Universidad de Navarra

Facultad de Ciencias Económicas y Empresariales

Working Paper nº 06/12

Non-linear Dynamics in Discretionary Accruals: An Analysis of Bank Loan-Loss Provisions

Marina Balboa
University of Alicante

Germán López-Espinosa
University of Navarra

Antonio Rubia
University of Alicante

Non-linear Dynamics in Discretionary Accruals: An Analysis of Bank Loan-Loss Provisions

Marina Balboa, Germán López-Espinosa, Antonio Rubia

Working Paper No.06/12
October 2012

ABSTRACT

Several studies have characterized the relation between discretionary accruals and earnings before-taxes to test for the existence of earnings smoothing behaviors. In this paper, we argue that the characteristic response of accruals to earnings is not linear, as the literature has shown. Instead, it is likely to be driven by non-linear patterns since both the incentives to manipulate earnings and the practical way to do so depend, in part, on the relative size of earnings. Using a sample of 9,442 US banks in the period 1999-2008, this paper shows that bank managers tend to use provisions as a smoothing devise when earnings are substantial ("cookie-jar" strategies), engage in earnings-decreasing strategies when losses are relatively large ("big-bath" accounting) and, most of the time, use provisions as an earnings-increasing tool. Hence, it is shown that nonlinear specifications are more informative with regard to the different strategies employed to manipulate earnings.

Marina Balboa
Faculty of Economics
University of Alicante
marina.balboa@ua.es

Germán López-Espinosa
School of Economics and Business Administration
University of Navarra
glespinosa@unav.es

Antonio Rubia
Faculty of Economics
University of Alicante
antonio.rubia@ua.es

Non-linear Dynamics in Discretionary Accruals: An Analysis of Bank Loan-Loss Provisions

Marina Balboa
Faculty of Economics
University of Alicante
Apdo. correos 99, 03080 Alicante (Spain)
Phone: +34 965903621
Fax: +34 965903621
marina.balboa@ua.es

Germán López-Espinosa
Faculty of Economics
University of Navarra
31080 Pamplona (Spain)
Phone: +34 948425600, ext.3165
Fax: +34 948425626
glespinosa@unav.es

Antonio Rubia
Faculty of Economics
University of Alicante
Apdo. correos 99, 03080 Alicante (Spain)
Phone: +34 965903621
Fax: +34 965903621
antonio.rubia@ua.es

Abstract

Several studies have characterized the relation between discretionary accruals and earnings before-taxes to test for the existence of earnings smoothing behaviors. In this paper, we argue that the characteristic response of accruals to earnings is not linear, as the literature has shown. Instead, it is likely to be driven by non-linear patterns since both the incentives to manipulate earnings and the practical way to do so depend, in part, on the relative size of earnings. Using a sample of 9,442 US banks in the period 1999-2008, this paper shows that bank managers tend to use provisions as a smoothing devise when earnings are substantial ("cookie-jar" strategies), engage in earnings-decreasing strategies when losses are relatively large ("big-bath" accounting) and, most of the time, use provisions as an earnings-increasing tool. Hence, it is shown that non-linear specifications are more informative with regard to the different strategies employed to manipulate earnings.

Key words: Earnings management; Income smoothing; Multi-way cluster; Panel data; Threshold regression.
JEL Classification: C21, C22, C23, G21, M41.

1. Introduction

Among the different forms of managerial manipulation framed into the category of earnings management, income smoothing has attracted considerable attention from regulators and academics. The central hypothesis is that managers have incentives to artificially reduce the variability of reported earnings relative to economic earnings by using the flexibility provided by the accounting standards, increasing (reducing) discretionary accruals when the firm generates large (small) operating income. The incentives to carry out these practices are manifold and include the desire to influence the risk perception of market agents, to maintain artificially favorable dividend policies, and to attain personal objectives within the context of the agency and compensation theories; see Brady and Sinkey (1988) and Healy and Wahlen (1999) for a discussion.

Several studies have analyzed the existence of these practices in the banking industry. In this sector, the loan loss provision (LLP henceforth) is widely considered as an optimal managerial tool for accounting manipulation, not only because it is the largest accrual in relation to size, but also because it offers a considerable degree of discretionary behavior; see Brady and Sinkey (1988). The basic prediction of the income-smoothing hypothesis is that LLP is positively related to before-provisions earnings, which gives rise to a simple testable hypothesis in the linear regression context. Most papers have addressed this issue through the use of pooled or panel-data regressions. However, the evidence so far is not completely conclusive in the banking industry. The main conclusions are sensitive to the choice of the sample and the specific econometric technique involved. For instance, Brady and Sinkey (1988), Ma (1988), Greenawalt and Sinkey (1988), Collins, Shackelford and Wahlen (1995), Bhat (1996), Kanagaretnam, Lobo and Matheu (2003), Bikker and Metzemakers (2005) and Laeven and Majnoni (2006), among others find evidence supporting this form of earnings management, while Scheiner (1981), Wetmore and Brick (1994), Beatty, Chamberlain and Magliolo (1995), Ahmed, Takeda and Thomas (1999) and Bouvatier and Lepetit (2008) do not.

Why is the evidence of artificial income smoothing so elusive? The discretionary nature of loan-provisioning makes it virtually impossible to establish a structural theory that fully describes the dynamics of this variable. In the absence of this guidance, researchers must face a number of subjective judgments related to econometric considerations, such as which particular variables to use, how to relate them to LLP, and how to estimate parameters and conduct inference. This form of uncertainty has given rise to a considerable lack of methodological consensus in this field that may explain, at least partially, the origin of the heterogeneous evidence. The possibility of any form of model misspecification in the empirical modeling of LLP is a major concern (Lobo and Yang, 2001), but this issue has received little attention.

In this paper, we argue that the relation between discretionary accruals and earnings may adopt a characteristically nonlinear form that depends on the size of economic income. This feature may have sheer consequences on the linear econometric analysis typically used to model accrual dynamics, for instance, to test the earnings-smoothing hypothesis or characterizing pro-cyclical patterns (DeAngelo, DeAngelo and Skinner, 1994; Ball, Kothari and Robin, 2000; Kothari, Leone and Wasley, 2005). More specifically, the conditional dynamics of discretionary accruals is likely to be characterized by a nonlinear function on earnings because both the incentives to manipulate earnings and the practical way to do so depend, in part, on the relative size of this accounting variable. The standard linear regression analysis neglects the possibility of nonlinear responses of this kind, which may lead to biases in the main conclusions as a consequence of functional form misspecification. To exemplify this concern, assume that the estimated value of the slope coefficient in a linear regression of LLP on earnings is exactly zero. Then, it seems natural to conclude that bank executives do not use LLP to manage earnings. However, this conclusion may also be reached spuriously if bank executives do engage actively in earnings manipulation, yet apply different strategies depending on the size of earnings. For instance, if managers decrease LLP when earnings are negative, but increase them otherwise such that the global expectation is approximately zero, the estimates from the linear regression would wrongly suggest absence of earnings management due to model misspecification. It suffices to extend the linear model to accommodate asymmetric patterns around the zero-threshold to detect the true underlying behavior and draw sound conclusions. In practice, nonlinear responses may be characterized by multiple regimes determined by unknown thresholds and different marginal propensities. This paper discusses the convenience of a more general methodological approach to characterize the dynamics of accruals, namely, nonlinear threshold panel regressions (Hansen, 1999, 2000), and provides empirical evidence on its suitability in an analysis on the US banking sector.

There are several reasons that may explain why this class of nonlinearities may underlie the dynamics of discretionary accruals. Among these, the compensation theory offers us a reasonable justification, since the incentives for bank managers to manipulate earnings stem, in part, from the existence of variable compensations. In practice, bonuses, stock options and other mechanisms of performance-based compensation provide bank managers with heterogeneous incentives to manage earnings because their performance is usually measured in terms of accounting profits; see, among others, Healey (1985). Since the expected present value of the total compensation depends on whether the realized value of the performance measure is below, within, or above certain thresholds (or target) levels embedded in these plans, executives have different incentives to increase or decrease earnings accordingly via discretionary accruals. As a result, the characteristic response that links accruals to the distribution of earnings is sensitive to thresholds-in-earnings, which may give rise to nonlinear patterns.[1] Given that variable compensation is a widespread practice in the financial industry, common patterns in the individual behavior of managers could emerge and be detected in panel data through nonlinear regressions, remarkably, even in the absence of specific data on the individual compensation plans.

Our study analyzes a panel formed by more than 9,400 banks operating in the US in the period 1999-2008. Using the standard cross-sectional and panel-data linear regression techniques, the preliminary evidence based on the standard regression analysis supports the income-smoothing hypothesis. However, in a robust analysis using different techniques to winsorize data, we observe that the statistical evidence is very sensitive to the tails of the distribution of earnings, particularly, to the set of largest

[1] The compensation theory provides both theoretical and empirical arguments supporting the existence of nonlinear patterns stemming from different incentives. For instance, Kirschenheiter and Melumad (2002) provide theoretical arguments sustaining that different forms of earnings manipulation can exist simultaneously. Also, Laeven and Majnoni (2006) and Bouvatier and Lepetit (2008) show asymmetric (i.e., non-linear) behaviors around the zero-earnings level. Section 2 surveys this literature.

positive earnings in the sample. This effect is not necessarily the consequence of outliers or measurement errors in the data, but also of neglected nonlinear patterns in the linear analysis. Using a piecewise linear specification defined on the empirical deciles of earnings, first, and then a more sophisticated nonlinear threshold regressions that allow endogenously for different regimes in earnings, we uncover a strong nonlinear relation between LLP and earnings. The overall picture that emerges suggests that, on average, bank managers tend to use the allowance as a smoothing devise when earnings are substantial ("cookie-jar" strategies), engage in earnings-decreasing strategies when losses are relatively large ("big-bath" accounting) and, most of the time, use LLP as an earnings-increasing instrument. The threshold analysis reveals three main regimes which are endogenously characterized in the period, respectively, by earnings (scaled by total assets) smaller than 1.81%, larger than 3.64%, and within these thresholds, determining whether big-bath, earnings-increasing or smoothing seems to be mainly applied. The hypothesis of overall smoothing management, therefore, is strongly rejected in favor of a more complex behavior which supports the coexistence of several forms of earnings management.

This paper can be related to different strands of literature in applied financial accounting. It belongs to the vast body of research concerned with accrual modeling and, more specifically, with the studies that have characterized nonlinear dependences between accruals and other accounting variables. Basu (1997) reported different incremental slopes in cash flow and earnings when these are regressed on positive and negative stock returns, which shows implicit evidence of nonlinear patterns between accruals and cash flows. Indeed, Ball and Shivakumar (2006) argue that the relation between accruals and cash flows cannot be linear because of timely loss recognition, which challenges the linear specification commonly used in accrual models; see also, Ball and Shivakumar (2005), Moreira and Pope (2007), Anderson, Woodhouse, Ramsay and Faff (2009) and references therein for recent studies. Our paper contributes to this literature by showing strong evidence of nonlinear patterns between the main accrual in the banking industry and earnings. To the best of our knowledge, the general existence of such patterns has not been discussed before, although Laeven and Majnoni (2006), Bouvatier and Leepetit (2008) and Balboa, López-Espinosa and Rubia (2010) report evidence of asymmetric responses around zero earnings. Our paper can also be related to different studies concerned with the effects of econometric misspecification in the analysis on accrual-related models. Kraft, Leone and Wasley (2006 and 2007) discussed the effects of outliers and omitted variables, respectively, when testing for the accrual anomaly. Our study provides evidence that neglecting nonlinearities may lead towards spurious conclusions on the extent and the existence of smoothing practices; e.g., linear models cannot detect the simultaneous coexistence of big-bath and smoothing techniques. Finally, this paper is related to the vast literature on earnings management and income-smoothing in the banking industry. Our study provides clear evidence that US bank managers tend to engage actively in different strategies to manage earnings by using allowances discretionarily.

