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Testing the Appositeness of Off-Balance Sheet Activities in the Indian Banking Industry: A Panel Double Bootstrap Approach

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The impact of shifting business towards off-balance sheet (OBS) activities on the technical efficiency of Indian commercial banks is investigated using data envelopment analysis (DEA) based panel double bootstrap approach. Our results show that inclusion of OBS items in the banks' output has positive causation with estimated efficiency. Thus, policies promoting OBS activities will help Indian banks not only in finding ways to exploit new profit opportunities but also in improving their efficiency.

I. Introduction

With the increasing development in the information technology sector, a substantial portion of banking businesses all over the world has seen a shift from conventional to non-conventional off-balance sheet (OBS) activities, mainly to diversify their earnings (Isik & Hassan, 2003).[1] Excluding the OBS activities in the banks' output underestimates the real output, which in turn affects the derived efficiency (Clark & Siems, 2002).

Since the financial deregulation of the banking industry in India in 1992, banks have been increasingly shifting their businesses from traditional business activities such as deposit-taking and financing lending to non-traditional fee-generating activities (Ray & Das, 2010). However, few studies have investigated his trend. Over the years, the exposure of Indian commercial banks to OBS items has increased significantly. The exposure of scheduled commercial banks (SCBs) has increased from 7,530.07 billion Indian rupees in 2001 to 225,744.45 billion Indian rupees in 2020. Consequently, banks in India have increased their earnings by exploring and adopting non-traditional sources of income such as exchange transactions, commission, securities, underwriting, among others. In fact, the data shows that the non-interest income of the SCBs, which is greatly influenced by OBS items, has increased from 165,867.00 million Indian rupees in 2001 to 2,344,224.67 million Indian rupees in 2020. With this in mind, we estimate bank efficiency with and without OBS items to investigate the relevance of non-traditional activities in Indian banking.

Using the data envelopment analysis (DEA) based panel double bootstrap approach, this study analyses the bank-specific measures of efficiency, in the presence and absence of OBS activities. The data for inputs and outputs is collected from the Reserve Bank of India and includes all state-owned (SOBs), private-owned (POBs), and foreign-owned (FOBs) that were operating in India from 2005 to 2020. We use the intermediation approach for the definition inputs and outputs.[2] Our output variables include performing loans, investments, and other income.[3] On the other hand, our inputs include fixed assets (book values of premises and other fixed assets), loanable funds (sum of deposits and borrowings), and operating expenses (labour and capital expenses). We present the efficiency results dichotomously, one based on the portfolio of two outputs (performing loans, investments), and the other based on the portfolio of three outputs (performing loans, investments, other income). This is done to examine the relevance of OBS items on Indian bank efficiency. All of these variables are expressed in crores of Indian rupees (1 crore = 10 million) and are well supported in the literature (see Casu et al., 2013; Gulati & Kumar, 2016).

This study contributes to existing literature in many ways. First, to overcome the problems of bias and serial correlation in the conventional two-stage analysis, we use the panel double bootstrap methodology of Du et al. (2018).

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1 The OBS activities include securitization, derivative securities, exchange contracts, endorsements, among others.

2 For a detailed description on selection of inputs and outputs, see Kumar and Gulati (2014).

3 *Performing loans* include non-performing loans adjusted advances. *Investments* comprise government securities and other investments. *Other income* includes fee-based income from exchange transactions, commission, securities and underwriting.

Second, we also examine the impact of the OBS items on technical efficiency of Indian banks. Lastly, we use a sample period that is consistent with the recent banking consolidation process.

II. Methodology

We employ the variable returns to scale DEA approach to evaluate the technical efficiency among commercial banks in India.[4] The potential level of efficiency is estimated from the frontier formed by connecting the linear combinations of "best practice" banks. We use the input-orientation model as managers have extra control over inputs than outputs. The input-technical efficiency of the k^{th} bank is obtained by solving the subsequent linear program (LP).

Min θ_k

s.t.

$$\sum_{i=1}^{N} \lambda_i \, x_{si} \leq \theta_k x_{sk} \qquad \forall s = 1,\ 2,\ \ldots,\ p \qquad (Inputs)$$

$$\sum_{i=1}^{N} \lambda_i \, y_{ri} \geq y_{rk} \qquad \forall\, r = 1,\ 2,\ \ldots,\ m \qquad (Outputs)$$

$$\sum_{i=1}^{N} \lambda_i = 1$$

$$\lambda_i \geq \ 0 \qquad \forall\, i = 1, 2, \ldots, N \tag{1}$$

Where x_{si} and y_{ri} refers to the amount of input *s* used and output *r* produced by i^{th} bank respectively; and θ^*, λ_i^* are the optimum solution. The input oriented technical efficiency of the k^{th} is bounded by $\theta^* \in (0, 1]$. If θ^* takes the value 1, the bank is said to be efficient.

