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Key Determinants of Indonesia's Banks Financial Performance

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ABSTRACT

Depositors, investors, as well as public in general need easily accessible indicators that are important to differentiate various banks. This research addresses simultaneously two important issues: analyzing and identifying which key publicly available financial indicators of banks are important, as well as approximating the weight of the aforementioned indicators when banks' comparisons are to be made. Utilizing the recent 2017 database from 90 conventional banks, this study analyzes 17 banking ratios using the method of principal component analysis. The calculations show that five components explain around 75 percent of total variation in the data. Those five components represent indicators on profitability, quality of capital, quality of loans, fee-based activities, and liquid assets in the balance sheets. Further, by combining five principal components, the result shows that even small banks can achieve good financial performances.

Keywords: Bank comparisons; capital quality; financial ratios; indonesia banking; loan quality; principal component analysis; profitability; JEL; G21; C38; D22.

INTRODUCTION

The banking industry in Indonesia has undergone massive changes in the past two decades. Since the Asian financial crises of 1998 that brought the Indonesian economy to its knee with an economic contraction of 13.1 percent and inflation of 58.4 percent in 1998 [31], the landscape of the banking industry has changed. Whereas in June 1997 (prior to the crisis) there were 238 banks [25], by the end of 2000 only 151 commercial banks remained [20]. By the end of 2016, the number has been further reduced to only 116 conventional commercial banks currently operating in Indonesia [13], with the numbers likely to be further reduced in the future.[1]

Despite many positive developments occurring since 1999, crises (small or otherwise) have occasionally occurred. Take the example of the 2008 controversial and sudden closure of Bank Century[2] [29] which caught the general public off-guard and created protests.

Most banks' closures are controversial because banks' existence and activities have not only economic but political ramifications as well [29]. Thus, the Indonesian government, including regulators (Bank Indonesia, OJK, and Indonesia Deposit Insurance – LPS), as well as the public, have profound interests in minimizing the emergence of such banking crises. In emerging market, a trouble in a single bank can be immediately translated into systemic crisis [14].

Theoretically, policy makers attributed two sets of factors to a banking crisis: macroeconomic environment as well as bank-specific financial ratios [17]. For developed countries, capital adequacy, asset quality, management, earnings, and liquidity (CAMEL) indicators are often used to represent financial ratios.

While the usage of CAMEL indicators for banks' evaluation seem ubiquitous in developed economics, the application of CAMEL in emerging market yields differing results. [6] argues that CAMEL approach works for Indonesia's bank prior to 1998 crisis, albeit with a different weighting from the regulatory weights. However, [17] finds that there are many reasons that CAMEL indicators do not work for banks in emerging markets. Indeed, [17] shows that profitability measure such as interest-rate spread is an important indicator to predict banking strength. In contrast, capital adequacy ratio is important for banks in developed economies [17].

For the public, the major drawback to CAMEL (or any model of banking supervision) as a

[1] There are 1,633 very small rural banks operating Indonesia by the end of 2016.

[2] Bank Century was later renamed as Bank Mutiara, and currently renamed yet again to become Bank J-Trust after being acquired by Japanese investor.

model for evaluating banks is its lack of transparency. In general, regulators have much more inherent knowledge of various aspects that determine financial performance of banks. However, much of the knowledge are not known to the public (the banks' most important stakeholder). The general public can only resort to information available in the media as well as information available from the official websites of banks (which are required by regulators to publish their quarterly financial statements).

The general public interest to protect its deposits in bank can be seen as a form of market discipline [4]. Indeed, market discipline is one of important pillar of banking supervision as espoused by Bank for International Settlement (BIS) [3], exhibiting positive effects although the impact may not be optimal [16].

Despite the positive effect of market discipline and existence of such financial statements to the public, it is often unclear to the general public which indicators are more important in differentiating two banks (or among various banks, in general).

International experiences regarding important indicators differs among countries, and hence cannot be used as a guidance. Profit performance in the Swiss banking sector was shown to be related to (among others) better capitalization, faster loan growth, and higher interest to income ratio [6]. Another study regarding banks in China found that economic and political factors played a more important role compared to bank's characteristics in differentiating banks' performance [28]. A comparative study found that liquidity and size of banks do not have influence on banks in China and Malaysia, while operating expenses (defined as Non-interest expenses/Average assets) play a key factor in banks' profitability [18].