The remaining sections of the paper are organized as follows. Section two reviews the literature that supports the existence of nonlinear patterns in accruals as a function of the level of earnings. Section three introduces the dataset used in this paper and analyzes the income-smoothing hypothesis by means of both pooled cross-sectional and panel- linear regressions. Section four provides evidence of nonlinear patterns on the basis of a piecewise linear analysis and nonlinear threshold regressions. Finally, Section five summarizes and concludes.

2. Motivation for nonlinear patterns in accruals

Loan-loss reserves and other accruals can exhibit nonlinear dynamics as a function of the level of earnings for several reasons. The compensation theory offers us a reasonable explanation to justify such patterns, although this is not the only possibility. In this section, we survey the main arguments and the literature in the compensation theory and corporate finance that support a potential nonlinear relation between accruals and earnings.

Traditionally, the financial industry has offered large personal short-term performance bonuses and other variable compensation schemes to managers who are able to accomplish corporative goals.[2] There exists substantial heterogeneity, but most executive compensation packages contain two basic elements: a fixed salary and a variable component that typically includes annual bonus tied to accounting performance, stock options and long-term incentive plans; see Murphy (1999) for a detailed survey. Empirical studies in the field have shown that although top executives are better paid in the US than in any other country (Abowd and Bognanno, 1995), the average size of the variable component relative to the total is greater as well (Murphy, 1999) and tends to reward the success in the short-term over the long-term. Hence, US top executives have strong incentives to seek short-term gains (Bebchuk, 2009) and misreport in their self-interest. The literature has indeed provided evidence on the empirical links between executives' compensation packages and their incentives to manipulate earnings; see, among others, Gao and Shrieves (2002), Cohen, Dey and Lys (2004), Cheng and Warfield (2005), Bergstresser and Philippon (2006), Shuto (2007) and Cornett, McNut and Tehranian (2009).

The fundamental premise of the compensation theory is that bank managers make corporate decisions attempting to optimize the present value of their bonus plan payments. Executives are expected (and encouraged) to use their talent and skills to achieve better payments, but in practice they can also use the accounting discretion at their disposal to manipulate artificially the reported measures of performance. The seminal paper in this area is from Healey (1985), who analyzed the effects of three compensation packages that relate annual bonus plans to accounting incentives: annual bonuses that are conditioned to the managerial ability to generate earnings above a certain lower bound; fixed bonus if the realized earnings exceed a certain upper threshold or cap; and a variable bonus when realized earnings range between the lower and upper bounds, the so-called incentive zone; [3] see also Kaplan (1985), Barro and

[2] In practice, short-term bonuses can represent the largest portion in the total compensation of most top executives, a tradition that began when most firms were private partnerships and partners shared directly the annual income of the firm. While average bonuses are expected to hover around half a million dollars, they are not evenly distributed. For instance, senior banking executives can receive millions, as publicly disclosed by many financial firms.

[3] As discussed by Murphy (1999), the characteristic cash bonus plan found in practice is based on this retribution scheme, with the performance measure being defined explicitly by at least one measure of accounting profit.

Barro (1990), Pourciau (1993), Sloan (1993), Gaver, Gaver and Austin (1995), Holthausen, Larcker and Sloan (1995), Balsam (1998) and Guidry, Leone and Rock (1999) for further studies. Depending on the particularities of the bonus plan involved, this literature shows that bank managers have very different incentives to manipulate earnings and, consequently, use LLP and other accruals in different and even opposite ways.

Contrary to the main prediction of the smoothing hypothesis, LLP and other accruals could be raised artificially when economic earnings fall below the minimum bound necessary to receive any bonus. This earnings-decreasing strategy is generally known as “big bath”, “take a bath”, or “saving for a better tomorrow” in the accounting literature, since the size of reported losses is increased by anticipating future discretionary accruals; see Degeorge, Patel and Zechhauser (1999). The key point of this strategy is that it implies no managerial cost at present but it increases the chances to receive bonuses in the future. On the other hand, the incentives to understate accruals are particularly strong when economic earnings are slightly below the lower bound, since managers attempt to report earnings that qualify them to perceive bonuses; see, for instance, Degeorge et al. (1999) and Koch and Wall (1999). More generally, managers tend to choose earnings-increasing alternatives when earnings fall in the incentive region, as reported by Healey (1985), as they wish to increase variable compensations. Finally, when economic earnings are so large that they exceed the upper bound of the incentive zone, managers tend to increase reserves and provisions to use them in unprofitable periods, thereby smoothing reported earnings according to a practice generally known as “cookie-jar accounting”, or “saving-for-a-rainy-day”; see the evidence reported by Holthausen, Larcker and Sloan (1995). These incentives are mainly related but not limited to bonus plans, since the nonlinear payoffs embedded in stock options generate similar patterns as well; see Gao and Shrieves (2002). Consequently, the compensation theory predicts a more complex, possibly non-linear relation between LLP and earnings than the income-smoothing theory.

Alternatively, the literature in corporate finance also provides arguments that may justify the existence of nonlinear patterns in discretionary accruals as a function of realized earnings because of a conflict of interest between firms’ insiders and outsiders. In particular, Zingales (1994) and Shleifer and Vishny (1997) argue that insiders have incentives to conceal their private control benefits from outsiders because, if these benefits are detected, outsiders will likely take disciplinary actions. Hence, Leuz, Nanda and Wysocki (2003) point out that managers and controlling owners have incentives to manage reported earnings to mask the true performance of the firm and reduce the likelihood of an outsider intervention. For instance, bank managers would use their financial reporting discretion to overstate earnings attempting to conceal losses that would prompt outsider interference, or increase reserves to understated earnings in years of particularly good performance and use them in years of bad performance.

3. Empirical links between LLP and earnings: linear regression analysis

In this section, we apply the standard linear regression analysis on data from a panel of banks in the US to discuss preliminary the effects of potentially neglected nonlinear patterns in accruals. As in the related literature, our main focus is to detect earnings management and, more specifically, income smoothing. In Section 4 we shall apply nonlinear techniques that generalize the analysis and allow more general forms of earnings management.

3.1 Data

The data analyzed in this paper comes from Orbis Bureau Van Dijk and comprises annual banking variables from the US in the period 1999-2008, totalling 81,568 observations from 9,442 banks. We collect observations for firm-specific variables that the previous literature has pointed out as potential drivers of the discretionary and nondiscretionary components of LLP. These include variables such as Total Assets, Loans, Impaired Loans, Loans Loss Provision, Profit before Tax and Total Capital Ratio. Additionally, we observe macroeconomic data (Gross Domestic Product growth) available from the IMF database to capture the general influence of the business cycle on the LLP dynamics, as this is expected to be a main driver of the non-discretionary component of the allowance.

Table 1 reports the usual descriptive analysis for the main variables involved in the regression analysis. Panel A shows that LLP represent around 0.28% of total assets on average, with a standard deviation of 0.82%. In the case of impaired loans, this figure represents 0.51% of total assets. The total amount of loans relative to total assets is 63.86%, with a deviation of 15.86%. The variable of most interest in this paper, profits before taxes and LLP (PB), shows a mean value of 1.45% over total assets, but with a slight high relative standard deviation of 2.59%. Panel B shows the conditional distribution of this variable according to whether it takes negative, zero or positive values. A distinctive feature of earnings in the banking industry is the predominance of positive values. In our sample, nearly 94% of the observations correspond to positive earnings.

[Insert Table 1 around here]

Table 2 shows the sample correlations between all the variables used in our analysis. There is a positive relation between LLP and impaired loans, as a proxy of credit risk exposure, and total loans, as a measure of credit portfolio. The linear correlations among the different explanatory variables in our analysis range from -0.39 to 0.14 and suggest mild dependences. The strongest correlation with the variable representative of loan-loss provisioning is the ratio of impaired loans to total assets (0.33), followed by the ratio of profits before taxes and LLP to total assets (0.21).

[Insert Table 2 around here]

3.2 Income-smoothing hypothesis

To formally test for the earnings-smoothing hypothesis, we characterize the dynamics of LLP through a linear model that relates this variable to profits before taxes and the remaining control variables; see, among others, Ahmed, Takeda and Thomas (1999). In particular, we assume that the relative level of loan provisioning of the *i*-th bank at the *t*-th year obeys the following dynamics:

$$LLPTA_{it} = \gamma_0 + \gamma_1 ILTA_{it} + \gamma_2 LTA_{it} + \gamma_3 TCR_{it} + \gamma_4 SIZE_{it} + \gamma_5 GDPG_t + \beta_E PB_{it} + \varepsilon_{it}$$
$$\equiv \gamma' ControlVar_{it} + \beta_E PB_{it} + \varepsilon_{it} \qquad (1)$$

where ε_{it} is a noise process assumed to obey general, standard restrictions, $\gamma = (\gamma_0, ..., \gamma_5)'$, and:

- $LLPTA_{it}$ measures total LLP deflated by the firm's Total Assets.

- $ILTA_{it}$ gauges Impaired Loans to Total Assets to proxy for the credit risk exposures.

- LTA_{it} represents Loans to Total Assets, widely considered as a proxy for the specialization of the bank and a measure of portfolio composition.

- $GDPG_t$ is the Gross Domestic Product (GDP, hereafter) growth, intended to proxy for the general economic conditions and business cycle dynamics.

- TCR_{it} is the Total Capital ratio and proxies for the level of solvency of banks.

- $SIZE_{it}$ is the natural logarithm of total assets to control for potential size effects.

- $ControlVar_{it}$ is a (6x1) vector containing a constant and all the control variables described thus far. We shall use this variable to simplify mathematical expressions in the sequel.

- PB_{it} is the Profit before Tax and LLP deflated by Total Assets, the main variable of interest in our analysis.

