

Size, Equity Backing, and Bank Profitability: A Case Study Using Panel Data from Bangladesh

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Abstract

This paper examines the statistical relationship between banks' return on equity on one hand, and their size (as measured by inflation-adjusted total assets) and capital structure on the other, using a set of panel data collected by the first author in 2014. The empirical approach applied allows for heterogeneity across observational units as well as nonlinearity and non-additivity in the conditional mean function, thus facilitating the identification of more complex forms of structural dependence that might remain undetected when using classical linear regression techniques. The results indicate that while a certain degree of equity capitalisation is a necessary precondition for profitability, the positive impact of an increased equity ratio on return on profitability seems to fade above a certain threshold level, the location of which, however, depends on bank size.

JEL classification numbers: G21, C23

Keywords: Bank profitability, size, capitalisation.

1 Introduction

Banks perform a number of highly important functions in an economy: They accept deposits, process accounts and payments, match supply and demand in the credit markets, and offer investment products and risk management instruments to clients. The degree of efficiency and reliability with which they perform these services can therefore be expected to materially impact the health and resilience of the economy they belong to (see Athanoglou, Brissimis, and Delis, 2005). Understanding the determinants of bank profitability may therefore be of considerable interest far beyond the banking sector only. The purpose of this investigation is to examine the impact of two suspected factors of

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influence, namely size (as measured by total assets) and equity capitalisation (as measured by the ratio of equity to total assets), on bank profitability, using a panel dataset gathered from banks in Bangladesh. The particular interest taken in the two above explanatory variables is motivated by two plausibility considerations:

- Equity serves as a risk cover that protects the bank against default should unexpected losses occur. All else being equal, the higher a bank's equity backing, the less risky it will be seen by other banks as well as nonbanks, which can be expected to translate into lower funding cost and subsequently higher profit margins in the lending business. On the other hand, interest paid on borrowed capital lowers the taxable income of the bank (thus providing a "tax shield"), whereas dividend payments to equity investors can only be made following the deduction of all tax items. As a consequence, a bank may seek to reduce its tax burden (and thus to increase its net income per share) by opting for a low ratio of equity to total assets. Hence, the question arises whether one of the two countervailing influences outweighs the other, or whether there is an optimum equity ratio somewhere between 0 and 100%, which best balances the benefits and costs of equity. In the last-mentioned case, the shape of the functional relationship between the return on equity and the equity ratio might very well take the shape of an "inverted U", as sketched in Figure 1.

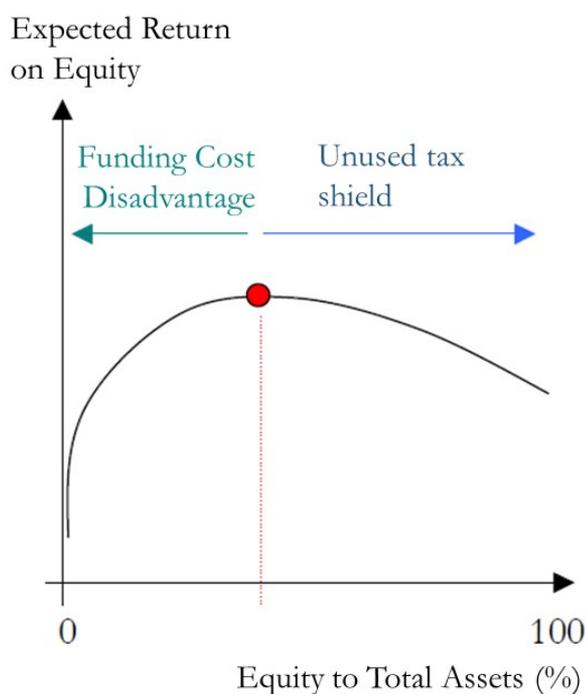


Figure 1: Relationship between the return on equity and the equity ratio

- Size, too, may be related to profitability due to two reasons: On one hand, banking is an activity that involves considerable fixed cost, possibly giving rise to increasing returns to scale. Moreover, growth in size opens up the possibility to increase the degree of diversification in a bank's lending and investment activities, and hence to improve the relationship between the expected portfolio return and the associated risk, leading to a more efficient use of the bank's equity base. On the other hand, the complexity of

a bank's operations, and the cost of coping with it, also tends to increase with size, which may limit the benefits of a large size, or even turn it into a disadvantage, at least beyond a certain threshold.