In Indonesia, a recent study showed that Non Performing Loan (NPL), the Loan to Deposit Ratio (LDR), the size of the bank, the Cost Efficiency Ratio (CER), and the Capital Adequacy Ratio (CAR) are important variables that determine efficiency of banks in Indonesia [30]. Another study utilizing data from the post-crisis era showed that three factors deemed important in determining profitability of banks are: operating expenses/ operating incomes, equity/assets, and credits/total assets [19]. Finally, a study by [5] showed that capital adequacy ratio (CAR) and size of a bank exert a positive effect on return on assets (ROA), while ratio of operating income and operating costs exert a negative influence on the return on assets (ROA).

Research Objective and Contributions

The papers cited in the preceding section shows that different indicators appear in different studies. These raises further important, as yet unanswered, questions. For example: is loan quality more important than profitability, or is the opposite true? Further, suppose profitability is more important relative to loan quality, what is the ratio/ weight of importance between the two measures?

There are several major contributions of this paper. This paper addresses the gap in research by sequentially answering two important issues: analyzing and identifying which key publicly available financial indicators of banks are important, as well as determining the weight of the aforementioned indicators when banks' comparisons are to be made. This paper also contributes to the empirical side in two further aspects. First, the contribution of the paper through its usage of the 2017 data from almost all conventional banks operating in Indonesia. Second, as will be shown in the next section, this paper is one of the pioneers in using principal component analysis to analyze banking industry in Indonesia.

RESEARCH METHOD

Principal component Analysis (PCA, henceforth) is chosen as the method in this research. The PCA is used because the method is particularly suited to answer several issues that have been outlined in the introductory part. First, given that there are many variables that can potentially be considered by the public to compare banks' performance, the PCA can reduce the large number of original variables to be considered down to a few components (which is a linear combination of the original variables). Other components contribute little to the data variation, thus can be considered as noises, and hence can be excluded from further analysis. Second, as a result of the construction of the so-called components, one can also obtain the weights of the original variables. Hence the relative importance of the original variables in explaining data variation can be obtained as well.[3]

There are different accounts regarding how PCA was first formulated. However the modern formulation and the name itself was first used by Hotelling in 1933 [1].

There are many applications of PCA across the scientific field in psychology, genomics, food sciences, and environmental science to name a few. In the field of economics, [27] used PCA to identify

[3] This will be explained mathematically in the next few paragraphs.

important variables to be fed as an input to Data Envelopment Analysis (DEA) to further identify efficient decision making unit in businesses [27]. [15] also used PCA in a setting where purchasing managers must evaluate and retain suppliers which meet several performance criteria in bottling machinery industry [15]. A study by [7] showed that principal components can be used in a formula to measure the level of e-government implementation [7].

In the banking sector, [26] also used PCA to identify important variables (and thus exclude unimportant ones) in order to avoid bankruptcy and avoid credit scoring problems [26]. [18] used PCA to reduce variables in order to rank banks in Serbia. [24] used PCA to classify banks into different operational strategies groups [19]. [33] utilized PCA to identify healthy and risky companies in order to help banking sector access the small-scale and medium-scale enterprises across Asia [33].

In Indonesia, the usage of PCA in the banking sector is rather limited. A study by [2] is the only research that we are aware of thus far. [2] conducted a survey incorporating slightly over 1,000 respondents in the Bengkulu province, yet failed to find relationships between the demographic of the respondents with benefits from banks [2]. Thus, this research will also fill in the gap in the literature regarding the application of PCA in the banking sector in Indonesia.

Mathematically, PCA seeks to transform the original data into a new set of orthogonal axes [9]. To start, let X be an m-observations by n-columns of variables, where each column has a zero mean. Also, let S be the covariance matrix of X where S has the property of being symmetric. Since S is a real and symmetric matrix then the Spectral Theorem in linear algebra can be applied [10].