Equation (1) is analogous to most of the empirical models used for testing income and/or capital management in the accounting literature. The variables $ILTA$ and LTA are firm-specific proxies of the credit risk which characterizes the nondiscretionary component in LLP. These variables are expected to have a positive effect on LLP, since bank managers increase provisions when the bank's credit portfolio increases or when credit quality deteriorates. The variable $GDPG$ proxies for the overall economic conditions as an external indicator of the credit risk. It is expected to have a negative effect on the loan loss provisioning. The variable TCR aims to gauge the discretionary use of provisions to manage regulatory capital. If bank managers have incentives to manage regulatory capital via LLP (e.g., using LLP to reduce the expected regulatory costs associated with violating capital requirements), then we should be able to observe a negative relation between LLP and capital ratios. The variable $SIZE$ is included as a control variable. We do not have any firm prior expectation about the impact of size on LLP: on the one hand larger banks may require larger provisions (positive relation), but on the other hand larger banks may be able to diversify credit risk better (negative relation). Our main interest in this model is on the β parameter, which relates the relative level of provisioning to before-provisions profit. If the resultant estimate is significant, then LLP are discretionarily set as a linear function of earnings, thus suggesting that reported earnings result from earnings manipulation.

Equation (1) is estimated through pooled time-series cross-sectional regressions with two-way cluster-robust standard errors accounting for bank and year clusters (Petersen, 2009; Gow, Ormazabal and Taylor 2010; Cameron, Gelbach and Miller, 2011; Thompson, 2011).[4] The distinctive characteristic of multi-way clustered errors in the pooled regression setting is that it allows us to carry out statistical inference which is robust by design to simultaneous dependences of unknown form in both the cross-sectional and time-series dimensions of the panel. Regression errors are assumed to be independent but not identically distributed across a number of clusters and can have fairly general patterns of within cluster correlation and heteroskedasticity. Additionally, we consider panel-data with fixed-effects regressions, as indicated by the Hausman test. The main advantage of the panel-data methodology is that it allows us to control for the unobservable individual heterogeneity, i.e., the individual characteristics that are not explicitly included in the empirical regressions. The main outcomes from this analysis (estimated parameters, robust *p*-values of the *t*-statistic for individual significance, and adjusted goodness of fit) are reported in Table 3.

[Insert Table 3 around here]

As expected, LLP are positively and significantly related to the variables that proxy for the credit risk conditions in the nondiscretionary component. Increments in the relative level of impaired loans and/or in the credit portfolio lead to increments of LLP. Also, and as reported in the related literature, LLP exhibits a cyclical pattern evidenced through the negative and significant dependence on the GDP growth. The analysis on the estimated coefficient related to the capital variable shows mixed evidence and is sensitive to the estimation technique. While pooled regression with cluster-robust standard errors shows a positive and significant relationship, the panel data methodology shows a negative and significant coefficient. The latter agrees with the empirical evidence in Moyer (1990), Beatty et al. (1995) and Ahmed et al. (1999), among others, and suggests that managers use LLP to reduce the expected regulatory costs associated with capital requirements.[5] A similar result is obtained in the estimated coefficient related to the size control variable.

Turning our attention to the coefficient related to the income variable, the estimate is 0.068, in the pooled regression, and 0.048, in the panel data regression. Both estimates are positive and significant, although the evidence in the panel data regression is only marginally significant at the conventional level. The main conclusion from this analysis, therefore, is that US bank managers in the period analyzed tend to engage in income-smoothing practices.

3.3 Tests for robustness of results

In an influential paper, Kraft, Leone and Wasley (2006) argue that several results in the empirical testing of accrual-related variables may be due to influential

[4] We have also considered the total capital ratio and year as clusters and also the deciles of size and total capital ratio in order to control for cross-sectional dependences. The use of deciles may be desirable when the number of clusters is too high. The results are robust to the use of all these variables and are available upon request.
[5] This result is also obtained under the pooled regression analysis after allowing nonlinear responses of LLP to the earnings variable (section 4).

observations (outliers) in the sample. As a robustness check of the consistency of the previous results to this consideration, we consider three different approaches based on Trimmed Least Squares (TLS henceforth) that remove a fraction $\alpha\%$ (winsorize) of the total sample, with $\alpha = \{1, 2.5, 5, 10\}$ set arbitrarily.

The first approach removes influential observations, which are identified as the largest prediction errors from equation (1). Specifically, given the estimated residuals from (1), the model is estimated again after excluding the observations corresponding to the largest $\alpha\%$ of squared residuals. The second approach focuses on values in the tails of the distribution of earnings, as this is the main variable of interest in our analysis. We remove observations corresponding to earnings equal to or larger than the $(1-\alpha)\%$ percentile of this variable, and then estimate equation (1) with the remaining observations. The third approach follows identically, this time removing observations related to the $\alpha/2\%$ and $(1-\alpha)/2\%$ percentiles of the empirical distribution of the earnings variable, i.e., winsorizing both tails. Table 4 and 5 report the results for the pooled regression cross-sectional analysis and the panel-data analysis, respectively. We discuss directly the results related to the earnings variable from the pooled analysis, since the main qualitative conclusions from the panel-data analysis are rather similar.

[Insert Table 4 around here]

[Insert Table 5 around here]

The robust analysis shows that the estimates related to the profit before taxes and LLP variable (PB variable) and, hence, the overall evidence for income smoothing, are fairly sensitive to values in the tails of the distribution of earnings and large estimation errors in the linear fitting. The TLS analysis reveals that after removing the observations that raise the largest prediction errors in the linear fitting, the estimates of the slope coefficient related to PB dramatically decrease. Under the second approach (removing observations related to the top percentile of earnings), we observe that the preliminary evidence of income smoothing completely vanishes after removing even a small fraction of observations. For all the cases analyzed, the estimates of the slope coefficient on PB are negative and significant. The estimates are fairly robust to the different trimming fractions and yield a value around -0.06. This evidence suggests that a small fraction of observations of the top percentiles may largely be responsible for the overall evidence of smoothing in the sample. Finally, similar results emerge when we winsorize both tails of the distribution of PB. For the trimming fractions $\alpha = \{2.5\%, 5\%\}$, the estimates are negative and significant. On the other hand, applying a relatively large trimming factor that removes the 5 and 95 per cent levels of the distribution leads to positive values of the PB coefficient. The main conclusions from this analysis can be summarized as follows.

First, the overall evidence from the robust analysis tends to favor a negative relation between LLP and earnings such that the relative level of LLP is reduced (increased) deliberately when earnings are positive (negative). The effect of this strategy is to increase the total volatility on reported earnings, in sharp opposition to the main prediction of the earnings smoothing hypothesis. This result agrees with the recent findings in Bouvatier and Lepetit (2008), who observe similar evidence using a sample of 186 European banks. While the income-smoothing theory fails to explain this feature, the evidence may be the result of bank managers attempting to maximize the present value of their performance-based compensations, as claimed by the compensation hypothesis. For most banks in the sample, which report positive earnings, a negative relation between LLP and earnings suggests income-increasing policies. This evidence would support the claims in Watts and Zimmerman (1986), who argue that bank managers with earnings-based compensations have always the incentive to manipulate earnings upwards. For the subset of banks with negative earnings, the negative relation implies "big-bath" or income-decreasing techniques that would attempt to increase the probability of reporting future earnings. Again, this may be consistent with strategies intended to maximize the present value of their intertemporal stream of expected wealth.

Second, the evidence supporting smoothing behaviors obtained from the standard analysis in our sample seems to be largely originated in a relatively small group of observations in the upper tail of the income distribution. When these observations are arbitrarily removed, the statistical evidence for smoothing weakens and eventually vanishes completely. However, the question that arises in this case refers to whether it is correct to conclude that bank managers do not engage in earnings smoothing practices when we delete the observations precisely for which bank managers have stronger incentives to apply these practices. Observations that do not seem to be fitted correctly by a linear model are not necessarily the consequence of "outliers" or "measurement errors" in the data, but also a symptom for model misspecification. Strictly speaking, removing observations arbitrarily is not a proper way of proceeding, since it may introduce selection bias and neglect meaningful patterns of the data. A more rigorous analysis would attempt to capture potentially neglected patterns. Since we have both theoretical reasons and previous evidence suggesting the likely existence of nonlinear patterns, we attempt to capture this in the following section.

4. Capturing nonlinear responses in loan-loss provisioning

In view of the preliminary evidence in the previous section, we extend the econometric analysis to account for potential nonlinear responses in the discretionay management of earnings as a function of the size of earnings. Our basic aim is to generalize equation (1) to allow the slope coefficient of LLP on PB to vary according to this variable, i.e., generalizing (1) by considering models within the general class of random coefficient regressions.

$$LLPTA_{it} = \gamma' ControlVar_{it} + \beta_{it} PB_{it} + \varepsilon_{it} \quad (2)$$

where, in our analysis, β_{it} is restricted to being a fixed function of PB_{it}, and a set of unknown parameters θ, i.e., $\beta_{it} = f\left(PB_{it};\theta\right)$. For example, the asymmetric-response model considered, among others, in Bouvatier and Lepetit (2008) can be embedded in this general approach setting $\beta_{it} = \beta_0 I\left(PB_{it} \le 0\right) + \beta_1 I\left(PB_{it} > 0\right)$, where $I\left(\cdot\right)$ is an indicator variable taking value one if the condition in parenthesis is true and zero otherwise, and $\theta = (\beta_0, \beta_1)'$; see Section 4.2 for further details.

Throughout the following subsections, we consider different functional specifications embedded in this general approach that grow in econometric complexity. The first one is a piecewise linear model that relates LLP to different statistical classes formed by the empirical deciles of PB in our sample. This approach is very intuitive, but provides direct evidence for or against the nonlinear hypothesis through the estimates of coefficients. Piecewise linear models have been used, among others, in Ball and Shivakumar (2006) and Anderson et al. (2009). A potential shortcoming of these models is that the classes or regimes are determined arbitrarily, e.g., fixing ranks or, in our case, deciles. Therefore, our second approach to accommodate possible nonlinearities uses threshold nonlinear regressions, as these allow us to circumvent this problem by determining classes endogenously.

