yearly frequency. They find that banks try to maintain a certain capital buffer above the regulatory requirements. Merkl and Stolz (2006) explore the banks' capital buffers and their reaction to changes in the monetary policy. Using quarterly data of banks' regulatory capital buffer, they can show that the capital buffer of a bank influences its sensitivity to a tightening of the monetary policy. Banks with a low capital buffer shrink their lending more strongly than banks with a high capital buffer. Bikker and Metzemakers (2007) analyze if the banks' capital is procyclical. They reach the conclusion that there is little procyclicality.

Our study is related to the studies cited above. However, the relatively high frequency (monthly data vs. yearly or at best quarterly data in the literature) enables us to estimate each bank's adjustment rate separately. We can thus keep track of how the adjustment rate is individually chosen by banks and how it interacts with other characteristics. In contrast, classic panel analysis does not allow for individual adjustment rates.

The paper is structured as follows. In Section 2 we introduce the model, and in Section 3 we put forward hypotheses on the adjustment dynamics and on the bank characteristics that influence the dynamics. In Section 4, we present the data and give some descriptive statistics. Section 5 gives the results of the empirical study, and Section 6 concludes.

2 Model

Our model is a discrete-time version of Collin-Dufresne/Goldstein's (2001) partial-adjustment model. Unlike in the Merton (1974) model, the amount of debt is not exogenous, but depends on a target debt ratio and the ability of the management to adjust that ratio. The dynamics of our setup are exactly the same as in Collin-Dufresne/Goldstein (2001), yet we observe the process at discrete times only.

We assume that the bank's assets $\tilde{A}_t$ follow a geometric Brownian motion,

$$\frac{d\tilde{A}_t}{\tilde{A}_t} = \tilde{\mu}\, dt + \tilde{\sigma} dW_t, \tag{1}$$

where W_t is a standard Wiener process, $\tilde{\mu}$ is the drift, and $\tilde{\sigma}$ is the volatility of the asset return. The process is observed at discrete times of step size Δ, so we set $A_n := \tilde{A}_{n\Delta}$. Note that with $\mu := \tilde{\mu}\Delta$ one immediately gets $\mathbf{E}\left(\frac{A_{n+1}}{A_n}\right) = \exp(\mu)$ from the solution of (1) in exponential form. The bank's debt D_n increases in the course of time at the same constant expected rate μ. In addition to this deterministic (or planned) growth of debt, the bank's management tries to adjust the current debt ratio $L_n := D_n / A_n$, i.e. the complement of the capital ratio, towards a predefined target level $\bar{L}$. Following Collin-Dufresne and Goldstein (2001), we specify the dynamics of adjustment such that it will be convenient to switch to the logs of assets and debt:

$$\frac{D_{n+1}}{D_n} := \left(\frac{L_n}{\bar{L}}\right)^{-\kappa} \mathbf{E}\left(\frac{A_{n+1}}{A_n}\right) = \left(\frac{L_n}{\bar{L}}\right)^{-\kappa} \exp(\mu) \tag{2}$$

Taking the logs of Equations (1) and (2) and using lower-case letters to denote the log variables, we can rewrite (1) and (2) as

$$a_{n+1} = a_n + \mu + \varepsilon_{n+1}, \tag{3}$$

with i.i.d. $\varepsilon_{n+1} \sim N\left(0, \tilde{\sigma}^2 \Delta\right)$ and

$$d_{n+1} = d_n + \mu + \kappa \cdot \left(\overline{l} - l_n\right) = d_n + \mu - \kappa \cdot \left(d_n - \left(a_n + \overline{l}\right)\right). \tag{4}$$

The right part of (4) illustrates how the log debt "pursues" log assets: If log debt exceeds log assets minus a buffer of size $-\overline{l}$, its growth rate falls below the mean growth of log assets, and vice versa. The coefficient $\kappa \geq 0$ is a measure of the speed of adjustment: The higher the value of κ, the quicker debt is adjusted. If κ equals zero, then the bank management does not adjust its debt after random shocks of the asset value but follows a simple strategy of constantly raising debt at a deterministic rate.

Remark In Collin-Dufresne and Goldstein's counterpart to Equation (4), there is no μ on the right side, which, at first glance, decreases the debt growth compared to our notation. But notation is the only difference in the end: What Collin-Dufresne and Goldstein call a target leverage is a bit lower than mean leverage in the long run. In our notation, target and long-term mean leverage coincide.

Taking the difference of Equations (4) and (3) and using the definition $l_{n+1} = d_{n+1} - a_{n+1}$, we derive the following empirical implication: If the parameter κ is greater than zero, then the log debt ratio l_n follows a stationary autoregressive process of order 1 (AR(1)):

$$l_{n+1} = \alpha + \beta \cdot l_n + \eta_{n+1} \tag{5}$$

with Gaussian η_{n+1} and

$$\alpha = \kappa \cdot \overline{l} \tag{6}$$

$$\beta = 1 - \kappa. \tag{7}$$

The standard deviation of η_n equals the asset volatility $\sigma_\varepsilon := \tilde{\sigma}\sqrt{\Delta}$.

Again, this model fits *precisely* in Collin-Dufresne and Goldstein's framework: Our AR(1) process is the observation of an Ornstein-Uhlenbeck process at discrete times.

As banks' capital ratios tend to be low compared to those of non-financials, the log debt ratio approximately equals the negative capital ratio CR_n; using this approximation and Equations (5) to (7), we see that the bank management is assumed to partially adjust the capital ratio CR to the predefined $\overline{CR}$:

$$\Delta CR_{n+1} \approx \kappa \cdot \left(\overline{CR} - CR_n\right) + \varepsilon_{n+1} \tag{8}$$

Remark Equation (8) appears to be a natural starting point of modeling adjusted capital ratios. However, we do not use it by two reasons. First, Equation (8) generates nonsensical capital ratios above one with positive probability. Second, there is no simple stochastic differential equation for the capital ratio, the discrete-time observation of which would follow (8); the same applies to the asset value process.