According to the theorem, if S is a real symmetric matrix, then there is an orthogonal matrix V that diagonalizes S. That is: $V^TSV = W$, where W is diagonal. Following [10], since V diagonalizes S, diagonal elements of W are eigenvalues, while columns of V are eigenvectors of S. Both V and W are matrices consisting of real numbers, and more importantly, columns of V (the eigenvectors) are orthogonal and are known as the principal components of the matrix S.

Without affecting previous results, one can arrange the obtained eigenvalues in decreasing order such that $l_1 > l_2 > \ldots > l_n$. In the case the covariance matrix, the sum of the elements in the diagonal of matrix W (the trace of W) is also the total variance of the original data S.

The fact that the trace of W also represents the total variance of the original data S yields two important facts that can be used later on. First, if one wishes to simply transform the original data to a new axis, then one can retain all columns of V and W albeit in a new axis. Conversely, one can discard certain small variances to focus on prominent features of the data. In the latter case, only certain columns of V and W will be retained according to certain (arguably subjective) criteria. These criteria will be explained later in the data analysis section.[4] Second, retaining a limited number of eigenvalues and eigenvectors lead to the fact that not all original variances will be replicated. In a sense, this is often desirable since some of the discarded variances are perhaps "noises" that does not contribute (and may even distort) identification of major features. This is especially true in machine learning where PCA is considered a major tool [23].

While the eigenvalues represent variance of the original data, the eigenvectors themselves have important interpretation as well. For example, the first column in the matrix V shows the contribution of all the *n* original variables made to the first principal component (i.e. first eigenvector). The same principle applies to other columns in the matrix V. In PCA, the sum of any eigenvector column is restricted to 1 (one), leading to how one can conduct interpretation of the eigenvector, as well as interpretation regarding the weight of the original variables. For example, assume the first eigenvector (which explains the most variance of the original data) has a high coefficient coming from the return-one-equity variable and a lower coefficient coming from the net interest margin. This implies the aforementioned variables exert a dominant feature to the data, i.e. large weights. Thus, the first eigenvector is a principal component reflecting profitability (i.e. profitability is the main feature of the data).

RESULTS AND DISCUSSION

Data and Descriptive Statistics

Data used in this analysis are from the 2017 audited financial report publicly published in the bank's website. The basic set contains balance sheets, income statements, and statement of contingencies from 90 conventional banks (excluding *Syariah* banks as well as *Bank Perkreditan Rakyat* (BPR, rural lending institutions).

Table 1 shows a brief summary of the asset data for banks included in this study. The data is categorized by BUKU classification[5]. There are only 5 banks in BUKU 4 and they contributed to

[4] This is one reason why one needs to sort the eigenvalues from high to low values.

[5] BUKU is a legal abbreviation of Bank Umum berdasarkan Kegiatan Usaha (commercial banks based on operational activities). This terminology is formally introduced in [12] and will be used in this paper. Some authors prefer to use GROUP terminology instead of BUKU.

56.1 percent of the total asset of the 90 banks in the data set. Banks in BUKU 3 and 4 (a combined total of 26 banks) contributed to 87.0 percent of total assets. In terms of profitability, banks considered in BUKU 3 and 4 contributed 92.1 percent of total banking profit for data in this sample.

Table 1. Summary of Assets and Profits of Banks in 2017, Categorized by BUKU (2017).

Buku	Number of Banks	Asset (in IDR Billion)	Asset Share (percent)	Profit (in IDR Billion)	Profit Share (percent)
1	17	56,451.2	0.85	1,060.4	0.71
2	47	803,551.8	12.13	10,807.7	7.20
3	21	2,051,572.2	30.96	28,926.7	19.28
4	5	3,715,340.3	56.06	109,256.1	72.81

Source: Audited 2017 financial statements

Given the implied wide range in size among banks, as seen in Table 1, comparison using nominal amount must be minimized (if not eliminated altogether). Hence, to achieve fair comparison among banks, it is important that the data be converted to financial ratios prior to analysis.

This paper considers profitability indicators, efficiency indicators, credit risk and market risk indicators, lending activity and liquidity indicators, capital indicators, and fee-based activity indicators. There are seventeen variables considered in this paper. The definitions are given in Table Appendix 1. Each of the 16 variables considered in this paper was also tested for normality using the Shapiro-Wilk test, providing a superior omnibus indicator of non-normality [32]. The result given in Table 2 shows that most of the variables are not, with the exception of NIM variable, normally distributed.