4.1 Piecewise linear analysis

Let $\pi_1,...,\pi_9$ be the empirical deciles of the distribution of PB_{it}, i.e., $\left\{\pi_s : \inf \Pr\left(PB_{it} \leq \pi_s\right) \geq 0.1s\right\}$, $s = 1,...,9.$ Given these values, the range of PB_{it}, can be partitioned into ten disjointed subsets, ranges, or statistical classes, which we shall denote as $R_1,...,R_{10}$, defined as $R_1 = (-\infty, \pi_1], \ldots, R_s = (\pi_{s-1}, \pi_s],..., R_{10} = (\pi_9, +\infty)$, *s=2,…,9*. Note that the sample probability of PB_{it} being at any of these intervals is 10%. Then, define a sequence of dummy variables on the classes R_s, $\left\{\mathrm{D}_{it}(R_s)\right\}_{s=1}^{10}$, such that $\mathrm{D}_{it}(R_s)$ takes a value equal to one if the earnings observation of the *i*-th bank at time *t* belongs to R_s, and zero otherwise. Then, in order to capture nonlinear patterns arising from variability in β_{it} as a function of PB_{it} in (2), we can consider a piecewise linear model defined on the deciles of PB_{it} characterized as $\beta_{it} = \sum_{s=1}^{10} \beta_s \times \mathrm{D}_{it}(R_s)$, or, equivalently:

$$LLPTA_{i,t} = \gamma' ControlVar_{it} + \sum_{s=1}^{10} \beta_s \left(PB_{it} \times \mathrm{D}_{it}(R_s)\right) + \varepsilon_{it} \qquad (3)$$

The choice of deciles is entirely arbitrary but seeks to obtain a good compromise between the goals of capturing a potentially wide range of variation in the (conditional) response of LLP to PB and keeping the model parsimony in the econometric approach.[6] Hence, the sequence of parameters $\{\beta_s\}$ captures the marginal response of LLP to earnings in each decile after controlling for the remaining variables. Because the model is linear in variables, all the coefficients involved can be estimated jointly and

[6] The unobservable function that characterizes the link between the relative levels of LLP and PB could be approximated arbitrarily well through a piecewise linear function when the number of segments included in the expansion is arbitrarily large and the function to be approached is smooth enough. In practice, however, there exists a trade-off between the number of parameters to be estimated in a regression model and the number of segments to be included in a finite-sample analysis.

consistently through least-squares. Under the restriction of homogenous response across the distribution of PB, i.e., $H_0 : \beta_1 = ... = \beta_{10} = \beta$, model (1) arises as a particular case, since trivially $\sum_{s=1,10} \mathrm{D}_{it}(R_s) = 1$. Hence, the statistical suitability of the linear model can readily be tested through a standard F-type test. Furthermore, the different implications in terms of earnings-management that the varying coefficients can capture can be analyzed statistically through different restrictions. For instance, if all the estimates of β_s are positive, but differ significantly among themselves, then the analysis provides support to the income-smoothing hypothesis and, furthermore, reveals different average propensities to use LLP as a smoothing instrument depending on the size of earnings. On the other hand, if any of these parameters is significantly negative, the results would support the existence of earnings-increasing strategies for ranges formed with positive values, or earnings-decreasing behavior for the negative classes. Because our main interest is on the estimated slope coefficients $\{\beta_s\}_{s=1}^{10}$, we summarize graphically the estimated coefficients in Figure 1 and discuss the main results for the sake of conciseness and saving space. Complete results from this regression are available upon request.

[Insert Figure 1 around here]

Figure 1 reveals that the sensitivity of LLP to earnings varies considerably across the deciles of the earnings variables, showing an upward trending function that takes negative values in the lower deciles and positive values in the larger. The figure suggests a strong degree of nonlinear behavior which is formally supported by joint tests of significance. The suitability of a single linear model characterized by a unique coefficient which implies $H_0 : \beta_1 = ... = \beta_{10}$ is strongly rejected, and so is the hypothesis of absence of earnings management, $H_0 : \beta_1 = ... = \beta_{10} = 0$.[7] Consequently, the estimates of model (3) provide formal evidence that the dynamics of LLP are better characterized by nonlinear features rather than a constant proportional relation, and that bank managers use LLP to over-state or under-state reported earnings in their self-interest. The adjusted goodness of fit largely improves from 15.43% in the restricted model (1), to 19.63% in (3), roughly representing an increment of 30%.

It is interesting to discuss in greater detail the coefficient estimates and the implications for earnings management. The slope related to the first decile of PB is largely negative $(\hat{\beta}_1 = -0.10)$ and strongly significant (*p*-value is 0.00). Since this class is formed mainly by negative earnings (negative earnings represent around 6% of the total sample), the analysis suggests that managers tend to use LLP in this region as an earnings-decreasing tool applying "big-bath" accounting. The estimate of the slope coefficient in the second decile is again negative $(\hat{\beta}_2 = -0.14)$ and largely significant. This class comprises strictly positive, but relatively small profits. The evidence suggests that bank managers engage in earnings-increasing strategies by discretionarily reducing LLP, attempting to avoid reporting small negative earnings; see also Degeorge, Patel and Zechhauser (1999). For earnings falling into the subsequent categories, we observe

[7] The F-test for the joint hypothesis of a common management strategy is 424.1, largely rejected at any of the conventional levels of significance.

a sequence of negative estimates in an upward trend $(\hat{\beta}_3 = -0.09, ..., \hat{\beta}_9 = -0.02)$, which suggest that the incentives to use LLP as an earnings-increasing device decrease progressively as the size of earnings increases. All these values are statistically significant. Finally, for earnings in the top decile of the distribution, the estimate is largely positive $(\hat{\beta}_{10} = 0.09)$ and highly significant. This corresponds to the income-smoothing hypothesis and suggests that large profits tend to be smoothed by increasing the size of LLP.

Note that the results in this analysis are coherent with the evidence based on the robust analysis in the linear analysis in section 3.3, but offer us a more complete picture. While both analyses agree and suggest that the most common strategy employed by bank managers in this sample is to increase the size of reported earnings by discretionarily reducing LLP, the piecewise linear analysis reveals that different strategies coexist depending on the size of earnings. For the set of largest earnings in the sample we observe strong evidence of earnings smoothing, whereas large relative losses are artificially increased by deliberately increasing LLP in take-a-bath strategies. The statistical evidence largely rejects the hypothesis of overall smoothing in the sample and suggests a more general type of managerial behaviour.

4.2 Threshold nonlinear regression models

Piecewise linear regression with pre-defined regimes is a fairly intuitive analysis that provides formal evidence and allows us to grasp the pattern of variable dependence that links LLP to earnings. However, a potential critique is that the overall evidence may be sensitive to the arbitrary choice of the classes that characterize the stepwise function β_{it}. We note that a similar analysis has been applied previously by Laeven and Majnoni (2006), Bouvatier and Lepetit (2008), and Balboa, López-Espinosa and Rubia (2010), who focus on asymmetric responses of LLP around the zero-earnings threshold,

$$LLPTA_{it} = \gamma' ControlVar_{it} + \beta PB_{it} + \beta^{*} \left[D_{it} \left(PB_{it} > 0 \right) \times PB_{it} \right] + \varepsilon_{it} \quad (4)$$

where $D_{it}\left(PB_{it} > 0\right)$ is a dummy variable that takes value one if PB_{it} is positive and zero otherwise. Like (3), this nonlinear generalization of model (1) reflects the arbitrary choice of threshold levels, although it has the advantage of being naturally motivated to capture asymmetries around gains and losses. In this section, we generalize both approaches by allowing different regimes as a function of unknown thresholds that can be estimated endogenously.

In particular, assume that there exists some unknown threshold value in the income variable, say τ, such that the propensity to manage earnings for earnings below this threshold is captured by, say, the β_1 coefficient, whereas the propensity to smooth earnings above this level is captured by β_2, with $\beta_2 \neq \beta_1$. Hence, similar to (4), we may specify the following econometric model:

$$LLPTA_{it} = \gamma' ControlVar_{it} + \beta_1 \left[D_{it} \left(PB_{it} > \tau \right) \times PB_{it} \right] + \beta_2 \left[D_{it} \left(PB_{it} \leq \tau \right) \times PB_{it} \right] + \varepsilon_{it} \quad (5)$$

Obviously, the linear model (1) arises as a particular case under the restriction $\beta_1 = \beta_2$. Similarly, this approach generalizes the basic setting considered in the previous section, since the regime is not predetermined exogenously a priori by the researcher, but rather endogenously from the data. For instance, the asymmetric model (4) is encompassed in this setting under $\tau = 0$ and a trivial parameter rearrangement.

Model (5) is a particular model of the general class of models embedded in (2) known as threshold nonlinear model, which can be further generalized towards accounting for multiple regimes. Thus, consider the set of (unknown) threshold values $\tau_1 < \tau_2 < ... < \tau_n$, *n>1*, partitioning the empirical range of PB_{it} into *n+1* disjoint intervals, $R_{1,\tau},...,R_{n+1,\tau}$, and assume that $D_{it}(R_{s,\tau})$, $s = 1,...,n+1$, is a collection of dummy variables taking value one if the value of PB_{it} falls in the $R_{s,\tau}$ region, and zero otherwise. Then, model (5) is straightforward and generalized as:

$$LLPTA_{it} = \gamma' ControlVar_{it} + \sum_{s=1}^{n+1} \beta_s \left[D_{it}(R_{s,\tau}) \times PB_{it} \right] + \varepsilon_{it} \quad (6)$$

These are the so-called threshold models discussed, among others, by Tong (1983, 1990), Chan (1993), Hansen (1999, 2000), and Caner and Hansen (2004). These are fairly parsimonious and emerge as special cases of more sophisticated frameworks, such as mixture models, Markov Switching models, and smooth transition models, all of which are characterized by the possibility of nonlinear patterns. The unknown parameters θ to be estimated are the slope coefficients that characterize the conditional mean, $\left(\gamma', \beta_1,...,\beta_{n+1} \right)'$, and the threshold values $\left(\tau_1,...,\tau_n \right)'$ that give rise to the different regimes. The vector parameter θ can be consistently estimated from a concentrated least-squares procedures, as is briefly summarized below.

For simplicity, consider the simplest case involving a single threshold parameter, τ. The unknown vector of parameters is $\theta = (\gamma_0,...,\gamma_5,\beta_1,\beta_2,\tau)'$ and its natural estimator is the minimizer of the sum of squared residuals, which is also equivalent to the maximum-likelihood estimator when the residuals are normally distributed. If we knew the true value of τ, the remaining parameters could be estimated consistently by least-squares because, as in the previous section, the parameters are linear conditional to the regimes that characterizes τ. This property suggests an estimation strategy in which we can identify sequentially the whole set of unknown parameters by minimizing the concentrated sum of squared residuals conditional to values of the τ parameter in a wide range. More specifically, for any posited value of τ, we can generate the dummy variable $D_{it} \left(PB_{it} > 0 \right)$, and then compute the sum of squared least-squares residuals from a least-squares fitting conditional to this choice. In practice, we can use the observed values of PB_{it} within a certain range, say Ψ, that ensures that at least a minimal percentage of the observations (in our case, we set 1%) lies in each regime. The least-squares estimation of the parameters is the overall minimizer of the residual variance in $\tau \in \Psi$, which can be reduced to searching over values of τ equalling the distinct values of the process PB_{it} in the sample, i.e., $\hat{\theta} = \arg\min_{(\gamma,\beta_1,\beta_2)} E\left(\hat{\varepsilon}_{ij}^2 \mid \tau \in \Psi\right)$. The estimated value of τ is that for which the sum of square residuals is minimized. Multiple thresholds can be inferred similarly using sequential estimation as in the change-point literature; see Hansen (1999) for details.

For the set of parameters that characterize the conditional mean of the process, $\left(\gamma', \beta_1, ..., \beta_{n+1}\right)'$, we can generally carry out standard inference based on the estimates of the covariance matrix, as in the linear case. However, testing certain restrictions, involves a more complex procedure. In particular, if we want to test the suitability of the model against a linear restricted model (i.e., whether the threshold effects are statistically significant), it should be noted that under the linear restriction $H_0 : \beta_{E,1} = ... = \beta_{E,n+1}$ the threshold values involved are not identified, so the distribution of the usual tests (e.g., the Likelihood-ratio test or the *F*-test) is not standard. The relevant critical values have to be tabulated by experimental methods such as bootstrap. We shall bear this in mind when testing the convenience of the restricted linear model in this general setting.