Equation (5) is central for testing the model. If a bank manages to keep the capital ratio relatively constant at a predefined level $\overline{l}$, then the parameter κ is greater than zero and, according to Equation (7), the parameter β in the autoregressive process (5) is less than one. That is exactly the necessary condition for stationarity of the AR(1) process. In contrast, if the management is unable or unwilling to adjust the capital ratio, there will be no mean reversion and the bank's capital ratio is just a unit root process, i.e. $\beta = 1$ and, equivalently, $\kappa = 0$. Therefore, the question of whether the bank management adjusts the capital ratio to a predefined level is equivalent to testing the hypothesis $H_0 : \kappa = 0$, i.e. purely random behavior of the capital ratio, against hypothesis $H_1 : \kappa > 0$, i.e. adjustment of the capital ratio to a target level. In econometric terms, the test is a unit-root test for which we will use the Augmented Dickey-Fuller (ADF) test. If we can reject the null hypothesis according to which the capital ratio follows a unit root process, we find support for the claim that the capital ratio is stationary and tends to return to a predefined level.

Remark We estimate separate equations for each bank because we are interested in each bank's coefficients and do not impose the assumption of equal slope or adjustment coefficients as it is necessary with the classic dynamic panel estimator or with the pooled mean group estimator of Pesaran et al. (1999). We do not use the seemingly unrelated regression (SUR) procedure of Zellner (1962), because the number of banks is not small relative to the length of the time series.

Having established whether a certain bank adjusts its level of capital ratios to a predefined level, we estimate α, β and σ_η^2 with an ordinary least squares (OLS) regression. From their estimation and with the help of the delta method, we get point estimates of the relevant parameters κ and $\bar{l}$ and determine the asymptotic joint distribution of these estimates. From asymptotic theory we know that

$$\sqrt{T}\left(\begin{pmatrix}\hat{\alpha}\\ \hat{\beta}\end{pmatrix}-\begin{pmatrix}\alpha\\ \beta\end{pmatrix}\right)\xrightarrow{d} N\left(0,\Sigma\right). \tag{9}$$

Let $\theta=(\kappa,\bar{l})'$ be the parameter vector and let $\hat{\theta}=\left(1-\hat{\beta},\hat{\alpha}/(1-\hat{\beta})\right)'$ be its estimate. The following expression is then asymptotically normally distributed:

$$\sqrt{T}\left(\hat{\theta}-\theta\right)\xrightarrow{d} N\left(0;\Omega\right) \tag{10}$$

with

$$\Omega=\begin{pmatrix}0 & -1\\ \frac{1}{1-\beta} & \frac{\alpha}{(1-\beta)^2}\end{pmatrix}\Sigma\begin{pmatrix}0 & \frac{1}{1-\beta}\\ -1 & \frac{\alpha}{(1-\beta)^2}\end{pmatrix} \tag{11}$$

Later, we will use the results of (10) and (11) to determine the cross sectional distributions of the point estimates $\hat{\theta}$ and their standard deviations.

3 Hypotheses

Banks can lower the capital ratio in two ways. They can extend their business volume or they can reduce capital, for instance by repurchasing their own shares or by paying large dividends. Correspondingly, banks can increase their capital ratio by shrinking the business volume or by raising additional capital.

In the empirical study, we analyze the behavior of the bank management concerning the capital ratio. We formulate three different hypotheses.

From the ability to take action as described above we derive our first hypothesis: Banks which are active in highly liquid markets, such as investment banks, can extend and shrink their business volume more easily than traditional commercial banks, which mainly hold illiquid loans. Banks with liquid assets are therefore more likely to adjust their capital ratio than other banks. We measure the degree of the assets' liquidity by the ratio *market*, which corresponds to the market price risk over risk-weighted assets, including market price risk; i.e. *market* is trading book risk as a share of the entire risk of the bank. We break down our sample of banks into three subsamples of equal size. The first subsample consists of the banks with the lowest values of the variable *market*, the third subsample comprises the banks with the highest values of the variable *market*, i.e. the banks with a large portion of trading book risk. If our hypothesis is true, the share of banks that adjust their capital ratio will be higher in the third subsample than in the other two subsamples, ie we hypothesize:

Hypothesis 1: *The more liquid a bank's assets (here: the higher the share of the trading book), the more likely is the bank to adjust its capital ratio.*

Not only the ability to adjust the capital ratio matters, but the incentive to actively control the capital ratio is important as well. Our second hypothesis is based on the assumptions that, first, return on equity, or ROE (without adjustment for risk) is still an important performance measure and, second, that there is a close relationship between regulatory capital and balance sheet capital, which the ROE is based on. If ROE is the common measure of profit, banks with a strong orientation towards shareholder value are more likely to keep the capital ratio in relatively narrow intervals. Ceteris paribus, a decrease in the capital ratio seems desirable, as it increases the ROE, albeit at a rising cost of harming their external rating. The economic literature also provides rational explanations for low equity ratios: First, the pecking order hypothesis (Myers and Majluf, 1984) states that information asymmetries between bank management and outside investors induce a preference order from internal capital via debt to equity financing. Yet, second, internal capital (as well as equity) has its own shortcomings. It bears the risk of being misused for the private benefit of bank managers (Jensen, 1986) but also the risk of bank managers renegotiating with equity holders for extra rents (Diamond and Rajan, 2000). The effect of these agency problems can be partially neutralized by a low capital ratio. Third, raising equity generates significantly higher transaction costs than raising public debt (Lee et al., 1996). To sum up, there are several reasons why a bank that is disciplined by the capital market should keep its capital ratio in a narrow range. In contrast, public sector banks have excellent external ratings due to explicit state guarantees until July 2005, whereas maximum profit is not their primary business objective. Therefore, we formulate the following hypothesis:

Hypothesis 2: *Private banks are more likely to adjust their capital ratio than public sector banks.*

Our third hypothesis is about the probability that a bank's capital ratio will drop below the regulatory limit, called *probability of insufficient regulatory capital* ($PIRC$). Out hypothesis is that this probability does not vary much across banks, because there seem to be compensating effects: first, banks with a low target capital ratio tend to invest in assets of low volatility; second, those banks seem to be able to adjust their capital ratios quickly. There may be wide differences across banks concerning target capital ratios, adjustment rates and asset volatilities; however, the variation in the probabilities of failing to meet the regulatory requirements is assumed to be much lower. Furthermore, we assume that it is the *regulatory* limit of capital that motivates banks to adjust their capital ratios, contrasting with the hypothesis that *zero* capital is the relevant threshold banks care for. The alternative hypothesis would be that the probability of zero capital does not vary much across banks. We denote the state of zero capital by *technical insolvency*; the corresponding *probability of technical insolvency* is denoted by $POTI$.

$PIRC$, the probability of failing the regulatory requirements, depends on three strategic parameters: the target debt ratio, the asset volatility, and the adjustment rate. The higher the target debt ratio, the more volatile the assets or the lower the adjustment rate, the more likely it is that regulatory failure will occur. To keep this probability constant in the event of increased asset volatility, one has to decrease the target debt ratio or to increase the adjustment rate. We run the following cross-sectional regression to test whether this compensatory behavior really exists:

$$\bar{l}_i - \bar{\bar{l}} = \beta_1 \left(\kappa_i - \bar{\kappa} \right) + \beta_2 \left(\sigma_{\varepsilon,i} - \bar{\sigma}_\varepsilon \right) + \nu_i, \tag{12}$$

where $\bar{\bar{l}}$, $\bar{\kappa}$, and $\bar{\sigma}_\varepsilon$ denote averages over the sample of banks. If there is relatively little fluctuation in the probability of regulatory failure, one will see compensatory effects leading to a positive sign for β_1 and a negative sign for β_2. Note that we neither associate causality with putting the target debt ratio on the left side of (12) nor do we hope to find something out about causality this way.

We more specifically investigate whether the relationship between the three strategic parameters can be explained by a single $PIRC$ that applies to all banks. As $PIRC$ is a function of the triple $\left(\bar{l}, \kappa, \sigma_\varepsilon\right)$, a unique $PIRC$ establishes a deterministic relationship between these parameters that appears as a curved surface in the space of points $\left(\bar{l}, \kappa, \sigma_\varepsilon\right)$. No bank will fulfill the relationship perfectly; some banks will not at all. In our context, "explaining the relationship" just means that the 3-dimensional scatterplot of the banks' observed parameter choices is close to the curved surface.

As we consider a bank's parameter triplet as a strategic long-term choice, the definition of $PIRC$ is correspondingly chosen as the probability of falling below the minimal regulatory capital under the *stationary distribution*. Intuitively, that is the distribution after a long time from now. Mathematically, we require strict stationarity, meaning that the process $(l_n)_{n\in\mathbb{N}}$ follows a distribution that is independent of time n. The AR(1) process of (5) with Gaussian increments is strictly stationary if and only if

$$l_0 \sim N\left(\bar{l}, \frac{\sigma_\varepsilon^2}{1-\beta^2}\right), \tag{13}$$

for which β must be smaller than one. Even if the distribution of l_0 is not identical with (13), it will be approximated by that of l_n for large values of n under mild assumptions.

A certain regulatory capital ratio must never fall below some critical threshold CR^*; the own-funds ratio, for instance, is always to be kept above 8%. It means for the log leverage ratio that $l_n \leq l^*$ with $l^* = \ln\left(1-CR^*\right) \approx -0.08338$ must hold for all n. We fix a certain n and define $PIRC$ as the probability of the event $\left\{l_n > l^*\right\}$. With (13) and strict stationarity, we obtain a probability that is independent of time n:

$$PIRC := \Pr\left(l_n > l^*\right) = \Phi\left(\frac{\sqrt{1-\beta^2}}{\sigma_\varepsilon}\left(\bar{l} - l^*\right)\right), \tag{14}$$

where Φ denotes the standard normal cumulative distribution function. Note that $PIRC$ defined this way is not the probability of migrating from $l_n < l^*$ to $l_{n+1} \geq l^*$ but equal to the expected share of the sojourn[2] time that l_n will spend above l^* or, equivalently, that the capital ratio will spend below CR^*.

Our assumption that $PIRC$ be the same for all banks establishes a deterministic relationship between β (being equal to $1-\kappa$), σ, and $\overline{l}$. To make it comparable to (12), we denote by Φ^{-1} the standard normal quantile function and transform (14) to an equation that takes the role of a regression forecast:

$$\overline{l} = l^* + \Phi^{-1}\left(PIRC\right)\frac{\sigma_\varepsilon}{\sqrt{1-\beta^2}} \ . \tag{15}$$

The full nonlinear regression model is obtained by adding a noise term χ_i:

$$\overline{l}_i = l^* + \Phi^{-1}\left(PIRC\right)\frac{\sigma_{\varepsilon,i}}{\sqrt{1-\beta_i^2}} + \chi_i \, . \tag{16}$$

Associating the errors with the targets $\overline{l}_i$ is somewhat arbitrary. We also could have rearranged (15) with σ_ε or β on the left-hand side or even stay with (14), adding errors to $PIRC$. While the last option would rule out a comparison with the linear model, we prefer $\overline{l}_i$ on the left-hand side of (15) since only this version has a plain additive constant (l^*) on the right-hand side, which makes it easier to be compared with the linear model.