Most probably the level of profitability attained by an individual bank is influenced by a number of additional characteristics, not all of which will be perceptible to an outside observer. Changes in the general economic environment that occur over time can also be reasonably expected to have an effect. Panel datasets, like the one used in this study, consist of repeated observations of a given number of entities over two or more time periods and hence offer the possibility to assess, albeit in an approximate manner, the impacts made by both of these sources of variation.

The remainder of this paper is organised as follows: In section 2, a brief overview of the relevant literature is provided. Section 3 contains a description of the data in use and some related background information. The econometric model employed and the related estimation method are explained in Section 4. In Section 5, the results are being presented and interpreted. The paper ends with a brief summary (Section 6).

2 Literature Review

Several researchers have so far sought to identify and explain the drivers of bank profitability empirically. Since, in spite of many attempts to harmonise regulatory standards worldwide, several structural differences between national banking systems and markets remain, most related studies have been country-specific. Examples are the investigations by Berger (1995) for the U.S., Kosmidou (2008) for Greece, Pasouras et al. (2005) for Australia, Guru et al. (1999) for Malaysia, Barajas et al. (1999) for Colombia, and Naceur (2003) for Tunisia. In contrast, Molyneux and Thornton (1992) choose a multi-country setting by examining the determinants of bank profitability for a panel of European countries. This example has been followed by Abreu and Mendes (2000), Staikouras and Wood (2003), and Pasiouras et al. (2005). The paper by Hassan and Bashir (2003) focuses on a sample of Islamic banks from 21 countries; whereas Demirguc-Kunt and Huizinga (1999) seek to relate banks' interest margins to a number of both bank specific characteristics and external factors including macroeconomic indicators, legal and regulatory factors, using data from more than 80 countries.

In the study by Goddard et al. (2004), which uses panel data on European banks during the 1990s, the authors find only very limited evidence for any consistent or systematic size–profitability relationship. Moreover, they come to the conclusion that the relationship between the capital–assets ratio and profitability is positive. A more recent study proceeding along a similar line is the paper by Javaid et al. (2011), which focuses on the top 10 banks' profitability in Pakistan over the period 2004 to 2008. Using a pooled ordinary least square (POLS) approach to examine the relationship between total assets, loans, equity, and deposits on one hand on the return on assets on the other, the authors conclude, inter alia, that higher total assets do not necessarily induce a higher level on profitability, which they ascribe to diseconomies of scales. Moreover, the authors find that the size of a banks' equity cover, as well as the share of deposits in total liabilities is positively related to profitability. Interestingly, a similar pattern of results has emerged from the panel study by Ani et al. (2012) on 15 Nigerian banks during the years 2001–10, which, in addition, finds that a high degree of diversification within a bank's asset portfolio positively affects profitability.

For Jordan, Imad et al. (2011) examine a balanced panel of ten banks gathered over the period of 2001 to 2010. They find that in the country under examination, profitability tends to be higher among well-capitalized banks incurring a relatively a low level of credit risk. However, the authors do not find conclusive evidence of a positive association between size and profitability. This somewhat contrasts with the outcome of another empirical investigation conducted by Naceur (2003) for 10 banks in Tunisia for the period from 1980 to 2000, which confirms the existence of a positive relationship between capitalisation and profitability but suggests that above a certain size threshold, the impact of a further increase in total assets on profitability becomes negative.

Given this rich body of seminal literature on the topic, the main contribution the present paper seeks to make lies more in the field of empirical methodology than in the type of data used or questions asked: Unlike most other models, in which the functional relationship between the variables is assumed to be linear and additive, the nonparametric “local least squares” approach employed here, pioneered by Hastie and Tibshirani (1993) and Racine and Li (2004), allows for nonlinearity and non-additivity in the conditional mean function. It hence facilitates the identification of more complex forms of structural dependence that might remain undetected when using classical linear regression techniques. Moreover, the methodology employed here allows both the intercept and the slope parameters of the regression equation to vary across cross-sectional units, and can hence capture individual heterogeneity in a more comprehensive manner than the classical fixed- and random effects models. The way in which this is achieved is elaborated further in Section 4.