The majority of literary works on performance analysis of banks have relied on the conventional two-stage approach, wherein efficiency scores are estimated by DEA and these efficiency estimates are then regressed on environmental variables in the second stage. However, such procedure has received criticism for at least two reasons. First, the efficiency scores estimated are likely to have an upward bias, as there is no certainty that the estimated frontier may be the true frontier. Second, Simar and Wilson (2007) (hereafter, SW) argue that the complicated, unknown, and serially correlated nature of efficiency scores in the conventional two-stage estimation make the standard approach of inference invalid. To overcome these issues, SW proposed the double bootstrap procedure by introducing two algorithms. Despite the substantial empirical application of the SW approach over the years, such studies are limited to cross-sectional data only and do not account for the impact of time on efficiency measurement. Recently, Du et al. (2018) (hereafter, DWZ) have extended the SW methodology in a dynamic setting, to take into account the impact of technology change over time. We employ the input-oriented counterpart of the DWZ methodology in this study.[5]

The bank wise bias-corrected efficiency estimates are regressed on bank specific variables using the bootstrap truncated model:

$$TEBC_{it}(\hat{\hat{\theta}}_{it}) = \alpha_0 + \beta' Z_{it} + \epsilon_{it} \tag{2}$$

where $\hat{\hat{\theta}}_{it}$ refers to the bias-corrected input oriented technical efficiency of i^{th} bank at time t, Z_{it} denotes the vector of environment variables Z given in Table 1, and ϵ_{it} is the error term.

III. Empirical Results

Table 2 shows both mean conventional technical efficiency *(TE)* and bias-corrected technical efficiency *(TEBC)* scores for Indian commercial banks using two output (without OBS items) and three output models (with OBS items) on annual frontiers.[6] In line with the literature, the average TE estimates are higher than average *TEBC* estimates in both models. The results from the Wilcoxon signed-rank test indicate that the differences are statistically significant, thereby suggesting an upward bias in the *TE* estimates. The average *TEBC* score as a whole during our sample period was 0.851 using the two-output model (without OBS items) and 0.878 using the three-output model (with OBS items). Thus, the efficiency of Indian banks increased when OBS items were included in the banks' output. These results, therefore, highlight that exclusion of OBS activities understates the efficiency estimates especially for banks that are active in non-traditional business transactions.

The results of Table 3 indicate a large difference in average efficiency based on ownerships. Except POBs vs FOBs in the two-output model, the differences in mean efficiency across ownership are statistically significant at 1% level. These results show that ignoring OBS items in the output understates FOBs' ranking. The principal reason behind this change in rankings in the three-output model (with OBS items) is because the FOBs receive a significant portion of their earnings from OBS activities instead of the traditional sources of income such as loans and advances (Kumar & Gulati, 2014). The average efficiency for SOBs, POBs and FOBs (with OBS items) during our sample period was 93.8%, 83.8% and 84.2% respectively. The relatively higher efficiency estimates of SOBs is mainly due to their exclusive access to much of government business, which generates large fee-based income, and therefore makes them more efficient (Ray & Das, 2010).

The results of bootstrapped truncated regression are shown in Table 4. The second and third columns of Table 4 present the results of two-output model (without OBS items) and three-output model (with OBS items) respectively. The coefficient of size is positive and significant in both models. Our results corroborate the findings of Das

4 For an extended discussion on *DEA* methodology, see Ray (2004).

5 For a detailed description on the double bootstrap methodology, interested readers can refer to Simar and Wilson (2007) and Du *et al.,* (2018). Therefore, we do not repeat that here.

6 We estimate DWZ model by modifying the MATLAB codes for the truncated regression by Zelenyuk and Zheka (2006).

Table 1. Description of variables explaining performance

Variables	Description	Expected Sign
Size	Logarithm of total assets	+/-
Return on assets	Net profit/total assets	+
Capital adequacy ratio	Capital/risk-adjusted assets	+
Loan quality	Net non-performing assets/net advances	-
Diversification	Non-interest income/total income	+

Note: This table provides detail description on determinant variables of technical efficiency. An additional constraint of Z is also added to LP for estimating bias corrected efficiency estimates.

