

MEASURING STRUCTURE OF PUBLIC SECTOR BANK'S PROFITABILITY

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ABSTRACT

Indian banking system is moving from the public dominated banks to the private and foreign banking. The rapid growth of the private banking has an impact over the profitability of the banks. This paper analyses the effect of emergence of new participant's i.e., private and foreign bank entry and documents important trends and patterns in foreign banks' presence. The data collected cover the period 2015-2018 and include the complete trail of public sector bank. It was document that there has been a sharp increase in foreign bank presence in most regions over this period, with especially low and lower middle income payment banker categories have emerged in the banking of country we analyses the trend of the total income of the public sector banks. By using autocorrelation function with SPSS-19 software the results revealed that the competition with the banks has results adversely to public sector banks and they need new strategies to increase their profits.

KEYWORDS: Indian Banking System, Foreign Banking, Public Sector Banks, Modern Banking.

Introduction

Modern banking in India originated in the last decades of the 18th century. Among the first banks were the Bank of Hindustan, which was established in 1770 and liquidated in 1829–32; and the General Bank of India, established in 1786 but failed in 1791 (Rungta, 1970; Mishra, 1991; Muthiah, 2011; RBI, 2015). The state of Indian banking prior to 1991 was different from today. Banks made no mention of profits or losses; they did not fix deposit or lending rates. There were no capital adequacy norms, nor rules for bad loans. The year 1991 marked a decisive changing point in India's economic policy since Independence in 1947. Following the 1991 balance of payments crisis, structural reforms were initiated that fundamentally changed the prevailing economic policy in which the state was supposed to take the "commanding heights" of the economy. After decades of far reaching government involvement in the business world, known as the "mixed economy" approach, the private sector started to play a more prominent role (Acharya, 2002; Budhwar, 2001; Singh, 2003). After liberalization the private banks and foreign banks have reached to Indian territory and competition between the both public and private banks have increased. After 2015 major changes in the banking system is the adequacy of capital as per Basel-III rules and the merger of banks has made remarkable change in the Indian banking. Thus it is important to measure that whether the banks can maintain their profitability or not.

Objective

The objective of the paper is to measure the trends in the profitability of the banks under new economic regime.

Reviews of Literature

According to Boyd and Graham (1986), expansion by BHCs into non-bank activities during the seventies tended to increase the risk of failure of banks during the less stringent policy period. Demsetz and Strahan (1997) who study the stock returns of BHCs between 1980 and 1993 find that although banks extended their product mixes, no risk reduction could be observed as banks tended to move to riskier activities and to lower their capital ratio. Kwan (1998), who investigated bank section 20 subsidiaries during the 1990-1997 period, underlines the increased volatility of accounting returns despite

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a non increase in bank profitability. Ning Zhu, Bing Wang, Yanrui Wu (2015) analyzed the directional distance function and the metafrontier-Luenberger productivity indicator are used to measure the efficiency and the total factor productivity in 25 Chinese commercial banks over the period between 2004 and 2010. It is found that the pure technical efficiency of the state-owned commercial banks is better than that of the joint-stock commercial banks and the city commercial banks, while non-interest income is the major source of inefficiency. In total, the Chinese banking industry performs well in terms of overall productivity. The technological scale change indicating the change of return to scale in technology is the driving force for overall productivity growth. However, the pure technical efficiency change and the pure technologic change are not significant, and the scale efficiency change has a negative effect to productivity. The potential technological relative change for the three groups is greater than zero.