4.3 Estimation results

We estimate model (6) with one and two threshold levels and, for completeness, we also analyzed the asymmetric model (4) as this has been considered in the previous literature. The estimated models are labelled as follows. Model I is the baseline model with constant slope coefficient in equation (1). Model II is the asymmetric model with a threshold set at the zero earnings level considered in the previous literature, i.e., equation (4). Model III generalizes this specification by allowing the threshold value to be determined endogenously in threshold regression, i.e., equation (5). Model IV analyzes a further extension of Models II and III by considering both a threshold effect at the zero level (asymmetry) and an unknown threshold which is estimated endogenously. Finally, Model V further relaxes this model and considers two unknown thresholds effects, i.e., equation (6), setting *n=2*. The results from the pooled regression are reported in Table 6.[8]

[Insert Table 6 around here]

Some comments follow. First, as expected from the previous analysis, we observe that any econometric model that accommodates the possibility of nonlinear responses of LLP to the level of earnings largely over-performs the linearly restricted specification in Model I. The statistical gains in terms of adjusted goodness of fit show increments ranging from 20%, when including asymmetric effects in Model II, to nearly 34%, when including two threshold levels in Models IV and V. Furthermore, all the models generate negative and statistically significant estimates for the coefficients related to some of the regions analyzed in each specification, from which the hypothesis

[8] It should be noted that these models have also been estimated through the use of panel data methodologies. The results are very similar and are available upon request.

of overall earnings smoothing is rejected in favour of more general managerial strategies in all the cases analyzed.

Second, the estimates of asymmetric Model II, corresponding to equation (4), lead to similar conclusions as those in Laeven and Majnoni (2006) and Balboa et al. (2010). In particular, bank managers tend to engage in “big-bath” techniques when banks generate negative earnings (the estimated value of the negative earnings-related coefficient is -0.133), whereas banks with positive earnings would on average apply smoothing techniques (the estimated coefficient is 0.090). The likelihood ratio test testing the suitability of the unrestricted, asymmetric model against the linear restricted specification largely rejects the null hypothesis in favour of asymmetric effects.

Third, Model III, corresponding to equation (5), generalizes the study treated in Model II by allowing the model to determine endogenously the most likely position of a threshold effect. As in the change-point literature, this is identified as the sample for which there is maximum evidence against the hypothesis of parameter constancy in the whole sample, i.e., the point at which the most important parameter discontinuity (not necessarily the unique) appears in the sample. In our case, the analysis suggests that the most important change when only a single threshold is allowed is not related to whether earnings are positive or negative, but rather to whether income is large enough to be smoothed or not. More specifically, earnings (deflated by assets) exceeding a threshold of 3.64% are smoothed through a propensity coefficient estimated at 0.097. This estimate is considerably greater that the on-average value reported under Model I, and is of the same order as the estimate attached to positive earnings in Model II. The threshold corresponds to the 98th percentile of the earnings variable, thus showing that the propensity to smooth is particularly high when the size of economic earnings is also high. For earnings not exceeding this threshold, we observe an average propensity coefficient which is negative (-0.077) and significant, thus suggesting that bank managers tend predominantly to use LLP discretionarily as an earnings-decreasing (increasing) tool when earnings are negative (positive, small and medium-sized). The bootstrap test for the linear hypothesis $H_0 : \beta_{E,1} = \beta_{E,2}$ is largely rejected through the sup-Wald statistic as in Hansen (1999).

Four, Model IV and V generalize the previous analysis by exploring the existence of multiple threshold effects. The results from Model IV show that considering the asymmetric effect (i.e., imposing a threshold at zero) in addition to the threshold analyzed in Model III provides an improvement in the overall goodness of fit of the model, but the increments are now much less important, yet still relevant. In this case, the estimate associated to negative earnings is negative and significant (-0.100), while the estimate associated to earnings between zero and the upper threshold is negative and significant, but much smaller (-0.056). Extreme earnings keep having a large propensity to be smoothed, as already determined under Model III. Finally, Model V provides a more complete picture by allowing for two threshold effects. Together with the threshold identified in Models III and IV, a new threshold value is now estimated around a level of relative earnings of 1.81%, which roughly corresponds to the 68th percentile in the empirical distribution of the earnings variable. The estimated coefficients related to the three earnings classes are -0.107 (lower class, below 1.81%), -0.049 (medium class, within 1.81% and 3.64%), and 0.097 (upper class, above 3.64%). The differences between these estimates are important enough as to strongly reject the null hypothesis of overall equality between coefficients (both vis-à-vis and overly) through bootstrap-based tests. When comparing the overall fitting of this model in relation to Model IV, we observe that allowing the threshold value to be estimated rather than fixed it at zero yields a slight increment. The difference, however, between setting $H_0 : \tau = 0$ or allowing this parameter to be freely estimated is both economically and statistically significant, as determined by a bootstrapped F-test.

The overall evidence from Model V suggests that the propensity to increase reported earnings decreases with the size of earnings and, eventually, disappears and is reverted towards smoothing when earnings are particularly large. This evidence is similar to that in Bouvatier and Lepetit (2008), although we offer a more complete picture and significant comments. The regimes are identified as a relatively large negative propensity to use LLP on the size of earnings (68% of the sample), a much smaller, but still negative and significant propensity (20% of the sample), and a large positive propensity to smooth the greatest profits (2%). Therefore, we observe that, depending on the size and sign of economic earnings, LLP can be used in very different ways to manipulate reported earnings. In our sample, and according to the empirical results from the threshold regression methodology, “big-bath”, income-increasing, and smoothing practices coexist.

Finally, Figures 2 and 3 relate, respectively, the nonlinear patterns estimated from Models IV and V to the dynamics suggested by regression analysis on the earnings deciles in the previous subsection. We can observe that the threshold estimates identify three regions in which, essentially, the propensity to use LLP is, on average, remarkably negative, mild negative, and positive. Since the threshold regression assume discrete regimes, we observe that the smooth, continuous pattern that the decile-regression evidences is captured through coefficient estimates that average the different propensities, basically capturing an upward trend in the propensity to smooth.

[Insert Figures 2 and 3 around here]

5. Concluding remarks

In this paper, we have discussed the existence of non-linear patterns that characterize the systematic response of the loan-loss provision to the profit before taxes. The central point in this paper is that discretionary accruals, such as loan-loss provisioning, may, in practice, exhibit nonlinear patterns on earnings stemming from different managerial incentives to use accruals as a tool to either increase or decrease reported earnings depending on the sign and the magnitude of this variable. This hypothesis can be founded in the existence of thresholds embedded in performance-based compensation plans that determine the expected payments of bank managers. While extending the analysis to accommodate possible nonlinearities is straightforward, neglecting such patterns in the empirical analysis may result in misleading conclusions to the existence and the extent of earnings management strategies.

Our empirical analysis on the US banking industry reveals the existence of strong nonlinear patterns between loan-loss provisioning and earnings that suggest that bank managers engage actively in different earnings management strategies as a function of the magnitude of earnings. We find strong evidence suggesting that income-smoothing practices are systemically applied on the largest earnings, but the hypothesis of the overall predominance of this behavior is largely rejected. According to our results, earnings-increasing behaviors are a more likely behavior than any other earnings management strategy when earnings are positive, while loan-loss provisions tend to be overstated to increase the size of reported losses when earnings are negative.

These conclusions provide indirect evidence that supports the main claims in the compensation theory. Our analysis does not use specific information on compensation plans. This is an issue for further research, since data on executive compensation would help to understand the reasons underlying the smoothing practices. However the empirical analysis of this issue would have to be limited to the sample of listed banks, thus limiting the scope of the threshold analysis. Even without those data, common patterns at the individual level emerge on average and can be identified from panel data using nonlinear regression techniques. If the analysis does not allow for the possibility of nonlinear patterns, the overall evidence from a linear regression model supports the income-smoothing hypothesis because of the strong influence of the largest observations.

A major conclusion from this paper, therefore, is that neglected nonlinear patterns can affect the results from standard analyses, which perhaps may explain some of the contradictory findings observed in the previous literature. A further generalization of the empirical analysis presented in this paper may consider so-called Smooth Transition Regression that models transition from one regime to another as a continuous process dependent on the transition variable. The evidence in this paper seems to point out that the characteristic response of loan-loss provisioning to the size of the earnings variable may be better characterized in such terms. This interesting topic is left for future research.

References

Abowd, J. and Bognanno, M. (1995). “International Differences in Executive and Managerial Compensation,” in R. Freeman, and L. Katz, ed., *Differences and Changes in Wage Structures*, Chicago: The University of Chicago Press, 67-103.

Ahmed, A.S., Takeda, C. and Thomas, S. (1999). “Bank Loan Loss Provisions: a Reexamination of Capital Management, Earnings Management and Signalling Effects”, *Journal of Accounting and Economics*, 28 (1), 1-25.

Anderson, K. Woodhouse, K., Ramsay, A. and Faff, R. (2009). “Testing for Asymmetric Effects in the Accrual Anomaly Using Piecewise Linear Regressions: Australian Evidence”, *Pacific Accounting Review*, 21 (1), 5-25.

Balboa, M., López-Espinosa, G. and Rubia, A. (2010). “International Accouting Differences and Earnings Smoothing in the Banking Industry”, Working Paper 516, *Fundación de las Cajas de Ahorro*.

Ball, R., Kothari, S.P. and Robin, A. (2000). “The Effect of International Institutional Factors on Properties of Accounting Earnings”, *Journal of Accounting and Economics*, 29, 1-51.

Ball, R. and Shivakumar, L. (2005). “Earnings Quality in U.K. Private Firms: Comparative Loss Recognition Timeliness”, *Journal of Accounting and Economics*, 39, 83-128.

Ball, R. and Shivakumar, L. (2006). “The Role of Accruals in Asymmetrically Timely Gain and Loss Recognition”, *Journal of Accounting Research*, 44 (2), 207-242.

Balsam, S. (1998). “Discretionary Accounting Choices and CEO Compensation”, *Contemporary Accounting Research*, 15 (3), 229-252.

Barro, R. and Barro, J. (1990). “Pay, Performance, and Turnover of Bank CEOs,” *Journal of Labor Economics*, 8, 448-481.

Basu, S. (1997). “The Conservatism Principle and Asymmetric Timeliness of Earnings”, *Journal of Accounting and Economics*, 24, 3-37.

Beatty, A., Chamberlain, S. and Magliolo, J. (1995). “Managing Financial Reports of Commercial Banks: The Influence of Taxes, Regulatory Capital and Earnings”, *Journal of Accounting Research*, 33 (2), 231-262.

Bebchuk, L., (2009). “Written Testimony, Hearing on Compensation Structures and Systemic Risk, June 11, 2009, Committee on Financial Services, U.S. House of Representatives”, Harvard Law School.

Bergstresser, D. and Philippon, T. (2006). “CEO Incentives and Earnings Management”, *Journal of Financial Economics*, 80, 511-529.

Bhat, V.N. (1996). “Banks and Income Smoothing: an Empirical Analysis”, *Applied Financial Economics*, 6 (6), 505–510.