Table 2 also indicates the existence of outliers in the data. In this case, outlier is defined as observation that lies above or below 1.5 times the interquartile range. In the case of LDR and CAR, there can be as many as nine outliers in the 90 observations in each variable (ten percent of the data). Despite the non-normality of the data, the statistical method used in this paper (PCA) does not assume normality [22]. Hence, PCA remains a valid method for analyzing the data.

Table 3 provides comparisons among the 16 used financial ratios (the variables) considered for this study. In Table 3, for example, low capital BUKU-1 and BUKU-2 have high capital adequacy ratio (CAR) of 28.84 percent and 25.49 percent, respectively. In contrast, the same group of banks have relatively low return on assets (ROA) at 1.32 and 1.17 percent, respectively.

In general, once the nominal effects are eliminated, higher capital and larger asset size (as represented by BUKU classification) do not necessarily lead to superior financial performance. Large banks (BUKU 3 and 4) dominate in terms of availability of low cost funding (low CASA_DPK ratio), efficiency (low BOPO), profitability (high ROA), and fee-based revenue. In contrast, small banks seem to do well with respect to providing large cushion for shocks (high CAR), profitability (high NIM), and the availability of liquid assets (ALIQ_ASET).

Table 2. Shapiro-Wilk Test for Normality and Identification of Outliers.

Variable Name	Test Value	p-Value	Number of Outliers
PROFIT_AKPROD	0.834	0.000	4
NPL_CKPN	0.657	0.000	5
NPL	0.944	0.001	2
KKR	0.851	0.000	4
CASA_DPK	0.948	0.001	0
LDR	0.283	0.000	9
LIAB_EQ	0.965	0.017	3
INTREV_INTCOST	0.836	0.000	5
FEEBASE_PROFIT	0.775	0.000	5
FEEBASE_OHEAD	0.521	0.000	6
BOPO	0.843	0.000	3
ROE	0.712	0.000	3
ROA	0.839	0.000	3
NIM	0.980	0.192	0
CAR	0.640	0.000	9
ALIQ_ASET	0.970	0.036	3

Table 3. Summary of Variables According to BUKU (2017 data).

Variable Names	BUKU 1	BUKU 2	BUKU 3	BUKU 4
PROFIT_AKPROD (percent)	1.00	0.85	1.26	2.27
NPL_CKPN (times)	2.68	1.85	1.46	0.67
NPL (percent)	2.78	3.05	3.00	2.66
KKR (percent)	11.68	13.51	13.32	11.74
CASA_DPK (percent)	25.78	38.76	44.46	64.78
LDR (percent)	89.18	106.49	102.34	88.02
LIAB_EQ (percent)	5.35	5.24	6.79	5.54
INTREV_INTCOST (times)	2.30	2.47	2.47	3.27
FEEBASE_PROFIT (percent)	8.04	11.22	22.48	20.40
FEEBASE_OHEAD (percent)	47.96	75.13	224.37	141.79
BOPO (percent)	89.78	88.23	81.90	70.77
ROE (percent)	6.72	4.90	8.45	13.91
ROA (percent)	1.32	1.17	1.58	2.73
NIM (percent)	5.19	5.06	4.13	5.34
CAR (percent)	28.84	25.49	20.36	20.88
ALIQ_ASET (percent)	22.10	24.32	24.58	25.26

Table 3 shows that the reliance on popular indicators to provide univariate measures of superiority simply do not work. Hence, Table 3 further emphasizes the need to find variables that are able to differentiate performance among various banks.

To sharpen the result, a more refined set of variables are needed. Correlation analysis conducted to all 16 initial variables available shows several highly correlated variables. Table 4 shows variables whose correlation is above 0.8.

Table 4. Variables Exhibiting High Correlations (> 0.8).