Table 2. Conventional and bias-corrected technical efficiency of Indian banking Industry

	Two Output Model (Without OBS items)		Three Output Model (With OBS items)	
Year	***TE*** $(\hat{\theta}_{\mathrm{it}})$	***TEBC*** $(\hat{\hat{\theta}}_{\mathrm{it}})$	***TE*** $(\hat{\theta}_{\mathrm{it}})$	***TEBC*** $(\hat{\hat{\theta}}_{\mathrm{it}})$
2005	0.898	0.793	0.913	0.849
2006	0.885	0.754	0.899	0.819
2007	0.931	0.845	0.938	0.884
2008	0.938	0.842	0.945	0.868
2009	0.951	0.873	0.956	0.902
2010	0.939	0.855	0.943	0.870
2011	0.937	0.848	0.942	0.869
2012	0.948	0.892	0.951	0.913
2013	0.941	0.874	0.943	0.890
2014	0.942	0.887	0.946	0.911
2015	0.952	0.889	0.954	0.904
2016	0.938	0.850	0.941	0.864
2017	0.926	0.841	0.933	0.860
2018	0.930	0.848	0.938	0.862
2019	0.925	0.857	0.939	0.897
2020	0.926	0.879	0.932	0.894
2005-20	**0.931**	**0.851**	**0.938**	**0.878**
	Wolcoxon signed-rank test Z=3.51 *p-value*=0.00		**Wolcoxon signed-rank test** Z=3.62 *p-value*=0.00	

Note: This table reports technical efficiency estimates obtained from conventional and bias corrected DEA model. For estimating the *TEBC* and for solving the serial correlation problem using DWZ, we use 1500 and 2000 bootstrap replications for loops one and two respectively.

and Ray (2010), highlighting the existence of economies of scale in the banking industry in India. Return on assets is also found to be positive and significant in both models, reflecting that profitable banks are more efficient. As expected, the coefficient of capital adequacy ratio is positive as well as statistically significant in both two-output and three-output models. The amount of capital with the bank has a direct link to its borrowing costs and therefore the well-capitalized banks are likely to be more efficient than undercapitalized banks. Furthermore, the coefficient of loan quality is negative in both of the above models, meaning that a larger volume of non-performing loans is associated with lower efficiency. In addition, more diversified banks are positively associated with technical efficiency–this is in line with the findings of Du et al. (2018). Lastly, the year dummies were negative and significant in both models, reflecting that over the years, efficiency of Indian banks has deteriorated.

As a robustness test, we carried out similar analysis following income approach by estimating two models. Model I (without OBS items) is based on the portfolio of two inputs (employee expenses, other operating expenses) and one output (net interest income) whereas Model II (with OBS items) includes all the above variables plus one addi-

Table 3. Technical efficiency across different ownership groups

	Two Output Model (Without OBS items)			Three Output Model (With OBS items)		
Year	***SOBs***	***POBs***	***FOBs***	***SOBs***	***POBs***	***FOBs***
2005	0.906	0.724	0.723	0.941	0.772	0.818
2006	0.866	0.676	0.698	0.897	0.740	0.807
2007	0.931	0.787	0.794	0.949	0.821	0.871
2008	0.934	0.775	0.796	0.942	0.802	0.844
2009	0.961	0.820	0.813	0.974	0.844	0.870
2010	0.948	0.804	0.785	0.958	0.822	0.804
2011	0.948	0.785	0.788	0.962	0.803	0.821
2012	0.968	0.851	0.832	0.979	0.877	0.860
2013	0.953	0.830	0.814	0.962	0.850	0.833
2014	0.946	0.835	0.862	0.956	0.854	0.913
2015	0.961	0.844	0.838	0.971	0.864	0.853
2016	0.904	0.819	0.805	0.918	0.836	0.819
2017	0.861	0.847	0.804	0.881	0.868	0.818
2018	0.865	0.850	0.824	0.888	0.869	0.824
2019	0.898	0.856	0.811	0.935	0.896	0.854
2020	0.883	0.901	0.851	0.902	0.912	0.867
2005-20	**0.920**	**0.811**	**0.801**	**0.938**	**0.838**	**0.842**
	Wilcoxon rank-sum test SOBs vs POBs Sig*** SOBs vs FOBs Sig*** POBs vs FOBs			**Wilcoxon rank-sum test** SOBs vs POBs Sig*** SOBs vs FOBs Sig*** POBs vs FOBs Sig***		