Bikker, J.A. and Metzemakers, P.A.J. (2005). “Bank Provisioning Behaviour and Procyclicality”, *Journal of International Financial Markets, Institutions and Money*, 15 (2) 141–157.

Bouvatier, V. and Lepetit, L. (2008). “Banks’ Procyclical Behavior: Does Provisioning Matter?”, *Journal of International Financial Markets, Institutions and Money*, 18 (5), 513–526.

Brady, M. and Sinkey, J.F. (1988). “Bank Loan-Loss Provisions and the Income-Smoothing Hypothesis: An Empirical Analysis, 1976-1984”, *Journal of Financial Service Research*, 1 (4), 301-318.

Cameron, A.C., Gelbach, J.B. and Miller, D.L. (2011). “Robust Inference with Multi-way Clustering", *Journal of Business and Economic Statistics*, 29(2), 238-249.

Caner, M. and Hansen, B.E., (2004). “Instrumental Variable Estimation of a Threshold Model”, *Econometric Theory*, 20: 813-843.

Chan, K.S. (1993). “Consistency and Limiting Distribution of the Least Squares Estimator of a Threshold Autoregressive Model”, *Annals of Statistics*, 21, 520-533.

Cheng, Q. and Warfield, T.D., (2005). “Equity Incentives and Earnings Management”, *Accounting Review*, 80, 441–476.

Cohen, D.A., Dey, A. and Lys, T.Z. (2004). “Trends in Earnings Management and Informativeness of Earnings Announcements in the Pre- and Post-Sarbanes Oxley Periods”, Working Paper. Northwestern University.

Collins, J.H., Shackelford, D.A. and Wahlen, J.M. (1995). “Bank Differences in the Coordination of Regulatory Capital, Earnings and Taxes”, *Journal of Accounting Research*, 33 (2), 263-291.

Cornett, M.M., McNut, J.J. and Tehranian, H. (2009). “Corporate Governance and Earnings Management at Large U.S. Bank Holding Companies”, *Journal of Corporate Finance*, 15, 412-430.

DeAngelo, H., DeAngelo, L. and Skinner, D.J. (1994). “Accounting Choice in Troubled Companies”, *Journal of Accounting and Economics,* 17(1-2): 113-143.

Degeorge, F., Patel, J. and Zechhauser, R.F. (1999). “Earnings Management to Exceed Thresholds”, *The Journal of Business*, 72 (1), 1-34.

Gao, P. and Shrieves, R.E. (2002). “Earnings Management and Executive Compensation: A Case of Overdose of Option and Underdose of Salary?, Working Paper. University of Tennessee.

Gaver, J., Gaver, K. and Austin, J. (1995). “Additional Evidence on Bonus Plans and Income Management”, *Journal of Accounting and Economics*, 19, 3-28.

Gow, I.D., Ormazabal, G. and Taylor, D.J. (2010). “Correcting for Cross-Sectional and Time-Series Dependence in Accounting Research”, *The Accounting Review,* 85 (2), 483-512.

Greenawalt, M.B. and Sinkey, J.F. (1988). “Bank Loan-Loss Provisions and the Income-Smoothing Hypothesis: An Empirical Analysis, 1976-1984”, *Journal of Financial Services Research*, 1 (4), 301-318.

Guidry, F., Leone, A.J. and Rock, S. (1999). “Earnings-bonus Plans and Earnings Management”, *Journal of Accounting and Economics,* 26, 113–142.

Hansen, B.E. (1999). “Threshold Effects in Non-Dynamic Panels: Estimation, Testing, and Inference”, *Journal of Econometrics*, 93, 345-368.

Hansen, B.E. (2000). “Sample Splitting and Threshold Estimation”, *Econometrica*, 68(3), 575-603.

Healy, P.M. and Wahlen, J.M. (1999). “A Review of the Earnings Management Literature and Its Implications for Standard Setting”, *Accounting Horizons*, 13 (4), 365-383.

Healy, P.M., (1985). “The Effects of Bonus Schemes on Accounting Decision”, *Journal of Accounting and Economics*, 7 (1-3), 85-107.

Holthausen, R.W., Larcker D.F. and Sloan, R.G. (1995). “Annual Bonus Schemes and the Manipulation of Earnings”, *Journal of Accounting and Economics*, 19, 29-74.

Kaplan, R. (1985). “Comments on Paul Healy: Evidence on the Effect of Bonus Schemes on Accounting Procedures and Accrual Decisions”, *Journal of Accounting and Economics*, 7, 109-113.

Kanagaretnam, K., Lobo, G.J. and Mathieu, R. (2003). “Managerial Incentives for Income Smoothing Through Bank Loan Loss Provisions”. *Review of Quantitative Finance and Accounting*, 20 (1), 63-80.

Kirschenheiter, M. and Melumad, N.D. (2002). "Can "Big Bath" and Earnings Smoothing Co-Exist as Equilibrium Financial Reporting Strategies?", *Journal of Accounting Research*, 40, 761-796.

Koch, T.W. and Wall, L.D. (1999). "The Use of Accruals to Manage Reported Earnings: Theory and Evidence", Federal Reserve Bank of Atlanta, unpublished Working Paper.

Kothari, S.P., Leone, A.J. and Wasley, C.E. (2005). "Performance Matched Discretionary Accrual Measures", *Journal of Accounting and Economics*, 39(1), 163-197.

Kraft, A., Leone, A.J. and Wasley, C. (2006). "An Analysis of the Theories and Explanations Offered for the Mispricing of Accruals and Accrual Components", *Journal of Accounting Research*, 44(2), 297-339.

Laeven, L. and Majnoni, G. (2006). "Loan Loss Provisioning and Economic Slowdowns: Too Much, Too Late?", *Journal of Financial Intermediation*, 12 (2), 178–197.

Leuz, C., Nanda, D. and Wysocki, P. (2003). "Investor Protection and Earnings Management: An International Comparison", *Journal of Financial Economics*, 69, 505-527.

Lobo, G. and Yang, D., (2001). "Bank Managers' Heterogeneous Decisions on Discretionary Loan Loss Provisions", *Review of Quantitative Finance and Accounting*, 16 (3), 223-250.

Ma, C.K. (1988). "Loan Loss Reserves and Income Smoothing: the Experience in the U.S. Banking Industry", *Journal of Business, Finance and Accouting*, 15 (4), 487-497.

Moreira, J.A.C and Pope, P.F. (2007). "Piecewise Linear Accrual Models: do They Really Control for the Asymmetric Recognition of Gains and Losses?", Working Paper 0703. Universidade do Porto.

Moyer, S.E. (1990). "Capital Adequacy Ratio Regulations and Accounting Choices in Commercial Banks", *Journal of Accounting and Economics*, 13 (2), 123-154.

Murphy, J.M. (1999). "Executive Compensation", Orley Ashenfelter and David Card (eds.), *Handbook of Labor Economics*, Vol. 3.

Petersen, M.A. (2009). "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches", *Review of Financial Studies*, 22, 435-480.

Pourciau, S. (1993). "Earnings Management and Nonroutine Executive Changes", *Journal of Accounting and Economics*, 16, 317-36.

Scheiner, J.H., (1981). "Income Smoothing: An Analysis in the Banking Industry", *Journal of Bank Research*, summer issue, 119-123.

Shleifer, A. and Vishny, R. (1997). "A Survey of Corporate Governance", *Journal of Finance*, 52, 737-783.

Shuto, A. (2007). "Executive Compensation and Earnings Management: Empirical Evidence From Japan", *Journal of International Accounting*, Auditing and Taxation, 16, 1-26.

Sloan, R.G. (1993). "Accounting Earnings and Top Executive Compensation", *Journal of Accounting and Economics*, 16 (1-3), 55-100.

Thompson, S. (2011). "A Simple Formula for Standard Errors that Cluster by Both Firm and Time", *Journal of Financial Economics*, 99 (1), 1-10.

Tong, H. (1983). "Threshold Models in Nonlinear Time Series Analysis", Lecture Notes in Statistics 21. Springer, New York.

Tong, H. (1990). Non-linear Time Series. Vol. 6, Oxford Statistical Science Series. The Clarendon Press Oxford University Press, New York.

Watts, R., and Zimmerman, J. (1986). Positive Accounting Theory. Englewood Cliffs, NJ: Prentice Hall, 1986.

Wetmore, J.L. and Brick, J.R. (1994). “Loan Loss Provisions of Commercial Banks and Adequate Disclosure: A Note”, *Journal of Economics and Business*, 46 (4), 299-305.

Zingales, L. (1994). “The Value of the Voting Right: A Study of the Milan Stock Exchange Experience”, *Review of Financial Studies*, 7, 125-148

Figures

Figure 1. Estimated coefficients in the decile pooled time-series cross-sectional regressions in equation (2).

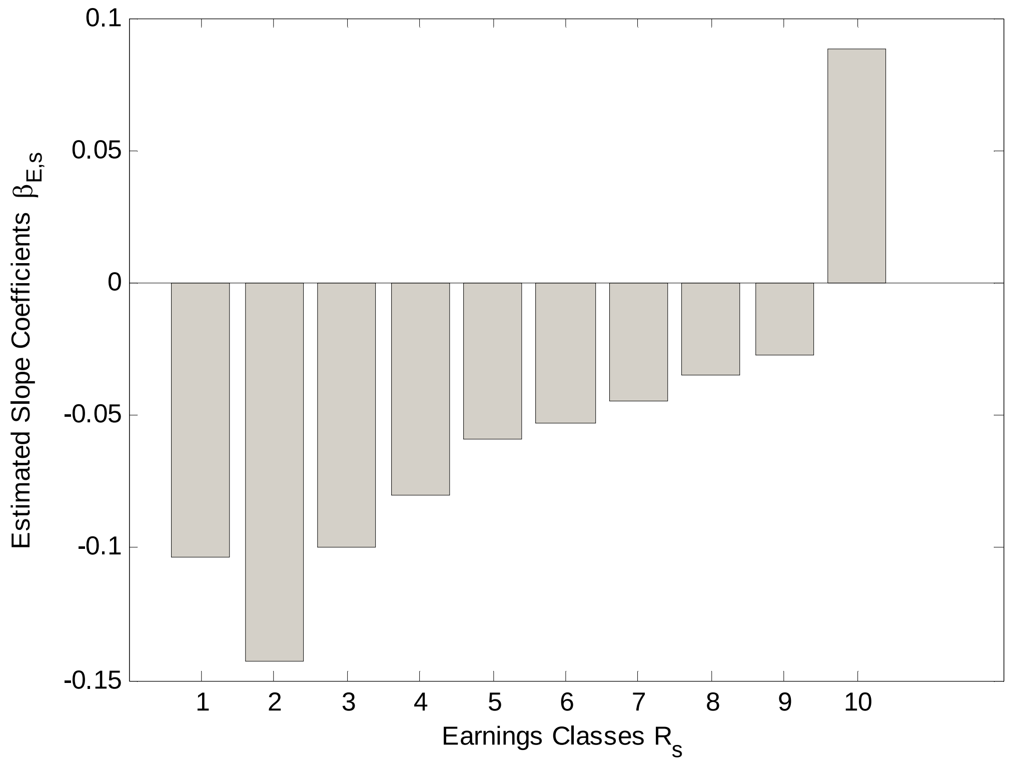


Figure 2. Estimated coefficients in the decile pooled time-series cross-sectional regressions in equation (3) together with the estimates from Model IV. The dotted and dashed-dotted lines show, respectively, the position of the zero-earnings threshold, and the estimated threshold values. The numbers related to each regime are the values of the estimated coefficients of LLP on earnings in Model IV.