3 Data and Background Information

The dataset on which the investigation is based is a panel of 10 private sector banks from Bangladesh observed over 10 consecutive years from 2004 for 2013. Having been compiled manually by the first author, using financial reports published by the banks, the dataset is an unbalanced panel since not for all banks, information could be made available across the entire sampling period. In it, profitability is measured by the return on equity, whereas size is measured by total assets. In order to avoid distortions caused by inflationary effects, the total amounts of assets given in the raw data were re-expressed in 2004 consumer prices using the inflation figures published by Bangladesh Bureau of Statistics, and expressed in billions of Bangladeshi Taka (BDT bn). Descriptive statistics of the accordingly prepared data can be found in Table 1 below:

Table 1: Descriptive Statistics of Variables in Use

	Return on equity	Equity ratio	Total assets (BDT bn, real)
Mean	0.2368	0.0802	4.7133
Standard Deviation	0.1438	0.0218	2.3810
Minimum	0.0450	0.0382	1.6061
5% quantile	0.0604	0.0462	1.8212
10% quantile	0.0794	0.0573	2.1469
25% quantile	0.1461	0.0651	2.8399
Median	0.2023	0.0733	4.1887
75% quantile	0.2729	0.0942	6.3305
90% quantile	0.4952	0.1120	7.8335
95% quantile	0.5843	0.1190	8.9288
Maximum	0.6214	0.1465	12.0521
# observations	90	90	90

4 Model Specification and Estimation

4.1 Problem Formulation and Objective

The purpose of the statistical model specification employed here is to estimate the conditional mean of the dependent variable Y under investigation (here: return on equity), as a function of a set of k explanatory variables gathered in the column vector X (which, in this case, consist of inflation-adjusted total assets and the equity ratio, so that $k = 2$). In what follows, y_{it} denotes the particular value taken by the dependent variable Y at observational unit (here: bank) i at time t , and x_{it} the corresponding realisation of X . Then the underlying sample, consisting of N (here: 10) cross-sectional units observed for a maximum of T (here, again, 10) consecutive periods, can thus be summarised by $\{y_{it}, x_{it}\}$ with $i = 1, \dots, N$ and $t \in T(i)$, with $T(i)$ being the subset of sampling periods for which observations on unit i are available.

The objective pursued here is to estimate the conditional mean function of Y without imposing any overly restrictive preconditions (such as linearity and additivity) on the form of the statistical relationship between Y and X . In addition, the possibility that the nature of the underlying statistical relationship may change over time and differ among individual observational unit should also be accounted for. Following Racine (2008, Section 6), the last-mentioned possibility can be accounted for by simply treating the index numbers i and t as additional explanatory variables, both of which are discrete in nature, but where the realisations of the t have a natural ordering whereas those of i are unordered. In a very general form, the statistical relationship under investigation can then be expressed as

$$Y = m(X, i, t) + u \quad (1)$$

where $m(\cdot)$ represents the (unknown) function conditional expectation function of Y , and u is a mean-zero random error distributed independently of X , i , and t .

4.2 Estimation Method: Local Least Squares

As shown by Hastie and Tibshirani (1993), one way of estimating an unknown function like $m(\cdot)$ in (1) is to use a pre-defined function of both the explanatory variables and a vector of unknown parameters θ in its place, where θ is allowed to vary with the specific values taken by the explanatory variables. In our application, after setting $\theta = [\alpha, \delta, \beta]'$, this would imply approximating (1) by

$$Y = \alpha(X, i, t) + \delta(X, i, t) \cdot t + X' \beta(X, i, t) + \varepsilon \quad (2)$$

Here, the scalar ε represents the cumulative impact of the random error u and any possible approximation error incurred when replacing $m(\cdot)$ by the corresponding term in (2).

Then, for any combination X^* , i^* , and t^* of values lying inside the empirically observed range of X , i , and t , respectively, a set $\hat{\alpha}(X^*, i^*, t^*)$, $\hat{\delta}(X^*, i^*, t^*)$, $\hat{\beta}(X^*, i^*, t^*)$ of related estimates can be calculated as the solution to

$$\left\{ \hat{\alpha}(\cdot), \hat{\delta}(\cdot), \hat{\beta}(\cdot) \right\} = \arg \min_{\tilde{\alpha}, \tilde{\delta}, \tilde{\beta}} \sum_{i=1}^N \sum_{t \in \mathcal{T}(i)} \left(y_{it} - \tilde{\alpha} - \tilde{\delta} \cdot t + x_{it}' \tilde{\beta} \right)^2 \cdot K_{h_1, \dots, h_k, \lambda, \kappa} \left(x_{it}, X^*, t, t^*, i, i^* \right) \quad (3)$$

