Journal of Banking and Financial Technology (2023) 7:1–13
https://doi.org/10.1007/s42786-023-00047-2

ORIGINAL ARTICLE

Impact of digital payment adoption on Indian banking sector efficiency

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Received: 9 June 2022 / Accepted: 16 March 2023 / Published online: 1 April 2023

Abstract
Combining Data Envelopment Analysis and dynamic panel data methods, we find that adoption of digital payment technologies by Indian banks has helped enhance their cost efficiency. Instead of directly reducing the inputs used in intermediation, the gain in efficiency may be on account of cheaper availability of such inputs when banks go digital. These gains may stem from assimilation into the entire digital payments ecosystem, as opposed to piecemeal adoption of technology. We find both cost and technical efficiencies exhibiting persistence. Banks' relative asset holdings in the industry, non-performing assets, cost of deposits and returns on advances and equity are other important variables that drive cost efficiency.

Keywords Payment systems · Banks and depository institutions · Panel data · Technological change

JEL Classification E42 · G21 · C23 · O33

1 Introduction

The banking sector is a crucial engine of economic growth as it channelises financial resources for productive activities. With rapid advances in the technology space globally, the financial sector has witnessed radical transformation and restructuring in businesses. In India, the financial sector reforms under the New Economic Policy regime from the 1990s have paved the way for technology-intensive banking with high priority accorded to modern payment and settlement systems [45]. Accordingly, India's digital payment ecosystem has witnessed rapid growth momentum, with increased onboarding of new users into digital payments post COVID-19 [47]. The innovations in the payment space provide customers with easy and hassle-free access to banking services. For banks, technology-intensive products can lead to improvements in internal processes, competitiveness, and cost and profitability advantages through network, scope, and scale economies leading to effective financial intermediation and risk management.

This study attempts empirical investigation into the channels through which payments technology impacts Indian commercial banks, with the goal of deriving useful policy perspectives. Despite sizeable literature on measurement of banking sector's efficiency, the empirical literature associating digital payments and bank efficiency is scarce for emerging market economies like India. We use Data Envelopment Analysis (DEA) to compute efficiency scores of banks and dynamic panel data methods to gauge the impact of technological innovations through digital payments on cost and technical efficiency scores over the period 2011–12 to 2018–19. Our empirical findings suggest that greater adoption of payments technology is associated with improvement in cost efficiency but not technical efficiency. This differentiated impact in the Indian context could be attributable to banks realising efficiency gains by economising on the expenditure on loanable funds, labour, and fixed assets rather than merely reducing the quantities of inputs. We find evidence of stickiness of efficiency scores over time. Higher share of non-performing loans and increased cost of deposits are negatively associated with bank efficiency, whereas, the rate of return on advances, return on equity and capital adequacy ratio may improve cost efficiency.

The views expressed in the paper are those of the authors and do not reflect the views of the institutions they are affiliated to.

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The remainder of the paper is presented in five sections including review of literature (Sect. 2), methodology and data (Sect. 3), stylised facts (Sect. 4), empirical findings (Sect. 5) and conclusion (Sect. 6).

2 Review of literature

Globally, studies provide evidence on the deployment of self-service technologies like Automated Teller Machines (ATMs) leading to a reduction in operating costs [31, 53], and enhancement in cost efficiency of the banking system [26, 42]. The adoption of innovative technologies by banks can lead to scale and experience economies [22], enhanced capacity to lend and benefits to customers [9]. Kumar [38] used DEA to compute the total factor productivity (TFP) of Indian banks to show electronic transactions leading to enhanced productivity levels. More recent studies show that electronic payments impact cost efficiency and financial performance [2, 23]. Further, the emergence of newer 'disruptive' technologies has entailed an overhaul of the traditional banking model owing to the potential of Fintech to augment operational efficiency, increase profitability, improve service delivery and strengthen risk control capabilities [55]. Mor and Gupta [40] find that the deployment of Artificial Intelligence (AI) in chatbots, virtual assistants and ATMs can reduce technical inefficiency of Indian banks. Advancements in payments technology also have a positive effect on profitability of banks through a reduction in labour and transaction costs [30, 32, 39]. Arora and Arora [4] find evidence of information technology (IT) investments positively impacting operating profits per employee. Research also underscores the importance of innovative payment channels like internet banking, point of sale (PoS) machines, and telephone banking in improving bank's market share [41]. Further, there exists association between customer satisfaction and cost-effective technological innovations in banks [1].