Note: This table reports technical efficiency estimates across different ownerships. Since we estimate input-oriented counterpart of DWZ approach, we followed two-sided truncated normal distribution for drawing errors, with right truncation at $1 - z_i\widehat{\beta}$ and left-truncation at $-z_i\widehat{\beta}$. *** indicates statistical significance at 1% level.

tional output (other income). The results are almost similar to our earlier results and thus confirm the robustness of our estimates.[7]

IV. Conclusion

Owing to the dynamic nature of the operating business environment over the years, banks have shifted their business from traditional to fee producing OBS business activities. Using DEA based panel double bootstrap approach, this paper examines the performance of the Indian commercial banks from 2005 to 2020. Our results show a significant difference in efficiency across banks based on ownership. State-owned banks are the most efficient in terms of technical efficiency, followed by foreign-owned banks and then domestic privately-owned banks. The results further indicate that the incorporation of OBS items in banks' output increases the efficiency of banks across all ownership categories. Thus, the exclusion of OBS activities in banks' output understates efficiency results and may lead to wrong conclusions being drawn. Therefore, policies promoting banking business towards OBS activities will help Indian banks to not only explore and adopt new and unexplored sources of income, thereby diversifying their production mix, but will also increase the overall efficiency of the banking industry.

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7 Due to space constraint, we are not reporting them here. However, they are readily available upon request.

Table 4. Results of bootstrapped truncated regression

Variables	Two Output Model (without OBS items)	Three Output Model (with OBS items)
Size	0.0950***	0.1001***
Return on Assets	0.0160***	0.0136***
Capital Adequacy Ratio	0.0042***	0.0047***
Loan Quality	-0.0123***	-0.0118***
Diversification	-	0.0427***
Year dummies	Yes	Yes
Constant	-0.1690***	-0.2273
Observations	936	877

Note: This table reports the double bootstrapped truncated results. The dependent variable is bias corrected technical efficiency scores. As input-oriented technical efficiency scores are bounded by (0, 1], superefficient banks are not included in the second-stage truncated regression. *** indicates statistical significance at 1% level.

References

Casu, B., Ferrari, A., & Zhao, T. (2013). Regulatory reform and productivity change in Indian banking. *Review of Economics and Statistics*, *95*(3), 1066–1077. https://doi.org/10.1162/rest_a_00298

Clark, J. A., & Siems, T. (2002). X-efficiency in banking: Looking beyond the balance sheet. *Journal of Money, Credit, and Banking*, *34*(4), 987–1013. https://doi.org/10.1353/mcb.2002.0053

Du, K., Worthington, A. C., & Zelenyuk, V. (2018). Data envelopment analysis, truncated regression and double-bootstrap for panel data with application to Chinese banking. *European Journal of Operational Research*, *265*(2), 748–764. https://doi.org/10.1016/j.ejor.2017.08.005

Gulati, R., & Kumar, S. (2016). Assessing the impact of the global financial crisis on the profit efficiency of Indian banks. *Economic Modelling*, *58*, 167–181. https://doi.org/10.1016/j.econmod.2016.05.029

Isik, I., & Hassan, M. K. (2003). Financial deregulation and total factor productivity change: An empirical study of Turkish commercial banks. *Journal of Banking & Finance*, *27*(8), 1455–1485. https://doi.org/10.1016/s0378-4266(02)00288-1

Kumar, S., & Gulati, R. (2014). *Deregulation and efficiency of Indian banks*. Springer India. https://doi.org/10.1007/978-81-322-1545-5

Ray, S. C. (2004). *Data envelopment analysis: Theory and techniques for economics and operations research*. Cambridge University Press. https://doi.org/10.1017/cbo9780511606731

Ray, S. C., & Das, A. (2010). Distribution of cost and profit efficiency: Evidence from Indian banking. *European Journal of Operational Research*, *201*(1), 297–307. https://doi.org/10.1016/j.ejor.2009.02.030

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, *136*(1), 31–64. https://doi.org/10.1016/j.jeconom.2005.07.009

Zelenyuk, V., & Zheka, V. (2006). Corporate governance and firm's efficiency: The case of a transitional country, Ukraine. *Journal of Productivity Analysis*, *25*(1–2), 143–157. https://doi.org/10.1007/s11123-006-7136-8