In the above equation, the function $K(\cdot)$, termed a *kernel function*, is a weighting function of which the value is negatively related to the distance between the triplets $\{X^*, i^*, t^*\}$ and $\{X, i, t\}$. In the particular case studied here, where all k ($=2$) elements of X are continuous, it follows from Racine and Li (2004) that the following form of $K(\cdot)$ can be used:

$$K_{h_1, \dots, h_k, \lambda, \kappa}(\cdot) = \prod_{j=1}^k \frac{1}{h_j} \phi \left(\frac{x_{it} - X^*}{h_j} \right) \cdot \lambda^{|t-t^*|} \cdot \left(\kappa^{1-I(i=i^*)} \right) \text{ with } h_j > 0 \text{ for all } j, \text{ and } \lambda, \kappa \in 0; 1 \quad (4)$$

In the above expression, $I(\cdot)$ stands for an indicator function which returns the value 1 whenever the expression in brackets is true, and 0 otherwise, and $\phi(\cdot)$ is the Standard Normal density. (Instead of the Standard Normal, several other symmetric univariate probability density functions could also be used without substantially affecting the accuracy of the estimates; see, e.g., Härdle, 1990, section 4.5). The scalar quantities h_1, \dots, h_k, λ , and κ are *bandwidth* parameters which jointly determine how quickly the weight placed on an individual observation $\{x_{it}, i, t\}$ in (3) declines as its distance from $\{X^*, i^*, t^*\}$ grows.

4.3 Choice of Bandwidth Parameters

For given values of h_1, \dots, h_k, λ , and κ , (3) is a standard, analytically tractable, weighted-least squares problem. In contrast, choosing appropriate values for the bandwidth parameters is considerably more involved but equally important: In cases where the chosen bandwidth parameters are “too small”, the resulting estimates tend to “fit the noise”, i.e. to be too sensitive to the specific realizations of the random influences present in the data, to possess excessive variance, and to be poorly generalizable. On the other hand, choosing them to be “too large” will cause important features in the unknown, true function $m(\cdot)$ and to go unnoticed. In the context of this investigation, the proposed solution to this dilemma is to follow Härdle (1990, section 5.1.1.) in choosing the “optimal” combination $h_1^{(opt)}, \dots, h_k^{(opt)}, \lambda^{(opt)}, \kappa^{(opt)}$ of bandwidth parameters by minimizing the cross validation criterion

$$CV = \sum_{i=1}^N \sum_{t \in \mathcal{T}(i)} \left(y_{it} - \hat{\alpha}_{-(i \cap t)} - \hat{\delta}_{-(i \cap t)} \cdot t + x_{it}' \hat{\beta}_{-(i \cap t)} \right)^2 \quad (5)$$

simultaneously with respect to h_1, \dots, h_k , λ , and κ . In equation (5), the symbols $\hat{\alpha}_{-(i \cap t)}$, $\hat{\delta}_{-(i \cap t)}$, and $\hat{\beta}_{-(i \cap t)}$ denote “leave-one-out” estimates of the related parameters, i.e. estimates calculated along the same lines as $\hat{\alpha}(x_{it}, i, t)$, $\hat{\delta}(x_{it}, i, t)$, and $\hat{\beta}(x_{it}, i, t)$ but by deliberately leaving out the data point $\{y_{it}, x_{it}\}$.

Minimizing (5) constitutes a multidimensional optimisation problem with possibly more than one local minimum. From the number of optimisation heuristics that can be used to tackle such a problem (see, e.g., the survey by Gilli and Winker, 2009), the Differential Evolution algorithm by Storn and Price (1997) is chosen here. Readers interested in the details of its implementation are referred to Gilli and Schumann (2010).

The optimised values of the bandwidth parameters allow for important, qualitative conclusions with regard to the nature of the underlying functional relationship under examination (see Racine, 2008, sections 4.2 and 6.1):