DeYoung and Roland (2001) look at the impact of fee-based activities on bank profitability and volatility for large U.S. commercial banks from 1988 to 1995. They conclude that fee-based activities, which represent a growing share of banking activities, increase the volatility of bank revenue. Amit Ghosh (2015) examined state-level banking-industry specific as well as region economic determinants of non-performing loans for all commercial banks and savings institutions across 50 US states and the District of Columbia for 1984–2013. Using both fixed effects and dynamic-GMM estimations, I find greater capitalization, liquidity risks, poor credit quality, greater cost inefficiency and banking industry size to significantly increase NPLs, while greater bank profitability lowers NPLs. Moreover, higher state real GDP and real personal income growth rates, and changes in state housing price index reduce NPLs, while inflation, state unemployment rates, and US public debt significantly increase NPLs. The findings imply that regular stress tests on banks' loan quality that typically underpin scenarios for a rise in NPLs, should take into account the impact of 'micro' or state-level economic conditions on NPLs, in addition to banks' capital and credit quality, and effective cost management in assessing banks financial health. A similar result is obtained by Stiroh (2004) who assesses the potential benefit of diversification for US banks engaging in non interest activities for the period 1984-2001. He shows that net interest income and non interest income (which is relatively more volatile) are increasingly correlated (lower diversification benefits). Stiroh and Rumble (2006) find similar results while considering US financial holding companies for the period 1997-2002. Skala, D. (2015) analyses income smoothing and cyclical of loan-loss provisions (LLP) in Central European banks. I provide strong empirical evidence that banks in the region use loan-loss provisions to smooth their income streams, and that these provisions are procyclical with respect to national business cycles.

In addition, I find that income smoothing may only partly be explained through the concept of 'saving for a rainy day'. Banks do use periods of high earnings to smooth income, but they also elect to build further reserves during periods of heavy losses—that is, on the 'rainy days' themselves. This behaviour deepens existing losses and may obscure the bank's underlying profitability. Introducing regulatory measures in line with the Bank of Spain's dynamic provisioning system would make income smoothing in Central European banks more transparent and could limit the scope for discretionary provisioning during periods of low profitability. Prasad G.V.B. and Veena (2011) in their study on NPAs Reduction Strategies for Commercial Banks in India stated that the NPAs do not generate interest income for banks but at the same time banks are required to provide provisions for NPAs from their current profits, thus NPAs have destructive impact on the return on assets in the following ways. Das, A., (1999) in his study compares performance among public sector banks for three years in the post-reform period, 1992, 1995 and 1998. He finds a certain convergence in performance. He also notes that while there is a welcome increase in emphasis on non-interest income, banks have tended to show risk-averse behaviour by opting for risk-free investments over risky loans.

Research Methodology

The research methodology accounts for this research work includes the following points:

- **Data Source**

The data for the current research paper was collected by using secondary sources of RBI publication so that the authenticity of data can be ensured. For this purpose the data from all 20 banking companies of public sector were selected.

- **Type of Sample**

The banking companies with the data from the period of 2015 to 2018 were gathered.

- **Universe of Study**

The total numbers banks operating in India including public, Private and foreign banks are included in the universe of the current study.

- **Data Analysis Tools**

The statistical tools & techniques used during the study include Pearson correlation analysis.

Data Analysis

The data of bank profitability of the all the publica sector bank is shown in table-1 as under:

Table 1: Trends of Bank Income

Banks	Interest Income				Other Income				Total Income			
Nationalized Banks	2015	2016	2017	2018	2015	2016	2017	2018	2015	2016	2017	2018
Allahabad Bank	19,716	18,885	17,660	16,358	1,996	1,910	2,644	2,693	21,712	20,795	20,305	19,051
Andhra Bank	16,369	17,635	18,027	17,975	1,500	1,564	2,308	2,372	17,868	19,199	20,336	20,347
Bank of Baroda	42,964	44,061	42,200	43,649	4,402	4,999	6,758	6,657	47,366	49,060	48,958	50,306
Bank of India	43,465	41,796	39,291	38,071	4,198	3,653	6,772	5,734	47,663	45,449	46,063	43,805
Bank of Maharashtra	12,665	13,053	12,062	11,096	1,006	1,019	1,508	1,506	13,671	14,072	13,570	12,602
Canara Bank	43,750	44,022	41,388	41,252	4,550	4,875	7,554	6,943	48,300	48,897	48,942	48,195
Central Bank of India	26,409	25,888	24,661	24,036	1,894	1,939	2,876	2,622	28,303	27,827	27,537	26,658
Corporation Bank	19,556	19,411	19,472	17,628	1,482	1,735	3,090	2,313	21,039	21,146	22,562	19,941
Dena Bank	10,763	10,646	10,182	8,932	721	717	1,251	1,164	11,485	11,363	11,433	10,096
Indian Bank	15,853	16,244	16,040	17,114	1,363	1,781	2,211	2,406	17,216	18,025	18,251	19,519
Indian Overseas Bank	23,938	23,517	19,719	17,915	2,139	2,528	3,373	3,746	26,077	26,046	23,091	21,662
Oriental Bank of Commerce	19,961	20,169	18,422	17,399	2,121	1,766	2,766	2,782	22,083	21,935	21,188	20,181