	BOPO	ROE	ROA	FEEBASE_OHEAD
PROFIT_AKPROD	-0.94	0.93	1.00	
BOPO		-0.87	-0.93	
ROE			0.94	
FEEBASE_PROFIT				0.90

Two direct measures of fee-based activities are also highly correlated. Thus, this paper excludes FEEBASE_OHEAD from the PCA analysis. Three direct measures of profitability (PROFIT_AKPROD, ROA, ROE) are highly correlated. Since many analyst use ROA as a measure of profitability, this paper excludes PROFIT_AKPROD and ROE from the PCA analysis. The ratio of operating cost to operating revenue (BOPO), often used as an indicator of efficiency, is also highly correlated with other measures of profitability. A high correlation between BOPO and other profitability indicators simply indicates that profitability and efficiency go hand in hand. The final data set after dropping the four measures described above includes 12 variables.

Results and Analysis

The original data was standardized to minimize misallocation of relative weight of the original variables due to differences in measurement units. Standardization results in an average of zero and a standard deviation of one for each variable. This procedure is a standard practice in the PCA literatures [21]. Given the standardized data, a covariance matrix is created to further undergo spectral decomposition.

Implementing a PCA on the data set yields 12 distinct eigenvalues that corresponded to 12 eigenvectors. Eigenvectors represent the direction of data variance, while eigenvalues represent the amount of data variance in a certain direction. As PCA seeks to explain most of the variance in the data, the larger eigenvalues with the corresponding eigenvectors are retained. A pair of eigenvalue-eigenvector is defined as a component.

Results of the eigenvalues calculations are shown in Table 5. The first principal component has an eigenvalue of 3.05, which explained approximately 25 percent of total variance of the data. The second principal component has an eigenvalue of 2.21, and explains 18 percent of total variance of the data. A combination of the first two principal components explains 43 percent of the total variance in the data.

Table 5. Eigenvalues and Variance Explained in Indonesia's Banking Data

No.	Eigenvalues	Variance Explained	Cumulative Variance
1	3.05	0.25	0.25
2	2.21	0.18	0.44
3	1.51	0.13	0.56
4	1.39	0.12	0.68
5	0.92	0.08	0.76
6	0.81	0.07	0.82
7	0.77	0.06	0.89
8	0.48	0.04	0.93
9	0.33	0.03	0.96
10	0.24	0.02	0.98
11	0.18	0.02	0.99
12	0.11	0.01	1.00

A common rule is to keep components with eigenvalue of 1 or greater [21]. Only four eigenvalues in Table 5 are larger than one, and thus, four principal components must be retained for further analysis, explaining 68 percent of total variation in the data.

Another common rule is that researchers select the number components to reach a certain threshold of cumulative "explained variance" [21]. Based on this rule, adding another principal component (PC number 5) will boost the total variation explained to 76 percent. The five aforementioned components accounted for 25.4%, 18.5%, 12.6%, 11.6%, and 7.7% of total variance in the data.

Since the fifth eigenvalue is quite close to one, it is included in the subsequent analysis. The result with five principal components is presented in Table 6.

Table 6. Loadings in the First Five Principal Components

Variable Names	PC1	PC2	PC3	PC4	PC5
NPL_CKPN	-0.384	-0.145	-0.087	0.432	0.482
NPL	-0.394	0.075	0.683	0.325	-0.319
KKR	-0.571	0.028	0.617	0.064	-0.054
CASA_DPK	0.604	0.589	0.227	0.018	-0.012
LDR	0.176	-0.682	0.019	-0.208	-0.147
LIAB_EQ	-0.387	0.680	-0.120	-0.104	0.053
INTREV_INTCOST	0.834	-0.077	0.406	0.034	-0.068
FEEBASE_PROFIT	0.278	0.244	0.110	-0.735	-0.170
ROA	0.713	0.231	-0.287	0.242	0.113
NIM	0.661	0.186	0.122	0.580	-0.096
CAR	0.347	-0.860	0.169	-0.018	0.118
ALIQ_ASET	0.183	0.136	0.536	-0.312	0.700

As discussed previously, a principal component is a linear combination of the 12 original variables. A dominant variable will contribute a large loading to a certain PC. Loadings are coefficients of an original variable used to measure importance of an original variable to a PC. Therefore, a higher positive loading on a variable implies a larger amount of positive influence a variable has over a principal component, and vice versa.