- A value of $\kappa^{(opt)}$ that is close to 1 indicates that the unobserved specific characteristics of the individual units $i = 1, \dots, N$ on Y , which captured by including i in the set of explanatory variables in (1), is largely negligible. In contrast, a value of $\kappa^{(opt)}$ that is only slightly above zero indicates that these unobserved individual characteristics strongly impact the conditional expectation of the dependent variable. If $\kappa^{(opt)}$ is somewhere in the middle between 0 and 1, some observational units may be pooled into groups with largely similar unobserved characteristics, while others may not.
- A value of $\lambda^{(opt)}$ that is close to 1 indicates that the nature of the statistical relationship between Y and X , after accounting for the possible impact of unobserved individual characteristics as above, was largely unaltered over time during the sampling period. On the other hand, a value of $\lambda^{(opt)}$ that is close to zero suggests that the statistical relationship under investigation underwent significant changes over time. In cases where $\lambda^{(opt)}$ is well above 0 but considerably below 1, the relationship examined was stable during some sub-periods of the sampling period and unsteady during others.
- In the case of the bandwidth parameters h_m , $m = 1, \dots, k$, that refer to continuous explanatory variables, a very large value of $h_m^{(opt)}$ indicates that all else being equal, the relationship between explanatory variable X_m and the expected value of Y is linear or close to linear across the entire range of observed values for X_m .

4.4 Estimation of Pointwise Confidence Intervals

Following a recommendation by Racine (2008, p. 44), pointwise confidence intervals for both the parameter estimates and the fitted values of Y are estimated by bootstrapping (see Efron, 1979). In its simplest variant, which has been employed here, this involves creating a large number B (here: 1,000) of pseudo-samples, each having the same number of

observations as the original dataset, by randomly sampling from the original sample with replacement. Then, the quantities of interest are re-estimated for each of these pseudo-samples separately, and the estimated confidence bands for these quantities are inferred from the empirical quantiles of the B resulting estimates. In what follows, an estimate is said to be significantly above (below) zero if zero lies outside the corresponding 95% confidence interval.

5 Results

General Approach

The interpretation of the results obtained by applying the above estimation procedure rests on three mutually complementary bases: Firstly, the values taken by the optimal bandwidth parameters $\kappa^{(opt)}$, $\lambda^{(opt)}$, $h_1^{(opt)}$, and $h_2^{(opt)}$ is examined in order to assess the extent of unobserved heterogeneity among the banks in the sample, the degree of intertemporal variation in the statistical relationship under investigation, and whether the marginal impact of a change in the equity ratio (x_1) or total assets (x_2) on the return on equity can well be approximated by a straight line. Secondly, descriptive statistics of the individual coefficient estimates are calculated in order to assess both the degree of heterogeneity prevailing in the parameter estimates and the frequency of significantly positive or negative values among them. Thirdly, following Racine (2008, pp. 44-45), so-called partial regression plots are displayed. A partial regression plot is a two-dimensional plot of the estimated value of the dependent variable versus one covariate where all remaining variables are held constant. The values taken by the optimal bandwidth parameters and the descriptive statistics of the coefficient estimates are presented in Table 2.

Table 2: Optimal Bandwidth Parameters and Descriptive Statistics of Coefficient Estimates

	$\hat{\alpha}$	$\hat{\delta}$	$\hat{\beta}_1$	$\hat{\beta}_2$
Optimal bandwidth	$\kappa^{(opt)} = 0.015$	$\lambda^{(opt)} = 0.219$	$h_1^{(opt)} = 0.024$	$h_2^{(opt)} > 1.8 \cdot 10^7$
Mean	0.00128	-0.01229	4.31914	0.00240
Standard Deviation	0.02438	0.03685	2.91286	0.03758
Minimum	-0.06771	-0.11486	-4.47124	-0.11766
5% quantile	-0.05256	-0.07264	0.27122	-0.06081
10% quantile	-0.01999	-0.05556	0.85260	-0.03839
25% quantile	-0.00866	-0.02906	2.27963	-0.02416
Median	-0.00086	-0.01420	3.93989	-0.00119
75% quantile	0.01311	0.00595	5.11794	0.03123
90% quantile	0.02268	0.01447	7.29932	0.04461
95% quantile	0.03999	0.02925	11.02015	0.06048
Maximum	0.10510	0.20591	11.95763	0.07604
% significantly > 0	15.56%	2.22%	72.22%	8.89%
% significantly < 0	7.78%	2.22%	0.00%	26.67%

Unobserved Heterogeneity among Cross-Sectional Units

The optimized value of the smoothing parameter pertaining to the bank identifier i , $\kappa^{(opt)}$, is only slightly above zero and thus indicates that unobserved bank-individual characteristics do indeed have a non-negligible influence on the outcome of the dependent variable. The fact that, according to Table 2, only a rather small percentage (23.34%) of the related parameter estimates differs significantly from zero, is only apparently in contradiction to this finding. Rather, it suggests that the unobserved heterogeneity prevailing among the banks under investigation captured less by differences in the intercept term than by the variations in the remaining parameters of the regression equation. This interpretation is also broadly consistent with the partial regression plot displayed in Figure 2, where the estimated conditional expectation of the return on equity, together with the related confidence intervals, is plotted against the different values of the bank identifier, with t set to 5.5 (i.e. the middle of the sampling period) and the remaining explanatory variables to their sample mean:

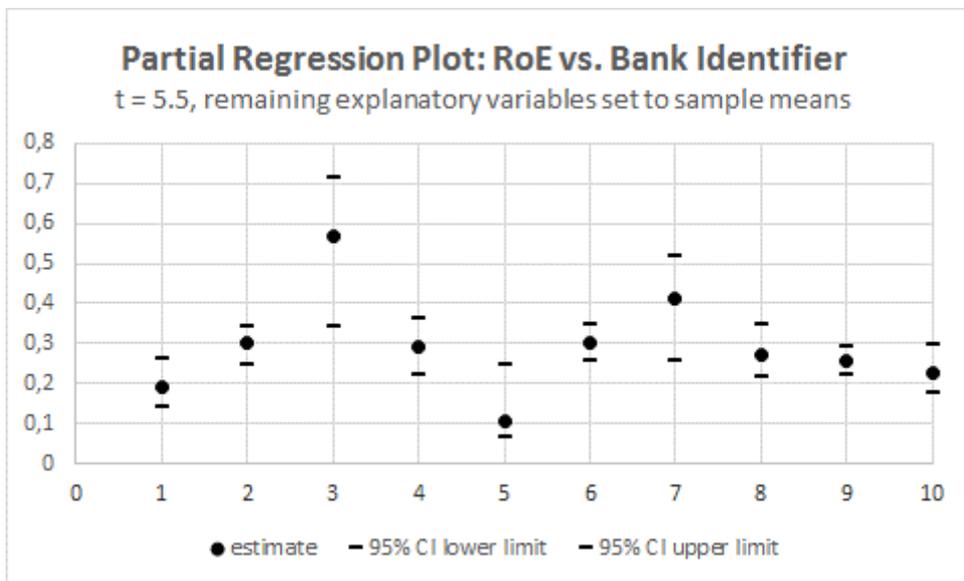


Figure 2: Partial regression plot

Intertemporal variation

$\lambda^{(opt)}$, the optimized value of the smoothing parameter pertaining to the time index t , lies markedly closer to zero than to one. This reveals that the nature of the statistical relationship investigated here undergoes noticeable changes over time, which are probably due to changes in the general market environment during the sampling period. Given the fact that the time index used in this model is an ordered, discrete variable, the fact that the related coefficient $\hat{\delta}$ only rarely differs from zero is not contradictory to this observation. Rather, it merely shows that the time-dependence of the banks' return on equity does not take the form of a linear-additive trend.