Punjab & Sind Bank	8,589	8,744	8,173	7,949	429	478	578	581	9,017	9,223	8,751	8,530
Punjab National Bank	46,315	47,424	47,276	47,996	5,891	6,000	8,951	8,881	52,206	53,424	56,227	56,877
Syndicate Bank	21,615	23,198	23,004	21,776	2,110	2,509	3,457	2,806	23,725	25,707	26,461	24,582
UCO Bank	19,359	18,561	16,326	14,020	2,004	1,596	2,114	1,121	21,363	20,157	18,440	15,141
Union Bank of India	32,084	32,199	32,660	32,748	3,523	3,632	4,965	4,990	35,607	35,831	37,625	37,738
United Bank of India	10,180	9,937	9,428	8,342	1,747	1,468	2,187	2,215	11,927	11,404	11,615	10,556
Vijaya Bank	12,274	12,084	12,379	12,590	879	874	1,651	1,601	13,153	12,958	14,031	14,190
State Bank of India (SBI)	1,52,397	1,63,998	1,75,518	2,20,499	22,576	27,845	35,461	44,601	1,74,973	1,91,843	2,10,979	2,65,100

Testing of H_1

H_1 : The time series data correspond to Total income of public sector banks exhibit a significant relationship/ pattern.

In order to test the hypothesis, Correlogram Analysis which includes investigating Auto Correlation Function (ACF) has been used in a bid to investigate if previous values of the series contain much information about the next value or there is a little relationship between one observation and the next. The ACF plays a very important role in time series forecasting and is a valuable tool for investigating the properties of an empirical time series. In the present case, ACF tool has been allowed to act upon the time series data of total income for the period of ten years viz. 2015 to 2018 correspond to 20 select public sector banks. The statement of null hypothesis assumes that there is no pattern whatsoever in the data series i.e. it is said to represent "white noise". Based on the asymptotic chi-square approximation, Box-Ljung Statistic has been used for testing the residuals from the forecast model. If the residuals are white noise, the Box-Ljung static has a chi-square distribution with $(h-m)$ degrees of freedom where h is the maximum lag being considered and m is the number of parameters in the model which has been fitted to the data.

$$Q = n(n+2) \sum_{k=1}^h (n-k)^{-1} r_k^2$$

Where,

Q = Box-Ljung Statistic

r_k = Autocorrelation coefficient for k lag

n = Number of observations in the time series

Table 2 and 3 describe the Auto Correlation Function (ACF) along with the test of significance for select Public sector banks.