Similar to the $PIRC$, we define the *probability of technical insolvency* ($POTI$) under the stationary distribution as the probability of negative capital at a fixed point of time n

$$POTI := \Pr\left(l_n > 0\right) = \Phi\left(\frac{\sqrt{1-\beta^2}}{\sigma_\varepsilon}\overline{l}\right) \tag{17}$$

and notice that $POTI$ should be interpreted with care: It is the mean share of the sojourn time the bank "spends in technical insolvency", which is unrealistic in that a bank would hardly

[2] Sojourn time: the total of periods that a process spends in some state or range of values.

return from this state. Yet our definition of $POTI$ is closely related to the probability that the bank will lose all capital in the next period conditional on positive capital today. The nonlinear regression corresponding to the assumption of a unique $POTI$ is

$$\overline{l}_i = \Phi^{-1}\left(POTI\right)\frac{\sigma_{\varepsilon,i}}{\sqrt{1-\beta_i^2}} + \chi_i \,. \tag{18}$$

Returning to the calibration of $PIRC$, we minimize the squared errors in (16) and compare its explanatory power with that of the linear regression. Note that (16) has only one free parameter, as opposed to three coefficients of the linear regression; equal power of both models would thus be evidence in favor of the nonlinear model. We compare the models with the Schwarz information criterion, which balances goodness of fit and simplicity.

We finally optimize both the critical threshold l^* and $PIRC$ to achieve the least squares in (16). In doing so, we can measure whether the data possibly fit better with the hypothesis of a unique $POTI$ rather than that of a unique $PIRC$. If the $POTI$ picture were to fit nicely, the calibration should end at an implied threshold l^* close to zero rather than close to $\ln\left(1-8\%\right)$, for the example of the own-funds ratio.

To sum up, we hypothesize:

Hypothesis 3: *There are compensatory effects between the three strategic parameters, ie the bank's target capital ratio, its adjustment speed and its asset volatility.*

4 Data

Our data consist of monthly observations of regulatory capital and risk-weighted assets for a subset of large German banks. Data on all German banks are available. However, we confine ourselves to a subset of these banks, because small banks show very little variation in their capital ratios most of the time but substantial jumps at the end of the year when retained earnings or losses abruptly change the capital ratio. To mitigate the problem of jumping capital ratios, we consider only those banks which meet the following two criteria:

1. The bank reports consolidated figures for regulatory capital and risk-weighted assets.
2. Average Risk-weighted assets exceed one billion euros.

In addition, we only include banks for which there are at least fifty monthly observations. After applying the criteria, the whole sample consists of 81 banks. 25 of these banks belong to the first pillar of the German banking system, the private banks; 32 banks are part of the public sector, which is composed of the savings banks and the *Landesbanken*, and 15 banks belong to the cooperative sector. Nine banks cannot be assigned to any of the above three sectors. As the sample is biased towards the large banks, it is not representative of the German banking sector.

For each bank and each point in time we calculate three different capital ratios: the Tier 1 ratio, the total-capital ratio, and the own-funds ratio. The first one—the *Tier 1 ratio*—is Tier 1 capital over risk-weighted assets. Risk-weighted assets are obtained by allocating the assets of the banking book to different risk buckets. The Basel Committee on Banking Supervision (1988) implicitly stipulates that the Tier 1 ratio exceeds 4 percent. The second and widest-spread ratio is the *total-capital ratio*. It is defined as total capital over risk-weighted assets. In addition to the Tier 1 capital, the total capital includes supplementary capital, such as parts of undisclosed reserves and subordinated debt with a long maturity. The Basel Committee on Banking Supervision (1988) fixes 8 percent as the lower limit for the total-capital ratio. Among the three capital ratios considered, the own-funds ratio is based on the most comprehensive definition of capital and assets. In addition to total capital, the own funds comprises subordinated debt with a relatively short residual term and unrealized profits in the trading book. The denominator consists of the risk-weighted assets in the banking book and, additionally, of those in the trading book. Also the own-funds ratio must not fall below 8 percent. Note that both numerator and denominator differ from the ones of the total capital ratio so that the own funds ratio does not need to be greater than the total capital ratio.

The German regulatory authorities have monthly data on equity ratios from October 1998 to December 2006, which means that we have a maximum of 99 observations for one bank.

In our opinion, the relatively high data frequency (monthly data vs. at best quarterly data) is a real asset. To be fair, when estimating parameters of processes with low adjustment rate, an increase in the data frequency is of minor use. However, the adjustment speed in our case is relatively high (the median is 20% per month, see Table) and, therefore, the relatively high data frequency makes a difference.

In Table 1 we give summary statistics of the three negative log debt ratios (which approximately correspond to the capital ratios) and the trading book risk, given as a percentage of total bank risk. Note that there are two dimensions, the cross-sectional dimension consisting of 81 units (banks) and the time dimension consisting of up to 99 observations.

[Insert Table 1 about here]

We see that the different capital ratios (approximated by the negative log debt ratios) are well above the lower limit of 4% and 8%, respectively; this is true even for the 10% lowest ratios. The share of market risk in comparison to the total risk is relatively low; on average, the trading book risk accounts for less than six percent of total risk.

For each bank, we calculate the time series mean of each of the four variables, ie the three target capital ratios (here: the negative of the log debt ratio) and the trading book risk (here: the variable *market*). The results are displayed in Table 2.