Contrary to the findings of these studies, another strand of literature does not find sufficient impact of digital innovations on banks' efficiency and financial performance [35]. The number of ATMs do not have statistically significant impact on efficiency [43]. Owing to the large investment needed in IT systems and the inability to curb labour expenditure given the manual nature of certain banking operations, there exists a negative association between ATM intensity and technical efficiency scores in India [49]. Thus, a rise in ATM deployment needs to be complemented with other electronic channels such as PoS, automated clearinghouse, remote banking system, and internet banking [34]. Moreover, a mere increase in the number of devices like ATMs, cards, and PoS machines does not necessarily result in improved efficiency. They need to be supported by direct usage by customers, as measured by the transaction values and volumes processed under these channels [37]. This limited association between banks' IT investments and performance indicates a '*profitability paradox*' [8].

3 Methodology and data

Studies on banks' efficiency and its various determinants utilise DEA and Stochastic Frontier Analysis (SFA). DEA, owing to Farrel [24] and Charnes et al. [16], is a non-parametric linear mathematical programming and deterministic approach that gauges efficiency of banks against an efficiency frontier- a benchmark based on observed data. SFA, on the other hand, is a parametric method that attributes variations in the efficiency scores to two components: symmetric random shocks, and managerial errors and coordination failures [12]. DEA is preferred to other efficiency measurement techniques due to various advantages: ease of use and ability to incorporate multiple inputs and outputs in estimating efficiency scores [33], no requirement of a pre-specified production function, thereby obviating the functional form misspecification problem [20], assessment of efficiency over time [15], and no a priori assumptions regarding the distribution of efficiency [43]. In India, several studies have adopted DEA [13, 20, 48]. However, a major shortcoming of DEA is that it assumes away the existence of random shocks to the production function. Nevertheless, research also points out similar results obtained under both parametric and non-parametric approaches to efficiency measurement [27].

We use DEA to calculate cost (CE) and technical (TE) efficiency scores of Indian banks. A digital index is constructed using technology variables: ATM, PoS, National Electronic Funds Transfer (NEFT), Debit Cards, and Credit Cards. Dynamic panel regression is used to ascertain the impact of the digital index on the efficiency levels of sample banks.

3.1 Computation of technical efficiency scores

The DEA model by Charnes et al. [16], popularly the CCR model, assumes constant returns to scale and the efficiency score obtained is known as overall technical efficiency (OTE). Depending upon the model's orientation (input or output), OTE can be interpreted as a firm's ability to obtain maximum possible outputs for a set of inputs or minimum wastage of inputs for a given level of output. Banker et al. [6] proposed the BCC model, a modified CCR model, with variable return to scale through a convexity constraint. The efficiency scores computed are termed pure technical efficiency (PTE) scores. For our research we use the output-oriented BCC model to compute the technical efficiency scores as the technology used by banks is not restricted to constant returns to scale.

3.2 Cost efficiency scores

The cost efficiency model (CEM) is an extension of basic DEA models, introduced by Farrel [24] and developed by Grosskopf et al. [28]. The calculation of cost efficiency of a decision-making unit (DMU) needs data on inputs, input prices and outputs. The CEM shows how far a bank's cost is from the best-practice bank's cost for producing the same bundle of output [56]. For our study, the new CEM by Tone [52] is used as it addresses certain shortcomings of the traditional method. In the standard CEM, two DMUs with the same level of inputs and outputs have the same CE, despite significant difference in input prices. In Tone's model, however, the product of price and input quantity is minimised, to reflect the 'true' CE of a firm relative to other firms. We used the DEA max solver program to compute CE (Type II) scores.

3.2.1 Panel data model specification

We compute TE and CE scores and the digital payment (volume) index (DIvol) for sample banks from 2011 to 2018. To explore the impact of payment technology on bank efficiency, the dynamic panel data estimation techniques proposed by Arellano and Bond [3] and Blundell and Bond [14] are employed. Since the dependent variables for the analysis are DEA efficiency scores that tend to exhibit persistence over a period [54], we use this methodology to capture the dynamic aspects of CE and TE. In the Arellano–Bond method, first difference of the regression equation is taken to eliminate the individual effects. Following this, deeper lags of the dependent variable are used as instruments for differenced lags of the dependent variable (which are endogenous). Blundell and Bond [14] derived a condition under which it is possible to use an additional set of moment conditions to improve the small-sample performance of the Arellano-Bond estimator. We use linear efficient two-step Generalised Method of Moments (GMM) estimators, as they are found to be more efficient in the literature. We use the *vce (robust)* option to estimate the Huber-White Sandwich Variance Covariance Estimator (VCE). This technique assumes that the errors are independently distributed across observations and allows the errors to be heteroskedastic.