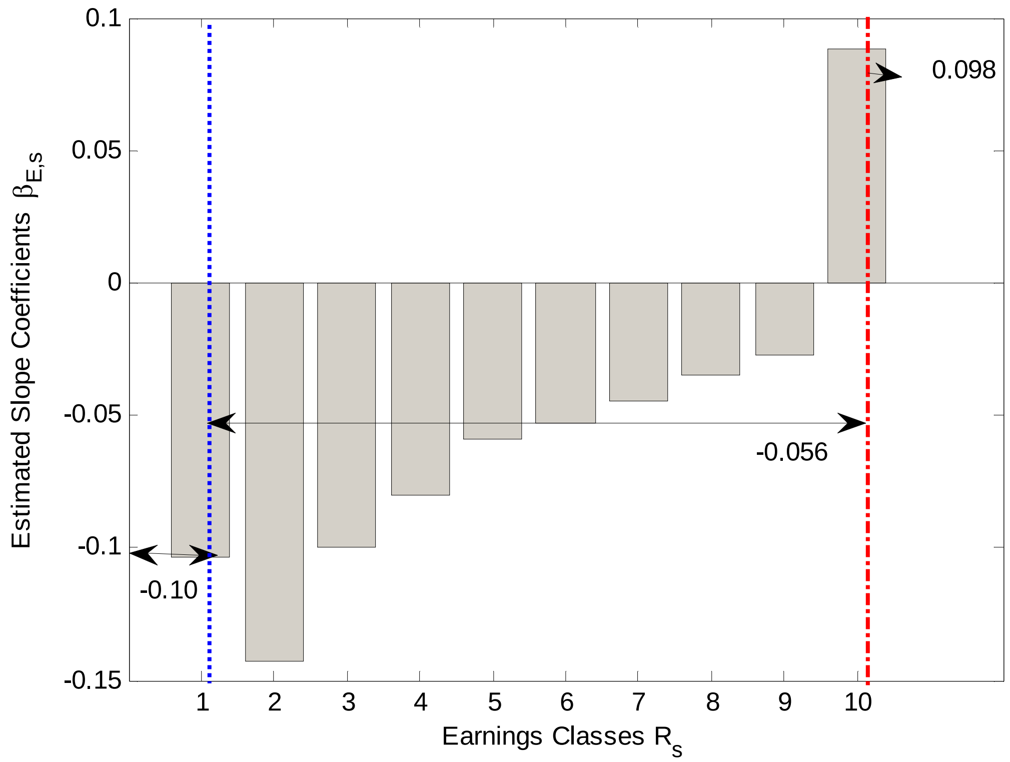
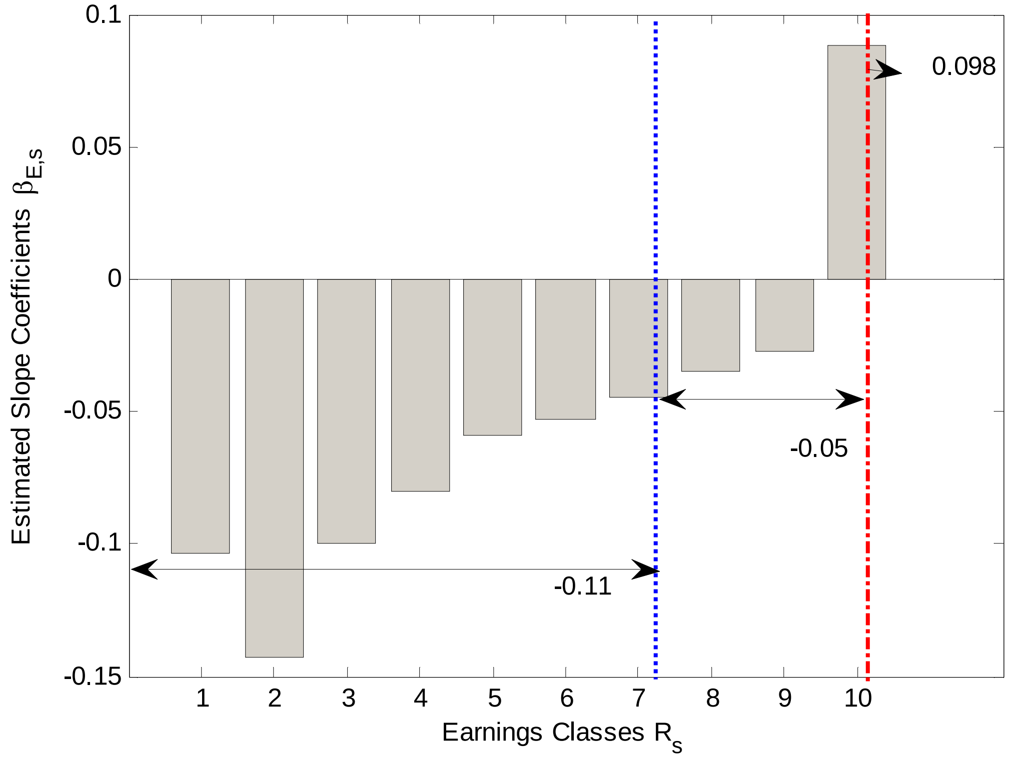


Figure 3. Estimated coefficients in the decile pooled time-series cross-sectional regressions in equation (3) together with the estimates from Model V. The dotted and dashed-dotted lines show, respectively, the position of the lower and upper estimated threshold values. The figures related to each regime are the values of the estimated coefficients of LLP on earnings in Model V.



Tables

Table 1. Descriptive statistics

Variable	Observ.	Mean	25%	Median	75%	Standard Deviation
Panel A						
Bank variables						
LLPTA	81,568	0.0028	0.0004	0.0014	0.0030	0.0082
ILTA	81,434	0.0051	0.0002	0.0020	0.0060	0.0102
LTA	81,568	0.6386	0.5484	0.6595	0.7517	0.1586
TCR	81,324	18.4179	11.9000	14.5000	19.4000	18.4751
SIZE	81,568	11.8984	10.9993	11.6803	12.5030	1.3342
PB	81,568	0.0145	0.0099	0.0148	0.0194	0.0259
Macroeconomic variable						
GDPG	10	2.6229	1.8137	2.5819	3.5733	1.3459
Panel B						
$PB_{it} > 0$	76,693	0.0166	0.0110	0.0153	0.0198	0.0245
$PB_{it} < 0$	4,854	-0.0181	-0.0236	-0.0099	-0.0035	0.0251
$PB_{it} = 0$	21	0	0	0	0	0

Descriptive statistics of the following variables: LLPTA: total loan loss provisions deflated by firm's total assets; ILTA: impaired loans to total assets; LTA: loans to total assets; TCR: total capital ratio; SIZE: natural logarithm of total assets; PB: profit before tax and loan loss provision deflated by total assets; GDPG: GDP growth (it should be noted that the number of observations used in the empirical analyses is around 81,000, depending on the specified model, since this variable takes the same value each year for all the banks in the sample).

Table 2. Correlation matrix

	LLPTA	ILTA	LTA	TCR	SIZE	GDPG	PB
LLPTA	1.00						
ILTA	**0.33**	1.00					
LTA	**0.10**	**0.14**	1.00				
TCR	**-0.02**	**-0.08**	**-0.39**	1.00			
SIZE	**0.06**	**0.05**	**0.14**	**-0.20**	1.00		
GDPG	**-0.09**	**-0.18**	**-0.06**	**0.03**	**-0.07**	1.00	
PB	**0.21**	**-0.02**	**0.04**	**-0.09**	**0.12**	**0.04**	1.00

Correlations between the variables included in the empirical analysis. LLPTA: total loan loss provisions deflated by firm's total assets; ILTA: impaired loans to total assets; LTA: loans to total assets; TCR: total capital ratio; SIZE: natural logarithm of total assets; GDPG: GDP growth; PB: profit before tax and loan loss provision deflated by total assets.
Values in bold are significant at the 5 percent level.

Table 3. Estimation of the basic linear model

Variable	Pooled regression double cluster	Panel data fixed effects
$Constant_{it}$	-0.003	0.019
	(0.02)	(0.00)
$ILTA_{it}$	0.248	0.258
	(0.00)	(0.00)
LTA_{it}	0.004	0.001
	(0.00)	(0.34)
TCR_{it}	2.32E-5	-1.72E-5
	(0.00)	(0.00)
$SIZE_{it}$	1.27E-4	-0.001
	(0.38)	(0.00)
$GDPG_t$	-2.41E-4	-3.03E-4
	(0.05)	(0.00)
PB_{it}	**0.068**	0.048
	(0.05)	(0.08)
R2 adjusted	0.154	0.143
Number observations	81,307	81,307

Estimation of the basic linear model through: a) pooled regression time-series with robust errors computed on double cluster (TCR and year); b) panel data methodology with fixed effects (as indicated by the Hausman test). Dependent variable $LLPTA_{it}$: total loan loss provisions deflated by firm's total assets. Independent variables: $ILTA_{it}$: impaired loans to total assets; LTA_{it}: loans to total assets; TCR_{it}: total capital ratio; $SIZE_{it}$: natural logarithm of total assets; $GDPG_t$: GDP growth; PB_{it}: profit before tax and loan loss provision deflated by total assets. Robust *p*-values in brackets. PB values in bold are significant at the 5 percent level.