The first PC, which accounted for 25 percent of total variance, is dominated by a few variables with loadings larger than 0.6. The largest loading (0.834) is INTREV_INTCOST. The other significant loadings in the first PC are: CASA_DPK, ROA, and NIM. These variables are related to profitability and ability to contain cost.

One key management aspect of interest cost is represented by CASA_DPK. A larger current account and saving account (CASA) relative to third party funds (*Dana Pihak Ketiga*, DPK) results in the lower the interest cost/funding cost for banks. Positive effect of a lower cost-of-fund on profitability is represented by positive loading (0.604) in the CASA_DPK variable.

The next step for bank, given interest cost, is to achieve higher gross margin through higher interest rate revenue. This is represented by INTREV_INTCOST variable, which enters the first PC with positive loading of 0.834. Finally, net interest margin (NIM) and return on assets (ROA) also enter profitability picture with positive loadings of 0.713 and 0.661, respectively.

Table 7. Characters of Top and Lowest Banks Sorted by the First PC

Variable Names	Top 10	Bottom 10
CASA_DPK (percent)	62.48	18.76
INTREV_INTCOST (times)	4.35	1.51
ROA (percent)	3.13	-0.99
NIM (percent)	7.60	2.76
Average Score	1.64	-1.71

While a loading coefficient explains the contribution of a single variable to a particular principal component, score measures the effect of all variables to a particular component. For example, to obtain the PC-1 score for Bank BRI then one must multiply the loadings in the first column of Table 6 with the (standardized) data for BRI. A high score for BRI (mostly because its profitability indicators have high values) implies that the bank has a high score in PC-1.

Table 7 shows the summary of key variables to group of banks sorted by scores in the first PC (PC-1). In general, the top ten banks in PC-1 have an average score of 1.64, compared to -1.71 average scores of the ten lowest banks. Thus low values in CASA_DPK, INTREV_INTCOST, ROA, and NIM all contributes negatively to profitability and PC-1.

Ten banks with high scores in PC-1 have an average CASA_DPK ratio of 62.5 percent (thus only 37.5 percent funds from costly time deposits), which leads to a low cost-of-fund. In contrast, average CASA_DPK for the ten banks with lowest PC-1 scores is at 18.8 percent (thus 81.2 percent from costly time deposits). Such a low CASA_DPK ratio implies that the bank relies on costly time deposits as its funding base. Banks with high PC-1 scores also have higher values on profitability indicators (INTREV_INTCOST, ROA, NIM).

Top ten banks ranked by scores of PC-1 are: BPD Kalimantan Tengah, Amar, ANZ Indonesia, Bank Central Asia, BPD Nusa Tenggara Timur, BPD Sulawesi Tenggara, BPD Yogyakarta, BPD Kalimantan Barat, BPD Maluku, and Bank Rakyat Indonesia. Unsurprisingly, six of the banks with largest PC-1 scores are regional government development banks (Bank Pembangunan Daerah, BPD). These banks have low funding cost since regional government budgets for day-to-day operations are placed in these banks. Bank Central Asia as well as Bank Rakyat Indonesia, two BUKU-4 banks, have low funding cost through their networks of ATM and mobile banking that position these banks as the leader in transactional banking. These banks are then able to convert the low funding cost into higher profits.

The second PC (18 percent of total variance) is dominated by CAR, LIAB_EQ and LDR. The CAR and LIAB_EQ variables are balance sheet items that relate to equity of banks.[6] The LIAB_EQ variable represents raw capital a bank has, as well as the third party funds the bank owes to the public. A larger LIAB_EQ leads to higher contribution to PC-2 (loading of 0.680). Against the tendency for banks to maximize its liability, CAR (a more refined measure of capital), enter with a negative loading (-0.860). Hence a bank with higher CAR will be penalized in the second PC. Table 3 indicates that small banks (BUKU-1 and BUKU-2) are banks with high CAR (28.84 percent and 25.49, respectively) compared to 20 percent for banks in BUKU-3 and BUKU-4. On the other hand, only banks in BUKU-3 have relatively high LIAB_EQ.