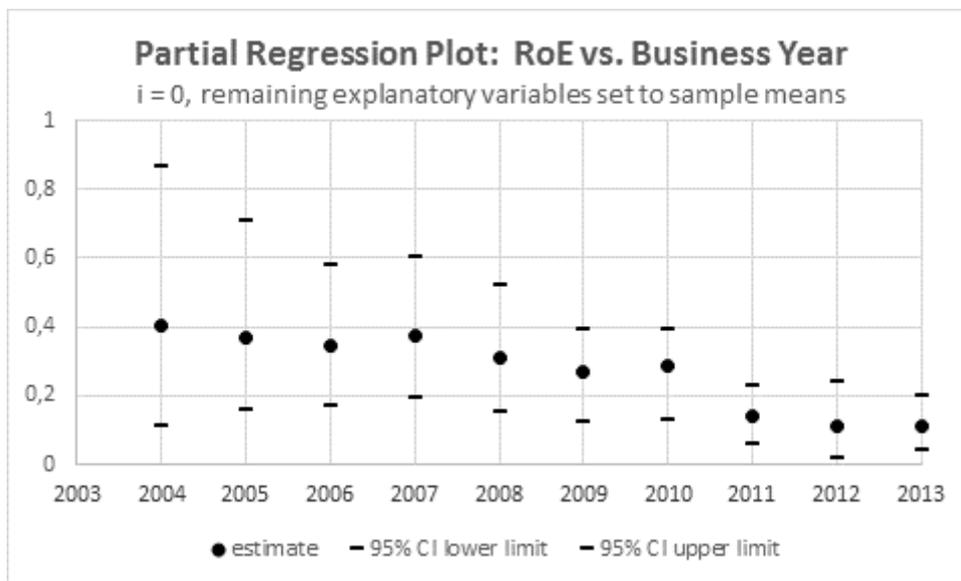


Figure 3: Partial regression plot

The partial regression plot in Figure 3, where the estimated conditional mean of the return on equity is plotted against the respective business years, with *i* being set to a “neutral” value (e.g. zero) and the remaining explanatory variables are set to their sample averages, reveals a significant decline in bank profitability in the three last years of the sampling period (2011 to 2013). This time period coincides with the ending and subsequent, abrupt reversal of an equity market boom that had prevailed in Bangladesh during the years 2009-10. Among the many factors contributing to the steep rise in stock prices in the two years preceding the crash (see Saha, 2012, for an overview) was the fact that during that time, banks and financial institutions had invested huge amount of deposit money in the stock market. Yet in December 2010, the country’s Securities and Exchange Commission and its central bank, Bangladesh Bank, took a number of measures to restrain irregular investment schemes and to curb the further inflow of borrowed funds into a market that was widely perceived to be grossly overvalued. Among the measures taken by Bangladesh Bank were the enactment of an upper limit on the percentage of bank deposits that could be invested in the stock market, increased reserve requirements, and a higher statutory liquidity ratio. Since the preceding stock market boom had apparently been fuelled largely by speculative purchases based on the assumption of a continuing net inflow of borrowed funds into the market, these measures prompted a sharp and protracted sell-off and forced several banks to liquidate positions taken on earlier. In many cases, this resulted in trading losses that subsequently lowered net income, which has clearly left its traces in our estimation results.

Total assets and equity ratio

When it comes to assessing the relationship between size and equity cover on one hand and the return on equity on the other, perhaps the most striking result is that, all else being equal, the estimated impact on marginal increase in the equity ratio on profitability, as measured by the coefficient estimate $\hat{\beta}_1$, is significantly positive for the large majority (72.22%) of observations and statistically insignificant for all others. The fact that the optimal bandwidth pertaining to the equity ratio is close to zero indicates that the underlying

statistical relationship is nonlinear in nature. Figure 4 displays a two-dimensional surface plot of the estimated return on equity as a function of both total assets and the equity ratio, together with the related 95% confidence interval. In Figure 5, the different areas on the plane spanned by the observed ranges two explanatory variables are marked according the size and statistical significance of the estimated return on equity.