[Insert Table 2 about here]

The total variance of a variable (as displayed by standard deviations in the fourth column of Table 1) is the sum of the serial variation around the banks' means and the variation of the banks' means itself (as displayed by standard deviations in the fourth column of Table 2). For instance, as the total variance of the negative log debt ratio (own funds) is 12.98E–04 (= $(3.60\%)^2$) and the variation of the banks' time series means (own funds) is 6.57E–04 (=

(2.56%)²), the variation of the negative log debt ratio (own funds) around the banks' means must then be 6.41E–04. For this variable, about half of the total variation is due to the cross-sectional differences between the banks (51%); the time series variation accounts for about 49% of the total variation. This almost equal splitting into cross-sectional and serial variation can be found for the other log debt ratios as well; for the variable *market* the cross-sectional variation is dominant.

5 Results

Our first step is to identify the banks which really adjust their capital ratios. The testing procedure allows us to split our sample into two parts: the banks for whose capital ratio we can reject the hypothesis of a unit root process and the banks for whose capital ratio we cannot reject this hypothesis. In Table 3, we report the number of banks for which we are able to reject the null hypothesis of a unit root process.[3]

[Insert Table 3 about here]

We see that we can reject the hypothesis of a unit root process, i.e. of unadjusted capital ratios, in 31 out of 81 cases for the own-funds ratio at the 10% level. It is not justified to conclude that the other 50 banks do not adjust their capital ratio. Rather, it may be that there is a mean reversion, but that the mean reversion is not strong enough to make the test reject the hypothesis of a unit root process. For the following analyses, we split the sample of 81 banks into those banks for which we can reject the null hypothesis of a unit root process at the 10%-level (adjusting banks) and into the rest of the banks. Depending on the capital ratio under consideration, the sample comprises 17 (Tier 1 ratio), 27 (total-capital ratio), or 31 banks (own funds ratio).

[3] Im et al. (2003) suggest a unit root test for panel data. However, this test does not provide any guidance of how many and which banks follow a unit root process. Therefore we omit this test and confine ourselves to the standard unit root test for single banks.

[Insert Table 4 about here]

Table 4 gives an overview of the estimated parameters, i.e. the adjustment coefficient κ, the target debt ratio $\overline{l}$ and the asset volatility σ_{ε}. We include only those banks for which we can reject the null hypothesis of a unit root process at the 10% level. To obtain the estimates, we run regression (5) for each bank; then we calculate the parameters according to the Equations (6) and (7). The standard errors in the last three columns are obtained from Equation (11).

We see that the adjustment coefficients vary greatly across banks, but the adjustment coefficient is significantly different from zero for most of the banks in the subsamples. For the own funds ratio we observe a median adjustment coefficient of 20.18% per month. This value means that the average bank closes the gap between the current and the target own funds ratio by some 20 percent per month. If there were no further random shocks, the bank would halve the gap in a bit more than three months. The adjustment coefficients we find in our data are significantly higher than the ones reported in the literature. Using market data instead of regulatory data and non-financial firms instead of banks, Flannery and Rangan (2006), for instance, estimate that one third of the gap (per year) is closed. By contrast, adjustment coefficients of 20% per month, as we find, mean that more than 90% of the gap is closed in one year. The differences in the results are not so surprising, when we keep in mind that large banks, which have direct access to the capital market, can easily adjust their capital ratios.

As stated before, the negative log target debt ratio is approximately equal to the capital ratio and, in the following, we will keep this interpretation in mind. We see that the target Tier 1 capital ratio for the median bank is about 8 percent and the median target values for the total capital and the own-funds ratio are a bit less than 11 percent. Seemingly, the target capital buffer of the median bank is about 4 percentage points for the Tier 1 ratio and 3 percentage points for total-capital ratio and own funds ratio.

The implicit asset volatility is a bit more than one-half percent per month or just above 2% per year. Using the Tier 1 ratio, we get slightly lower estimates for the asset volatility than using the two other capital ratios.

Having now split up the sample into adjusting and non-adjusting banks, we deal with our hypotheses. Our first hypothesis is that banks with a large share of liquid assets can more easily adjust their capital ratio to a target level. To check this hypothesis we break down our sample of 81 banks into three subsamples of 27 banks each. As stated before, the first subsample contains the 27 banks with the most illiquid assets (as measured by the variable *market*, i.e. the trading book risk as a share of the entire risk), the second and third subsample contain the banks with medium and highly liquid assets, respectively.

[Insert Table 5 about here]

Table 5 shows that the number of banks with unit root process rejected for is the highest for the third of banks with the most liquid assets. Applying Pearson's χ^2-test of equal numbers in the three thirds, we can reject this hypothesis for the own funds ratio ($\chi^2\left(5.12,2\right) = 7.7\%$). It is not surprising that we find the most supporting result for the own-funds ratio because market risk is a direct component of the own-funds ratio.

Table 5 and the χ^2-test confirm our first hypothesis. But the result should be handled with care as it may be driven by hidden covariates. For instance, the sector affiliation may be such a hidden covariate: private banks tend to have a high share of market risk and—at the same time—private banks tend to adjust their capital ratio (see Table 6).

Our second hypothesis is that privately owned banks adjust their capital ratio more rapidly than public sector banks. In Table 6, we display the results of the Augmented Dickey-Fuller (ADF) Test for the own-funds ratio broken down into the different banking sectors.

[Insert Table 6 about here]

Whereas it is possible to reject the unit root process hypothesis for 64% of the private banks (16 out of 25 private banks), the corresponding share for the public sector banks is 13% (4 out of 32 public sector banks). This result supports our second hypothesis, i.e. that privately owned banks are more likely to adjust their capital ratio than public sector banks. The χ^2 test of equality of all four shares is rejected at the 1% level ($\chi^2(17.16,3) = 0.1\%$). For the other two ratio, the results are similar.