Table 8 shows the summary of key variables to group of banks sorted by scores in the second PC (PC-2). The top ten banks in PC-2 have an average

[6] The LDR has a large loading in the second PC. Incorporating LDR into the equity narrative is rather difficult. This is a common problem in PCA [21]. To overcome the interpretation problem, researchers can conduct matrix rotation. This rotation, however, is conducted using a different, separate, method known as factor analysis.

score of 0.98, compared to -2.02 average scores of the ten lowest banks. Table 8 shows that relatively low values of CAR (and LDR) in the 2017 data contribute to higher score in PC-2. However, banks with the highest scores in PC-2 correlate positively with banks with high liability to equity ratio. Top ten banks have an average Liability to Equity ratio (LIAB_EQ) of 8.08 times, compared to 2.25 multiple for the bottom ten banks.

Note that banks with highest PC-2 scores have an average CAR at 15.98 percent that is still above the regulatory requirement. In contrast, banks with the lowest PC-2 scores have an average CAR of 51.82 percent, indicating a high capital but also a failure to convert the equity into good lending opportunity.

Table 8. Characters of Top and Lowest Bank Sorted by Scores of the Second PC

Variable Names	Top 10	Bottom 10
LIAB_EQ (times)	8.08	2.25
CAR (percent)	15.98	51.82
LDR (percent)	89.10	179.32
Average Scores	0.98	-2.02

Table 9 reports the summary for PC-3, PC-4, and PC-5. The third PC (12.6 percent of variance) is clearly dominated by non-performing loans (NPL), and bad loans plus restructured loans (KKR), and hence the PC-3 can be interpreted as representing the quality of bank's credit. In the third PC, non-performing loans, NPL, and low quality loans, KKR, (including restructured credits in the bank's balance sheet) have large loadings of 0.683 and 0.617, respectively.

Interpretation of the third PC is different from the first and second PC. Whereas higher profitability (PC-1) and better capital utilization (PC-2) correlates with positive result for banks in first and second PC, the opposite is true in PC-3. For PC-3, high scores imply negative results. High scores mean high proportions of bad loans in the bank's balance sheet, as well as high proportions of non-performing and restructured loans (high KKR) in the banks' balance sheets.[7]

The fourth PC (which explain 11.55 percent of variance) represents fee-based activities. Note that interpretation of PC-4 is similar to interpretation of PC-3 since FEEBASE_PROFIT ratio enters PC-4 with a negative loading (-0.735). Hence banks with high PC-4 scores are actually banks that have low revenue coming from fee-based activities.

[7] It is possible for us to define NPL in KKR at the beginning in such a way that "inverse" NPL and "inverse" KKR is entered as the raw data. In this case, the higher "NPL" and "KKR" would enter the third PC with positive loadings.

Table 9. Characteristics of Top and Lowest Bank Sorted by Scores of PC-3, PC-4, and PC-5

Variable Names	Top 10	Bottom 10
	PC-3	
NPL (%)	5.07	0.84
KKR (%)	26.72	2.79
Average Scores	1.88	-1.45
	PC-4	
FEEBASE_PROFIT (%)	3.57	35.19
Average Scores	1.47	-1.91
	PC-5	
ALIQ_ASET (%)	38.18	15.64
Average Scores	1.94	-1.31

Admittedly not too many banks can engage in fee-based activities (which includes activities such as trade financing credit card transactions). Table 2 shows that BUKU-3 and BUKU-4 can have revenue equivalent to 20 percent of profit. BUKU-1 and BUKU-2, given their small capital and limited allowed activities, only have small revenue from fee-based activities. Hence this PC is skewed against small banks. In summary, the fourth PC affects small banks negatively.

Finally, the fifth PC (explaining 7.67 percent of total variance) represents how much liquid assets (such as bonds and other fixed income assets) a bank has in its book. There is a tendency for banks in Indonesia, especially those with low funding cost, to seek placements in safer investment (government bonds) rather than conducting risky lending activities. In summary, the fifth PC affects banks with liquid assets positively.

One notable addition to the analysis is with regard to credit provision (NPL_CKPN) variable. Table 3 clearly shows that small banks have a tendency to provide smaller provisions and hence these banks are at risk should the loans turn sour. However, the NPL_CKPN variable only impart small loading in all of the previous five principal components. Hence, while NPL_CKPN may be important on its own, the PCA result merely shows that the NPL_CKPN ratio is not an important variable in explaining variation among banks.