3.3 Data

We use a balanced panel[1] comprising 328 bank-level observations (41 banks for 8 years: 2011–12 to 2018–19), comprising 21 public sector banks (PSBs), 17 domestic private banks (PBs), and 3 foreign banks (FBs), out of total 94 scheduled commercial banks (SCBs). For 2018–19, our sample banks accounted for 94.7 per cent of the deposits of the entire banking sector. Balance sheet data on assets, liabilities, incomes, and expenses were taken from Reserve Bank of India's annual publications ('Statistical Tables Relating to Banks in India', 'Branch Banking Statistics') and payment systems data (NEFT, ATM, PoS and Cards) are from the Reserve Bank's monthly data releases.

3.3.1 Input and output variables for efficiency score

The literature provides no consensus on specification of inputs and outputs for a banking firm. Broadly, two approaches are followed: the production or value-added approach and the intermediation approach. For the first, banks are considered as primary providers of financial services (loans and deposits), while capital and labour are treated as inputs. For the second, banks as financial intermediaries collect deposits from savers and channelise these funds into loans and investments. Banks are liable to pay interest to the depositors (interest expenditure) and earn interest from the borrowers (interest income). Since this approach includes variables concerned with the overall cost of the banking sector, it is considered appropriate to reflect on the economic viability of commercial banks [25]. Berger and Humphrey [10] point out the suitability of the intermediation approach for measuring bank-level efficiency, and the production approach for assessing efficiency at the branch level. We selected input and output variables, as explained in Appendix Table 3, based on the intermediation approach, and utilised three input variables (loanable funds,[2] fixed assets, and total employees), their corresponding prices, and two output variables (net interest income and non-interest income) for computation of CE scores. The same set of variables was used for TE computation, which does not account for input prices. Thus, TE scores denote the

[1] Our dataset avoids biases at both the beginning and end of the time period considered. The former may arise due to the impacts of the Global Financial Crisis in 2008 as well as the Payment and Settlement Systems Act, 2007, whose provisions were implemented in the successive years and decisively shaped the digital payments industry in India. We limit our dataset up to FY2019, given that the impact of COVID in the years after could lead to biased results.

[2] Loanable funds comprise deposits and borrowings after deducting the balances with RBI. For efficiency score calculations, we take loanable funds as sum of deposits and borrowings only. For robustness, we also calculated the efficiency scores using loanable funds (Deposit + Borrowing – Balances with RBI) and found that the scores obtained were the same.

Table 1 Summary Statistics for Efficiency Scores Source: Author's calculations

Year	TE				CE			
	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
2011	0.698	0.208	0.334	1	0.508	0.229	0.227	1
2012	0.652	0.215	0.303	1	0.554	0.250	0.266	1
2013	0.804	0.190	0.393	1	0.548	0.268	0.235	1
2014	0.738	0.198	0.342	1	0.546	0.269	0.214	1
2015	0.701	0.220	0.332	1	0.561	0.285	0.218	1
2016	0.685	0.238	0.308	1	0.539	0.281	0.190	1
2017	0.695	0.237	0.284	1	0.535	0.279	0.201	1
2018	0.709	0.225	0.409	1	0.496	0.250	0.234	1

ability of the observed banks to maximise net interest and non-interest incomes given the inputs of deposits, borrowings, physical capital, and labour. CE scores denote how the banks minimise the expenditure on these inputs, given the level of interest and non-interest earnings.

3.3.2 Variables for regression analysis

We construct the digital payments index comprising transaction volumes of key digital payment indicators. The volume index included NEFT transactions, card transactions (credit and debit cards) and the number of ATM and PoS machines deployed by the bank over the financial year. Each indicator is calculated as the percentage share of the individual bank in the sample total for that year. Following this, the mean of these five shares is computed to arrive at the index value for the bank, implying equal weighing of the parameters. The final values thus calculated are rescaled such that they range between 0 and 100 each year.