Our third hypothesis is about compensatory effects with respect to the three strategic variables target debt ratio, adjustment rate and asset volatility. To analyze these effects we run regression (12) for the banks for which we can reject the unit root hypothesis at the 10%-level (We removed one outlying bank because its estimated target log debt ratio was above $\ln(1-8\%)$ for the own funds ratio and the total-capital ratio).

[Insert Table 7 about here]

For the own-funds ratio, we find compensatory behavior concerning the three strategic variables: Banks with high target log debt ratios (i.e., low capital) tend to have high adjustment rates and low asset volatilities. For the Tier 1 ratio and the total-capital ratio the coefficient for the adjustment rate has the wrong sign. The negative coefficients of the asset volatility confirm the results of Gropp and Heider (2007). They do cross-sectional regressions of bank leverage and find a negative relationship between leverage and a risk measure related to asset volatility. Adjustment rates are not analyzed, however.

In order to see if a unique $PIRC$ being striven for by all banks can explain the compensatory effects in the strategic variables, we estimate Equation (16) and (18) for the own-funds ratio. The sample is again restricted to the 31 banks with rejected unit root tests, except for the one outlier. In Table 8, we show the goodness of fit and the implicit probability of falling the capital requirements.

[Insert Table 8 about here]

First, only the $PIRC$ is calibrated towards least squared errors; the critical own-funds ratio CR^* is fixed at the regulatory level of 8%, which corresponds to $l^* = -0.0834$. We obtain an implicit stationary probability of insufficient capital of 0.93%, which means that, on average, a bank lacks regulatory capital 0.93% of the time. Note that we observed actions of rather healthy banks. For that, our implicit $PIRC$ is presumably higher than its physical counterpart since bank managers, facing a big danger of regulatory intervention, will put more effort into maintaining a proper capital ratio than linear mean reversion presumes.

Second, we optimize with respect to both the $PIRC$ and the threshold l^* using least-squares. The corresponding best-fitting critical own-funds ratio CR^* is slightly above the regulatory 8%, whereas the implied $PIRC$ more than doubles due to its convexity in l^*. It is this strong sensitivity to l^* that suggests not to interpret the level of the best-fitting $PIRC$ directly. We put emphasis on the size of the threshold and on the ability to explain the interaction of the strategic parameters by a single background factor.

Third, to check whether the implied threshold of the second analysis is robust, we estimate (18) by calibrating the $POTI$. The model does not fit at all, and the implicit $POTI$ is physically zero.

Fourth, we compare the explanatory power of the models by the Schwarz information criterion (SIC); the lower its value, the better the model. The SIC rewards both for small errors and for the parsimonious use of parameters. According to the SIC, the nonlinear model based on $CR^* = 8\%$ fits best, while the two-parameter nonlinear model and the linear model are nearly on a par. Figure 1 summarizes the relationship of the models' SIC. We let the (non-optimized) capital threshold take values from 0% to 16% and plot the SIC of the corresponding best-fitting nonlinear model. The SIC of the linear model gives a flat line, as it does not depend on l^*; the two-parameter nonlinear model is represented by a single point. The graph confirms the mild advantage of the one-parameter nonlinear model above the linear one and sharply disqualifies the zero-capital model.

[Insert Figure 1 about here]

In addition, we apply a log-likelihood test to see whether restricting l^* to –0.083 reduces the explanatory power, compared with optimizing l^*. As Figure 1 already suggests, the null hypotheses (no loss of explanation) is not rejected, contrasting the test of $l^* = 0$ against optimized l^* with a clear rejection.

As a supplementary analysis, Figure 2 makes clear that the nonlinearity of our model is substantial. According to (15), the surface maps relevant values of σ_ε and κ to the predicted target log debt ratio.

[Insert Figure 2 about here]

To sum up, we state that the "regulatory threshold story" fits better with our data than a linear model and much better than the "technical insolvency story".

6 Conclusion

The aim of the paper is to obtain an insight into how German banks' management adjusts capital ratios. Using relatively high-frequency data, we can analyze the capital ratio for each bank separately. It turns out that the capital ratio adjustment in private banks and banks with liquid assets tends to be more pronounced. Banks seem to choose a mix of adjustment rate, asset volatility and target debt ratio so as to maintain a certain probability to fulfill the regulatory requirements on the own-funds ratio.

In our model, the bank management adjusts the debt (and thereby the equity) to maintain a certain capital ratio. In reality, however, the bank management can as well adjust the capital ratio by increasing or decreasing the business volume. Further research is needed to distinguish which channel the bank management uses to adjust the capital ratio.

Our findings add another drawback to the Merton model and its application to estimate the banks' probabilities of default. The Merton model assumes that the banks' capital ratios are only driven by random shocks. However, we find evidence that part of the capital ratios' dynamics are due to management behavior. Future research has to deal with the question of how to incorporate the management behavior into a model of bank failure.

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Variable	Observa-tions	Mean	Stand. dev.	10% low-est	Median	10% largest
Negative log debt ratio (Tier 1 capital)	7081	8.90%	7.25%	5.46%	7.44%	12.26%
Negative log debt ratio (total capital)	7081	13.52%	11.23%	9.64%	11.58%	16.72%
Negative log debt ratio (own funds)	7081	12.02%	3.60%	9.41%	11.13%	15.26%
Share of market risk (market)	7081	5.54%	10.05%	0.00%	1.81%	14.50%

Table 1: Summary statistics of negative log debt ratios and of the variable *market*, measured by trading book risk over total bank risk. Please note that the negative log debt ratio is approximately equal to the capital ratio.