CONCLUSION

Conclusion

Using Principal Component Analysis, this study has identified five important components that differentiate bank's performance in Indonesia. Those components (in order of importance) correspond to measures of profitability, equity and its quality, quality of loans, revenue from fee-based activities, and availability of liquid assets in bank's book. Profitability measures are in the first PC, and it explains 25.4 percent of total variance. Loan quality indicators, on the other hand, are in the third PC and explain only 12.6 percent of total variance. The order of the PC (as well as value of loadings in each PC) can be used as a rough measure of importance among various indicators.

Suggestions

The results of this study are important to the public. Regulators have always had the upper hand *vis-a-vis* the public in terms of knowing updated and thorough information about conditions in any banks. The public (especially fund owners) is always wary about bank's closure and the closure's potentially negative impact on the public's wealth. This study provides a clear and limited set of variables that public and fund owners need to carefully watch. For example, this study provides a strong recommendation toward choosing banks with high NIM, ROA, CAR, and NPL. These variables are necessary (though not sufficient) conditions to watch for. The aforementioned variables become even more important if the public further knows the ROA of a bank when compared against the industry average (which is published regularly by the OJK).

As a further result, with more in-depth analysis, this study is also useful for public or private institutions that are interested in publishing ranking of banks. Scores produced by PCA help identify banks by their performance in the five principal components and their loading. Analysts may proceed to rank the banks accordingly with less subjectivity involved.

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APPENDIX

Definition of Variables

Name	Definition
PROFIT_AKPROD	Profit divided by productive assets (the majority of which are from loans, marketable securities, and provision for losses)
NPL_CKPN	Loans 90+ days past due divided total loans
NPL	Loans 90+ days past due divided by provision for bad loans
KKR	(Loans 90+ days past due + restructured loans) divided by total loans
CASA_DPK	(Current and savings accounts) divided by third-party funds
LDR	Loans divided by third-party funds
LIAB_EQ	Total liability divided by equity
INTREV_INTCOST	Interest revenue divided by interest cost
FEEBASE_PROFIT	Non-interest operational revenue divided by (interest and non-interest operational revenue)
FEEBASE_OHEAD	Non-interest operational revenue divided by salary expense
BOPO	(Interest cost + non-interest operational cost) divided by (interest revenue + non-interest revenue)
ROE	Profit divided by Equity
ROA	Profit divided by Asset
NIM	(Interest revenue minus interest expense) divided by Productive Assets
CAR	Equity divided by risk-weighted assets (credit risk, market risk, operational risk)
ALIQ_ASET	(Cash + Placement at Bank Indonesia + Placement at other banks + Marketable Securities (available for sale) divided by Asset

Source: Indonesia banking standards and author's definitions

Summary Statistics of Variables Used In the Study

Variable Name	Min	Q1	Q2	Mean	Q3	Max
NPL_CKPN	8.899	49.356	66.841	92.143	99.874	1045.7
NPL	91.46	96.04	97.19	97.04	98.46	99.95
KKR	41.03	82.39	90.24	86.98	95.76	99.91
CASA_DPK	3.488	17.571	38.416	39.083	56.652	85.813
LDR	42.02	81.08	89.51	101.22	97.27	840.88
LIAB_EQ	7.065	15.044	18.149	23.301	23.342	130.277
INTREV_INTCOST	121.4	189.3	221	248.6	287.5	695.4
FEEBASE_PROFIT	0.9709	5.512	9.8809	13.7581	17.3879	78.2577
FEEBASE_OHEAD	6.749	31.318	58.586	108.526	119.573	1210.323
BOPO	57.23	106.54	120.04	120.06	134.51	191.52
ROE	-68.379	2.658	6.971	6.57	12.401	21.547
ROA	-8.4631	0.6229	1.5206	1.3779	2.5435	4.5563
NIM	1.004	3.485	4.67	4.881	6.474	10.294
CAR	0	18.54	21.68	24.67	25.12	94.31
ALIQ_ASET	8.245	18.079	23.391	24.012	28.12	53.609