Taking cues from the literature, other bank-specific covariates are also used for better model specification and insights. The number of bank offices measures not only the bank 'size' but also the degree of dependence on offline infrastructure for operations. Higher the number of branches, greater may be the level of inefficiency of the bank owing to subpar managerial control [20], and higher personnel and administrative costs [43]. Banks with larger asset holdings are expected to benefit from scale economies and exhibit cost efficiency [36, 46]. Five variables impacting the profitability of the bank are used: the net Non-Performing Asset (NPA) ratio indicating the real loss taken by the bank on bad debts, the cost of deposits for the bank (COD, i.e., interest paid on deposits divided by average deposits), the return on advances (ROA, which equals the interest or discount on advances and bills divided by the average advances), the capital adequacy ratio (CAR, a proxy for the bank's capacity to meet time liabilities and manage risks such as credit, operational and market risks), and the return on equity ratio (ROE, a ratio relating net profit or net income to shareholders' equity). Research shows that higher levels of NPAs tend to be detrimental to efficiency scores and bank performance [7, 20, 29]. Further, we expect higher ROA to lead to more efficiency, as supported by Berger and Mester [11], and Chen and Lin [17]. There is an alternative perspective pertaining to the impact of capital adequacy norms on banks' efficiency. For regulators, higher CAR is indicative of higher bank efficiency on account of low cost of funds and improved financial health [20]. From the commercial bank's side, CAR hinders bank's performance [18] as it can lead to overcautious lending, heightened risk aversion [13] and reduced bank profitability [39]. ROE puts pressure on banks to perform well as they are listed in the stock market, therefore, it is expected to be positively associated with banking efficiency. ROE is highly dependent on the effective use of resources by banks [51].

4 Stylised facts

Summary statistics of input, output and control variables used in DEA are provided in Appendix Tables 4 and 5. Electronic payments in India have witnessed a manifold increase. The annual average (across sample banks) NEFT transaction volumes increased by more than ten times between 2011 and 2018 (Appendix Table 6). Similarly, transactions through credit cards and PoS machines surged by nearly five times. In contrast, growth of debit card transactions and ATMs was lower, perhaps due to earlier arrival and adoption in India. There is evidence of rapid growth in transactions through ATMs and debit cards in the previous decade [50]. Table 1 presents summary statistics for technical and cost efficiency scores.

5 Empirical results

We estimate models for both CE and TE with the digital volume index as well as its individual components separately as explanatory variables. Note that all model specifications presented pass the post-estimation check for autocorrelation (Arellano-Bond). The key findings are as follows.

5.1 Persistence effect

The first-order autoregressive term of CE and TE is positive and statistically significant in all specifications (Table 2), justifying the use of dynamic panel data modelling. This implies the stickiness of relative CE and TE in the Indian banking industry. Between CE and TE models, the persistence effect reduces in magnitude for the former, as controls are added to the model, while it magnifies for the latter. TE is almost exclusively explained by its persistence, along with autoregression of higher order (two).

5.2 Effect of payments technology adoption on cost efficiency

Controlling for bank size and business-side determinants, the coefficient for digital payments technology adoption emerges positive and statistically significant for banks' CE. All other covariates except return on advances and return on equity adversely affect CE. Thus, better adoption of technology makes business sense for banks, as it provides a pathway to improve cost efficiency of operations relative to other banks [21]. Payments technology such as ATMs, PoS and cards may help improve CE by (a) reduction in man-hours otherwise dedicated towards cash withdrawals, balance checking, passbook printing, etc. and routing employee's time towards more productive types of work; (b) formalised and automated accounting of transactions; (c) network effects- banks having a wider card and ATM network may be able to procure more and better customers, especially among the young demographic; (d) reduction in costs stemming from human error; and (e) reduction in costs of regulatory compliance.