Variable	Ob-servations	Mean	Stand. dev.	10% low-est	Median	10% largest
Negative Log debt ratio (Tier 1 capital)	81	8.93%	5.71%	5.97%	7.53%	12.61%
Negative Log debt ratio (total capital)	81	13.55%	7.93%	10.09%	11.77%	15.82%
Negative Log debt ratio (own funds)	81	12.03%	2.56%	9.98%	11.38%	15.20%
Share of market risk (*market*)	81	5.34%	9.45%	0.11%	1.60%	12.79%

Table 2: Summary statistics of the time series means for the relevant variables. Please note that the negative log debt ratio is approximately equal to the capital ratio.

Significance level	Number of banks	Number of banks with unit root process rejected for		
		Tier 1 ratio	Total-capital r.	Own-funds r.
1%	81	6	14	12
5%	81	12	22	24
10%	81	17	27	31

Table 3: Summary results of the Augmented Dickey-Fuller (ADF) Test for the three different capital ratios. We include a constant but no trend term in the estimation. The number of lags is determined with the Schwarz information criterion.

Parameter	Capital ratio	Number of banks	Estimated coefficient			Estimated standard errors		
			10% lowest	Median	10% largest	10% lowest	Median	10% largest
Adjustment coefficient (per month)	Tier 1	17	7.16%	19.48%	48.89%	3.27%	7.65%	15.57%
	total-cap.	27	12.08%	24.30%	54.05%	4.57%	8.08%	20.37%
	own-funds	31	9.47%	20.18%	51.09%	4.17%	7.80%	15.24%
Negative log target debt ratio	Tier 1	17	5.67%	8.08%	12.66%	0.07%	0.31%	1.68%
	total-cap.	27	9.69%	10.87%	15.87%	0.12%	0.30%	0.72%
	own-funds	31	9.82%	10.55%	13.29%	0.12%	0.27%	0.65%
Asset volatility (per month)	Tier 1	17	0.12%	0.42%	2.01%	-	-	-
	total-cap.	27	0.24%	0.73%	2.39%	-	-	-
	own funds	31	0.25%	0.59%	1.47%	-	-	-

Table 4: Summary statistics of the relevant estimated parameters. Please note that the negative log debt ratio is approximately equal to the capital ratio.

Liquidity of assets (*market*)	Number of banks	Number of banks with unit root process rejected for (10%-level)		
		Tier 1 ratio	total-capital ratio	own-funds ratio
Bottom third	27	4	8	8
Medium third	27	6	8	8
Top third	27	7	11	15
All	81	17	27	31

Table 5: [Hypothesis 1] Number of banks with unit root process rejected for at the 10% level, broken down into three subsamples according to the liquidity of the assets. The liquidity of a bank's assets is measured by the variable *market*, denoting the trading book risk as a share of the entire risk of the bank.

Sector	Private	Public sector	Cooperative	Other	All
Not significant	9	28	9	4	50
Significant at the 10% level	16	4	6	5	31
All	25	32	15	9	81
Share of significant banks	64%	13%	40%	56%	38%

Table 6: [Hypothesis 2] Summary results of the ADF Test for the own-funds ratio, broken down into the banking sectors.

Explanatory variables	Tier 1 ratio	Total-capital r.	Own-funds r.
Adjustment rate	-0.067	-0.014	0.047
	(-4.10)***	(-0.75)	(3.67)***
Asset volatility	-0.620	-0.549	-3.030
	(-8.56)***	(-8.86)***	(-7.76)***
R^2	0.8829	0.7865	0.6938
Observations	17	26	30

Table 7: [Hypothesis 3] Results for the regression (12). Dependent variables: log target debt ratios. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. *t*-values in brackets. Outliers, i.e. log (target debt ratio) > –0.083 (for total-capital ratio and own-funds ratio), are removed.

Model	Implicit/fixed threshold (reported: CR^*)	Implicit probability	Errors ($\sqrt{MSE}$, mean)	Schwarz Information Criterion	R^2
Regulatory threshold (→ $PIRC$)	fixed at 8%	0.93%	1.20% –0.18%	–8.701	64.7%
Optimized threshold	calibrated to 8.52%	2.14%	1.16% 0	–8.659	67.1%
Threshold zero (→ $POTI$)	fixed at 0%	0.00%	5.04% –2.79%	–5.828	–525.0%
Linear model (see Table 7)	—	—	1.10% 0	–8.651	69.4%

Table 8: [Hypothesis 3] Results for the estimation of the nonlinear equations (16) and (18) and corresponding results of the linear regression (12), all based on own-funds ratios. Dependent variable of all models: estimated target log debt ratios. The nonlinear model is calibrated to least squared errors (1) by *PIRC* only (capital threshold fixed at 8%); (2) both by *PIRC* and capital threshold CR^*, and (3) by the *POTI* only (threshold fixed at 0%). Errors in Line 2 and 4 have nonzero mean for lack of a free constant. The sample is restricted to observations with rejected unit root hypothesis at a significance level of 10%, after elimination of one outlier with an estimated target capital ratio far less than 8%.