Table 4. Trimmed pooled regression with two-way cluster methodology

Panel A: Deletion of observations related to the largest $\alpha\%$ of squared residuals				
Variable	$\alpha = 1\%$	$\alpha = 2.5\%$	$\alpha = 5\%$	$\alpha = 10\%$
Constant_{it}	-0.001	-0.001	-0.001	-0.001
	(0.26)	(0.39)	(0.19)	(0.00)
ILTA_{it}	0.188	0.169	0.168	0.191
	(0.00)	(0.00)	(0.00)	(0.00)
LTA_{it}	0.003	0.003	0.003	0.002
	(0.00)	(0.00)	(0.00)	(0.00)
TCR_{it}	9.43E-6	8.33E-6	7.28E-6	6.46E-6
	(0.00)	(0.00)	(0.00)	(0.00)
SIZE_{it}	2.95E-5	1.83E-5	2.79E-5	2.98E-5
	(0.54)	(0.68)	(0.52)	(0.23)
GDPG_{t}	-1.72E-4	-1.32E-4	-1.28E-4	-1.17E-4
	(0.04)	(0.04)	(0.03)	(0.01)
PB_{it}	0.009	-2.30E-4	0.010	**0.024**
	(0.06)	(0.97)	(0.17)	(0.00)
R2 adjusted	0.247	0.266	0.293	0.386
Number observations	80,631	79,548	77,593	73,563
Panel B: Deletion of observations larger than the $(1-\alpha)\%$ top percentile of earnings				
Constant_{it}	1.41E-4	4.94E-4	6.74E-4	9.24E-4
	(0.72)	(0.60)	(0.47)	(0.31)
ILTA_{it}	0.221	0.228	0.230	0.228
	(0.00)	(0.00)	(0.00)	(0.00)
LTA_{it}	0.003	0.003	0.002	0.002
	(0.00)	(0.00)	(0.00)	(0.00)
TCR_{it}	-5.23E-6	-8.30E-6	-9.80E-6	-1.18E-5
	(0.48)	(0.01)	(0.01)	(0.00)
SIZE_{it}	6.44E-5	5.14E-5	4.38E-5	3.36E-5
	(0.45)	(0.61)	(0.64)	(0.74)
GDPG_{t}	-1.74E-4	-1.63E-4	-1.61E-4	-1.68E-4
	(0.04)	(0.06)	(0.05)	(0.04)
PB_{it}	**-0.039**	**-0.059**	**-0.065**	**-0.074**
	(0.00)	(0.00)	(0.01)	(0.00)
R2 adjusted	0.218	0.249	0.256	0.259
Number observations	80,821	79,659	77,635	73,537
Panel C: Deletion of observations related to $(1-\alpha)/2\%$ top and bottom percentile of earnings				
Constant_{it}	-0.002	1.88E-4	4.13E-4	2.56E-4
	(0.11)	(0.97)	(0.66)	(0.81)
ILTA_{it}	0.215	0.210	0.218	0.214
	(0.00)	(0.00)	(0.00)	(0.00)
LTA_{it}	0.003	0.003	0.002	0.002
	(0.00)	(0.00)	(0.00)	(0.00)
TCR_{it}	1.19E-6	-6.46E-6	-1.43E-5	-2.08E-5
	(0.00)	(0.09)	(0.00)	(0.00)
SIZE_{it}	7.61E-5	5.28E-5	4.28E-5	3.59E-5
	(0.40)	(0.57)	(0.64)	(0.67)
GDPG_{t}	-2.12E-4	-1.89E-4	-1.87E-4	-1.80E-4
	(0.03)	(0.05)	(0.04)	(0.03)
PB_{it}	**0.042**	**-0.028**	-0.020	0.014
	(0.00)	(0.01)	(0.08)	(0.07)
R2 adjusted	0.184	0.213	0.226	0.214
Number observations	80,810	79,723	77,725	73,688

Trimmed pooled regression time-series with robust errors computed on double cluster (TCR and year). Dependent variable LLPTA_{it}: total loan loss provisions deflated by firm's total assets. Independent variables: ILTA_{it}: impaired loans to total assets; LTA_{it}: loans to total assets; TCR_{it}: total capital ratio; SIZE_{it}: natural logarithm of total assets; GDPG_{t}: GDP growth; PB_{it}: profit before tax and loan loss provision deflated by total assets. Robust *p*-values in brackets. PB values in bold are significant at the 5 percent level.

Table 5. Trimmed pooled regression with panel data fixed effects

Panel A: Deletion of observations related to the largest $\alpha\%$ ***of squared residuals***				
Variable	$\alpha = 1\%$	$\alpha = 2.5\%$	$\alpha = 5\%$	$\alpha = 10\%$
$Constant_{it}$	0.011	0.012	0.012	0.012
	(0.00)	(0.00)	(0.00)	(0.00)
$ILTA_{it}$	0.193	0.181	0.180	0.189
	(0.00)	(0.00)	(0.00)	(0.00)
LTA_{it}	0.002	0.002	0.002	0.002
	(0.00)	(0.00)	(0.00)	(0.00)
TCR_{it}	-7.92E-6	-8.95E-6	-1.07E-5	-1.18E-5
	(0.00)	(0.00)	(0.00)	(0.00)
$SIZE_{it}$	-8.67E-4	-9.26E-4	-9.43E-4	-9.52E-4
	(0.00)	(0.00)	(0.00)	(0.00)
$GDPG_t$	-1.91E-4	-1.62E-4	-1.54E-4	-1.53E-4
	(0.00)	(0.00)	(0.00)	(0.00)
PB_{it}	**-0.005**	-0.03	7.91E-5	**0.010**
	(0.03)	(0.07)	(0.95)	(0.00)
R2 adjusted	0.271	0.296	0.329	0.390
Number observations	80,493	79,274	77,241	73,176
Panel B: Deletion of observations larger than the $(1-\alpha)\%$ ***top percentile of earnings***				
$Constant_{it}$	0.011	0.011	0.011	0.010
	(0.00)	(0.00)	(0.00)	(0.00)
$ILTA_{it}$	0.238	0.237	0.238	0.237
	(0.00)	(0.00)	(0.00)	(0.00)
LTA_{it}	0.001	0.001	0.001	0.002
	(0.00)	(0.00)	(0.00)	(0.00)
TCR_{it}	-2.15E-5	-2.29E-5	-2.44E-5	-2.54E-5
	(0.00)	(0.00)	(0.00)	(0.00)
$SIZE_{it}$	-7.48E-4	-7.46E-4	-7.32E-4	-7.09E-4
	(0.00)	(0.00)	(0.64)	(0.74)
$GDPG_t$	-2.10E-4	-1.98E-4	-1.91E-4	-1.89E-4
	(0.00)	(0.00)	(0.00)	(0.00)
PB_{it}	**-0.035**	**-0.044**	**-0.050**	**-0.055**
	(0.00)	(0.00)	(0.00)	(0.00)
R2 adjusted	0.217	0.222	0.225	0.225
Number observations	80,821	79,659	77,635	73,537
Panel C: Deletion of observations related to $(1-\alpha)/2\%$ ***top and bottom percentile of earnings***				
$Constant_{it}$	0.013	0.011	0.010	0.009
	(0.00)	(0.00)	(0.00)	(0.00)
$ILTA_{it}$	0.232	0.226	0.226	0.228
	(0.00)	(0.00)	(0.00)	(0.00)
LTA_{it}	0.002	0.001	0.001	0.001
	(0.01)	(0.00)	(0.01)	(0.13)
TCR_{it}	-1.79E-5	-1.61E-5	-2.13E-5	-3.55E-5
	(0.00)	(0.00)	(0.00)	(0.00)
$SIZE_{it}$	-9.48E-4	-7.62E-4	-7.20E-4	-6.18E-4
	(0.00)	(0.00)	(0.00)	(0.67)
$GDPG_t$	-2.55E-4	-2.21E-4	-2.17E-4	-1.99E-4
	(0.00)	(0.00)	(0.00)	(0.00)
PB_{it}	-3.79E-4	**-0.023**	**-0.014**	**0.025**
	(0.96)	(0.00)	(0.01)	(0.00)
R2 adjusted	0.199	0.206	0.204	0.194
Number observations	80,810	79,723	77,725	73,688

Trimmed panel data fixed effects regression with robust errors. Dependent variable $LLPTA_{it}$: total loan loss provisions deflated by firm's total assets. Independent variables: $ILTA_{it}$: impaired loans to total assets; LTA_{it}: loans to total assets; TCR_{it}: total capital ratio; $SIZE_{it}$: natural logarithm of total assets; $GDPG_t$: GDP growth; PB_{it}: profit before tax and loan loss provision deflated by total assets. Robust *p*-values in brackets. PB values in bold are significant at the 5 percent level.

Table 6. Estimation with two-way cluster methodology

	Pooled regression double cluster				
Variable	**M. I**	**M. II**	**M. III**	**M. IV**	**M. V**
$Constant_{it}$	-0.003 (0.02)	-0.003 (0.01)	-0.003 (0.05)	-0.003 (0.05)	-0.002 (0.14)
$ILTA_{it}$	0.248 (0.00)	0.240 (0.00)	0.230 (0.00)	0.230 (0.00)	0.229 (0.00)
LTA_{it}	0.004 (0.00)	0.003 (0.00)	0.004 (0.00)	0.004 (0.00)	0.004 (0.00)
TCR_{it}	2.32E-5 (0.00)	-8.45E-6 (0.05)	-8.71E-6 (0.02)	-1.13E-5 (0.02)	-1.48E-5 (0.00)
$SIZE_{it}$	1.27E-4 (0.38)	1.61E-4 (0.25)	2.63E-4 (0.04)	2.54E-4 (0.06)	2.37E-4 (0.06)
$GDPG_{t}$	-2.41E-4 (0.05)	-2.24E-4 (0.05)	-1.35E-4 (0.23)	-1.44E-4 (0.20)	-1.51E-4 (0.17)
PB_{it}	**0.068** (0.05)	-	-	-	-
$D_{it}\left(PB_{it}>0\right)\times PB_{it}$	-	**0.090** (0.04)	-	-	-
$D_{it}\left(PB_{it}\leq 0\right)\times PB_{it}$	-	**-0.133** (0.00)	-	**-0.100** (0.00)	-
$D_{it}\left(0<PB_{it}\leq \tau_{high}\right)\times PB_{it}$	-	-	-	**-0.056** (0.00)	-
$D_{it}\left(PB_{it}>\tau_{high}\right)\times PB_{it}$	-	-	**0.097** (0.04)	**0.098** (0.04)	**0.097** (0.03)
$D_{it}\left(PB_{it}\leq \tau_{high}\right)\times PB_{it}$	-	-	**-0.077** (0.00)	-	-
$D_{it}\left(PB_{it}\leq \tau_{low}\right)\times PB_{it}$	-	-	-	-	**-0.107** (0.00)
$D_{it}\left(\tau_{low}<PB_{it}\leq \tau_{high}\right)\times PB_{it}$	-	-	-	-	**-0.049** (0.00)
R2 adjusted	0.154	0.186	0.203	0.203	0.206
Number observations	81,307	81,307	81,307	81,307	81,307

Pooled regression time-series with robust errors computed on double cluster (TCR and year). Dependent variable $LLPTA_{it}$: total loan loss provisions deflated by firm's total assets. Independent variables: $ILTA_{it}$: impaired loans to total assets; LTA_{it}: loans to total assets; PB_{it}: profit before tax and loan loss provision deflated by total assets; TCR_{it}: total capital ratio; $SIZE_{it}$: natural logarithm of total assets; $GDPG_{t}$: GDP growth; $D_{it}\left(PB_{it}>0\right)\times PB_{it}$: interaction between a dummy variable (1: PB_{it} is greater than zero; 0: otherwise) and PB_{it}; $D_{it}\left(PB_{it}>\tau_{high}\right)\times PB_{it}$: interaction between a dummy variable (1: PB_{it} is greater than the higher threshold, which is endogenously estimated with a value of 3.64%; 0: otherwise) and PB_{it}; $D_{it}\left(PB_{it}\leq \tau_{low}\right)\times PB_{it}$: interaction between a dummy variable (1: PB_{it} is lower than the lower threshold, which is endogenously estimated with a value of 1.81%; 0: otherwise) and PB_{it}. The remaining interactions between the corresponding dummy variable and PB_{it} can be easily interpreted, given the former definitions. Robust *p*-values in brackets. PB values in bold are significant at the 5 percent level.