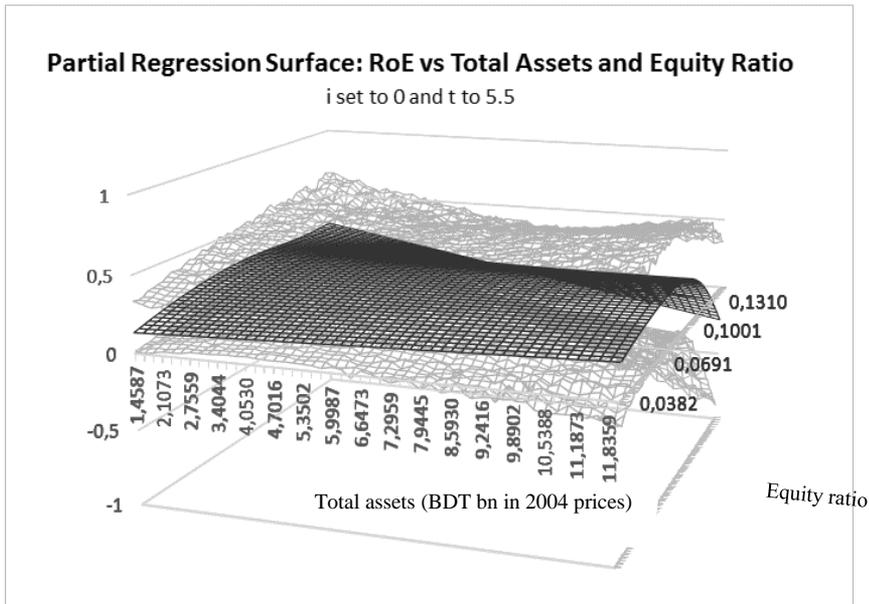


Figure 4: Partial regression surface

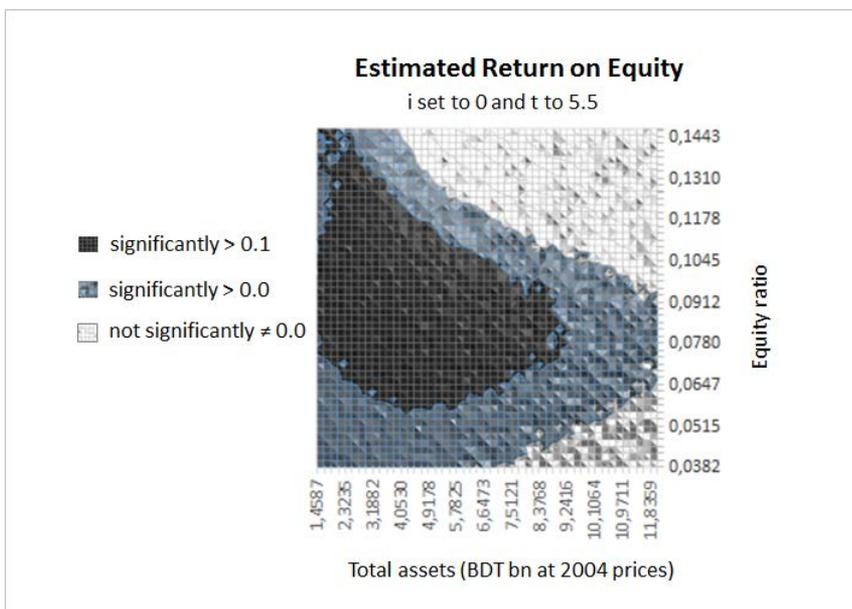


Figure 5: Estimated return on equity

For banks that are near the bottom end of the size scale, i.e. with total assets at around BDT 2.5 bn in 2004 prices and below, there is a positive association between the size of the

equity cover and profitability up to a threshold of around 10%, above which the curve appears to flatten. For larger banks, there is some, although limited, evidence of the “inverted U” shape of the relationship between the equity ratio and the return on equity hypothesized in the introduction. In cases where the initial level of the equity ratio is low, an increase in this variable tends to have a positive impact on profitability; however this effect tends to fade once the equity ratio passes a certain threshold level, which obviously is lower the larger the bank is in terms of total assets. However, since the confidence interval for the estimated regression surface widens greatly as the equity ratio becomes higher, it cannot be determined with a sufficient degree of certainty whether the estimated return on equity starts to fall if the equity ratio rises beyond a certain point.

The very large value for the optimised bandwidth value pertaining to the size variable points to the prevalence of a linear relationship between total assets and the expected return on equity across the entire range of available observations. At the same time, the descriptive statistics for the related slope parameter evince that the marginal impact of an increase in total assets on profitability varies considerably across observations. For an almost two-thirds majority of the observations in the sample, the estimated effect of a marginal increase in total assets on profitability is not statistically significant. Among the remaining observations, significantly negative coefficient estimates are found almost three times more frequently than significantly positive ones. Size, where it matters at all, more often seems to be an impediment to profitability than a favourable factor. For banks with a low to average equity ratio, Figure 3 indicates that the estimated size-profitability relationship takes the form of a slightly ascent line, the slope of which, however, does not significantly differ from zero. Among banks with a high equity ratio, the marginal impact of an increase in total assets on profitability appears to be negative, but here, too, the related confidence interval around the regression surface becomes so wide for large values of the size variable that it does not permit any firm conclusions.

6 Summary and Conclusions

This paper has examined the statistical relationship between banks’ return on equity on one hand, and their size (as measured by inflation-adjusted total assets) and capital structure on the other, using a set of panel data from Bangladesh collected by the first author in 2014. The empirical approach applied allows for heterogeneity across observational units as well as nonlinearity and non-additivity in the conditional mean function, thus facilitating the identification of more complex forms of structural dependence that might remain undetected when using classical linear regression techniques. The results indicate that while a certain degree of equity capitalisation is a necessary precondition for profitability, the positive impact of an increased equity ratio on return on profitability seems to fade above a certain threshold level, the value of which, however, depends on bank size. For a majority of observations in the sample, the estimated effect of a marginal increase in total assets on profitability is not statistically significant. Among the remaining observations, significantly negative coefficient estimates are found far more frequently than significantly positive ones. Size, it seems, more often is an impediment to profitability than a favourable factor.

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