Table 2: Autocorrelations

Series:Bank_1 Allahabad Bank					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	.159	.354	.201	1	.654
2	-.181	.289	.592	2	.744
Series:Bank_2 Andhra Bank					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	.235	.354	.443	1	.506
2	-.392	.289	2.283	2	.319
Series:Bank_3 Bank of Baroda					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	-.037	.354	.011	1	.917
2	.031	.289	.022	2	.989
Series:Bank_4 Bank of India					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	-.168	.354	.225	1	.636
2	.155	.289	.514	2	.774
Series:Bank_5 Bank of Maharashtra					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	.076	.354	.046	1	.831
2	-.431	.289	2.276	2	.321
Series:Bank_6 Canara Bank					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	-.253	.354	.511	1	.475
2	-.488	.289	3.365	2	.186
Series:Bank_7 Central Bank of India					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	.144	.354	.167	1	.683
2	-.180	.289	.557	2	.757
Series:Bank_8 Corporation Bank					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	-.503	.354	2.025	1	.155
2	-.044	.289	2.048	2	.359
Series:Bank_9 Dena Bank					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	-.106	.354	.090	1	.764
2	-.102	.289	.215	2	.898
Series:Bank_10 Indian Bank					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	.086	.354	.059	1	.808
2	-.105	.289	.191	2	.909
Series:Bank_11 Indian Overseas Bank					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	.289	.354	.668	1	.414
2	-.464	.289	3.246	2	.197
Series:Bank_12 Oriental Bank of Commerce					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	.231	.354	.427	1	.514
2	-.353	.289	1.924	2	.382

Series:Bank_13 Punjab & Sind Bank					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	.174	.354	.241	1	.387
2	-.500	.289	3.239	2	.214
Series:Bank_14 Punjab National Bank					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	.306	.354	.748	1	.009
2	-.442	.289	3.087	2	.011
Series:Bank_15 Syndicate Bank					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	-.171	.354	.235	1	.628
2	-.499	.289	3.228	2	.199
Series:Bank_16 UCO bank					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	.198	.354	.312	1	.576
2	-.269	.289	1.178	2	.555
Series:Bank_17 Union Bank of India					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	.285	.354	.649	1	.420
2	-.493	.289	3.562	2	.168
Series:Bank_18 United Bank of India					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	-.168	.354	.226	1	.635
2	.105	.289	.359	2	.836
Series:Bank_19 Vijaya Bank					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	.228	.354	.415	1	.519
2	-.500	.289	3.412	2	.182
Series:Bank_20 State Bank of India (SBI)					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	.149	.354	.178	1	.026
2	-.226	.289	.788	2	.032

a. The underlying process assumed is independence (white noise).

b. Based on the asymptotic chi-square approximation.

Table 3: Summary Explanations of ACF for the select banking Companies

Name of Company	Maximum Autocorrelation at lag 1	Box-Ljung Statistic		Remarks
		Value (Q)	Sig. (p value)	
PNB	.306	.748	0.009	The value at lag 1 explains 30.6% of the next estimated value which is statistically significant at $\alpha=.05$ ($P=.009<.05$) i.e. significantly different from $r_k = 0$
SBI	.149	.178	0.026	The value at lag 1 explains 55.8% of the next estimated value which is statistically significant at $\alpha=.05$ ($P=.026<.05$) i.e. significantly different from $r_k = 0$
Other 18 banks	The value at lag 1 is not significantly different from $r_k = 0$ at $\alpha=.05$ ($P>.05$). Thus, the time series data significantly resemble with white noise series.			

The analysis connotes that the time series data correspond to bank profitability for PNB and SBI banks demonstrate a significant relationship of profit with the previous year's profit. The lag 1 value of total income explains heavily the next year values in cases of these two banks where significant relationship exists. Thus, the increased requirement of profitability public sector banks is significantly established.

Conclusion

The Public sector banking industry in India has ousted the growth pattern of other sectors and witnessing relatively steep growth rate. Moreover, the industry is equally growing in size with the incorporation of new banks and payment bankers and change in the economy with demonetization. Consequently, the banks are caught in pincers due to the growing competition with public and foreign banks. A plethora of research works in the related area has been so far undertaken in the banking sector; however, the public sector banking industry is largely ignored. The study uncovers the fact that the time series data correspond to total income for each bank, while only PNB and SBI demonstrates a significant auto correlation. Moreover, the lag 1 value of total income explains heavily the next year values in all the cases where significant relationship exists. Thus we can say that in case of these two banks the total income has relation with the previous year while out of the 20 banks the profits of only 8 banks has shown increasing trends and only two has shown the major changes. The results also revealed that the competition with the banks has results adversely to public sector banks and they need new strategies to increase their profits.

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