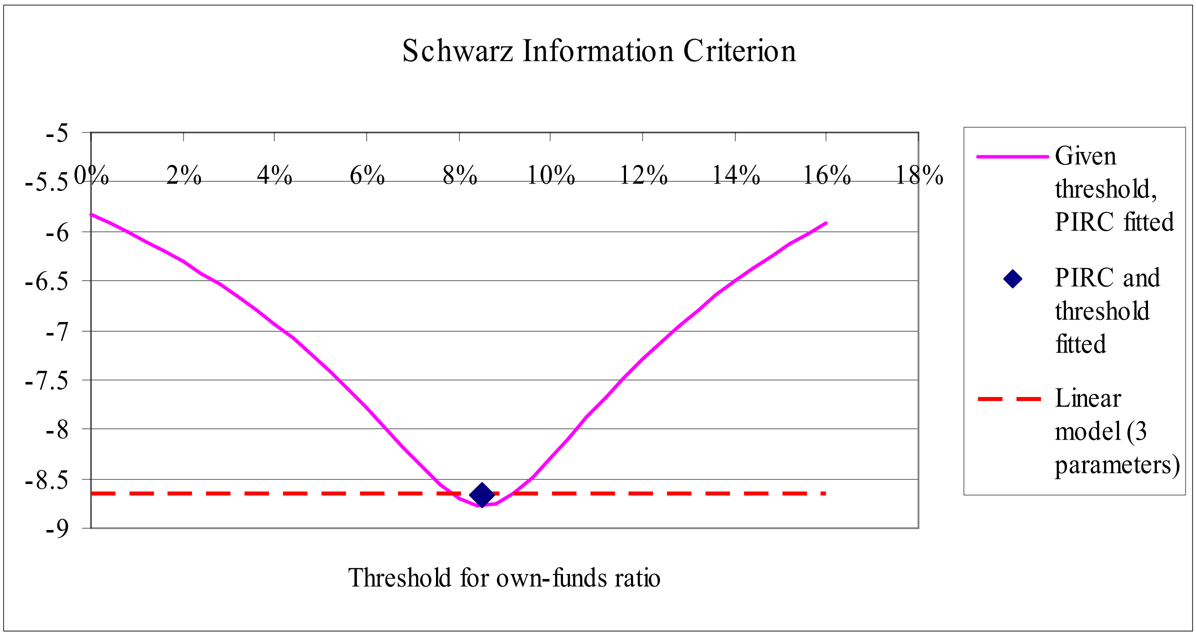

Figure 1: [Hypothesis 3] Schwarz information criterion (SIC) for the linear model and different versions of the nonlinear model. According to given critical capital thresholds (on the abscissa), the solid line plots the SIC value after optimization of the probability to fail the given threshold; the left edge corresponds to the zero-capital model. Diamond: SIC of the nonlinear model when also the threshold is optimized. Dotted line: SIC of the linear model (unaffected by threshold).

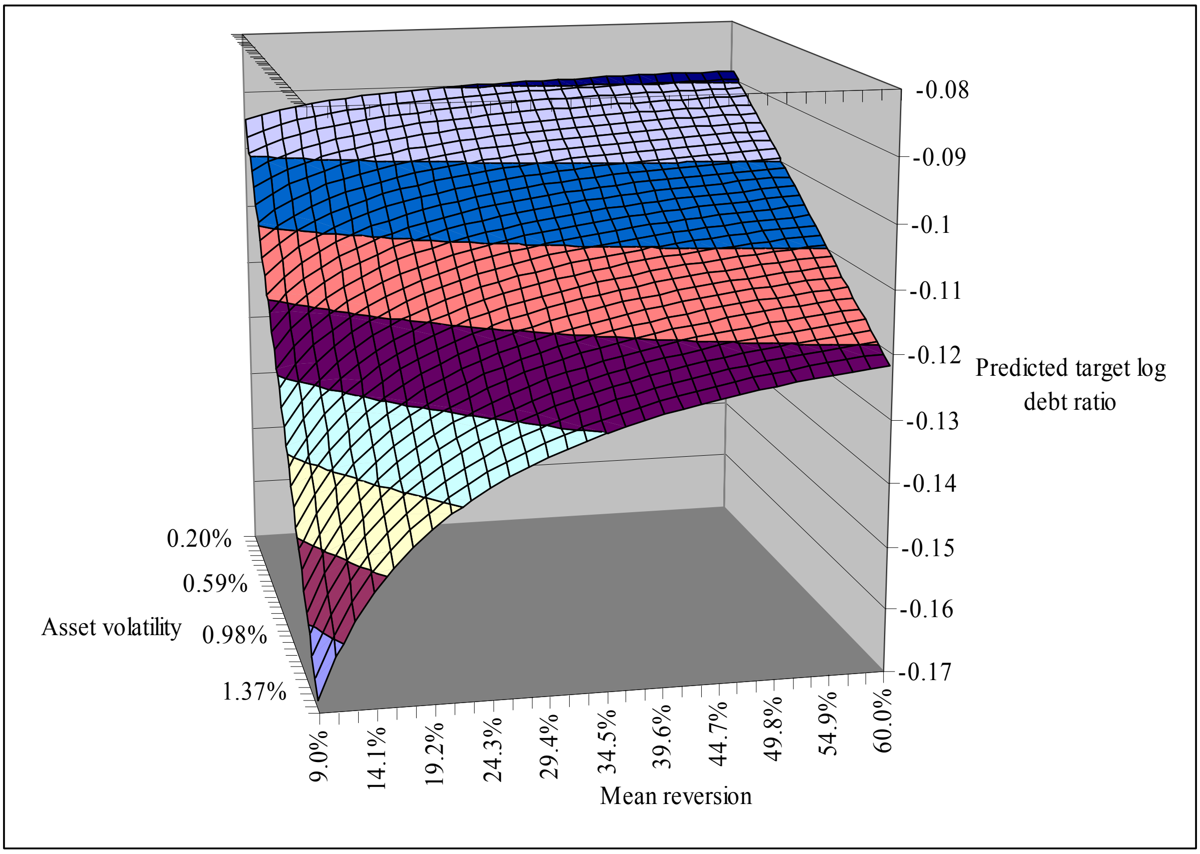

Figure 2: [Hypothesis 3] Target log debt ratio as a function of asset volatility and mean reversion, according to the estimated nonlinear regression forecast (15); estimation from Table 8, Line 2: capital threshold at 8%, *PIRC* = 0.93%; both variables between their lower and upper deciles of the sample.