Unlike CE, there is no evidence that banks' TE is affected by technological innovation. This implies that rather than help banks economise on inputs (labour, fixed capital, and loanable funds) to generate the same income from advances and investments, digital payment technologies help by economising on the cost of these inputs. These benefits may stem from a reduction in cost of loanable funds, since banks that are highly digital may be able to mobilize deposits more readily, as well as raise loans cheaply due to ready availability of accurate and electronic ledgers. It may be due to reduction in expenditure needed on fixed assets. Illustratively, increased penetration of debit cards, ATMs and PoS machines can directly help in reducing the need for opening brick and mortar branches. Digital technologies may also have helped banks economise on labour costs. On the other hand, the efficiency of processes through which a bank converts inputs and deposits to its income stream

Table 2 Impact of digital index on cost and technical efficiency of Indian SCBs Source: Author's calculations

Variables	(1) lnCE	(2) lnCE	(3) lnCE	(4) lnTE	(5) lnTE	(6) lnTE
L.lnCE	0.838*** (0.0943)	0.683*** (0.151)	0.468*** (0.150)			
L.lnTE				0.345*** (0.0973)	0.539*** (0.0772)	0.346*** (0.0720)
L2.lnTE				− 0.169** (0.0794)		
Constant	− 0.133* (0.0702)	− 0.196 (0.120)	− 0.566** (0.281)	− 0.434*** (0.0881)	− 0.149 (0.0912)	0.166 (0.277)
Digital index	0.00192 (0.00117)	0.00580* (0.00326)	0.00732* (0.00392)	0.0139 (0.00941)	0.00503 (0.00546)	0.00143 (0.00476)
Net NPA			− 0.0161* (0.00825)			− 0.0381*** (0.00910)
Cost of deposits			− 0.0886** (0.0398)			− 0.105* (0.0574)
Log of asset share		− 0.101 (0.0619)	− 0.213*** (0.0733)		− 0.0313 (0.0716)	− 0.139 (0.130)
No. of branches		− 2.24e-05 (3.46e-05)	3.00e-05 (3.43e-05)		− 2.24e-05 (3.64e-05)	3.36e-05 (4.23e-05)
Return on Advances			0.0647* (0.0338)			0.0423 (0.0426)
Return on Equity			0.00142* (0.000856)			0.000805 (0.00144)
Capital Adequacy Ratio			0.00343 (0.00912)			-0.00833 (0.0122)
Observations	287	287	287	246	287	287
Number of banks	41	41	41	41	41	41

Standard errors in parentheses

***p < 0.01, ** p < 0.05, * p < 0.1

may still be governed by factors such as quality of management and the institutional and regulatory framework of the industry.

To elucidate if individual payment technologies affect CE differently, we use the components of the digital index as standalone predictors (Appendix Table 11). Here, we find no statistically significant impact of the payment modes when introduced separately. Hence, banks may need to deploy the entire gamut of digital payment modes to reap efficiency gains, rather than relying only on a select few modes. These gains may stem from inclusion in the entire digital ecosystem, as opposed to piecemeal adoption of technology. As another robustness check, we include an indicator for demonetisation[3] in the model (Appendix Table 12). We find evidence that demonetisation affected banks' CE. The number of bank offices variable also showed a statistically significant and positive impact on CE.

5.3 Effect of bank size

Bank size emerges as an important determinant of CE (Appendix Table 13). The number of bank offices had no statistically significant impact. However, the percentage share of the asset holdings showed detrimental impact on CE, attributable to larger banks' relative inefficiency due to complexity of operations, management, and duplication of efforts [5]. It is also possible for larger banks to be more efficient, owing to advantages generated by their market power and ability to diversify credit risk. Larger banks can afford to have a diverse portfolio of loans and hence, better manage risks and costs associated with simple portfolios. Xiaogang et al. [57] showed that medium size banks are the most inefficient. Smaller banks are relatively more efficient than the medium sized banks, whereas large banks appear to be the most efficient ones. As the bank size changes from small to medium the efficiency reduces but even larger banks lead to higher efficiency attainment, directing 'U' shape relationship of bank size and efficiency scores. This could be the possible reason that the coefficient of asset share displays a negative sign in the analysis. To confirm the 'U' shape relationship, we introduced non-linearity by including the square of the total asset share in the model. The coefficient is positive but statistically insignificant. Initially, relative cost efficiency dwindles with an increase in bank size, but after a certain size threshold, it may start increasing again.

5.4 Profitability variables

Our empirical findings validate the role of business side variables including net NPA ratio, ROA, COD, RoE and the CAR. COD is a significant variable that constrains banks from attaining higher CE, in addition to the losses incurred by the bank, as captured by the net NPA ratio. Lower cost of funds indicates improved resource mobilisation and higher efficiency levels of banks [44]. A significant negative association of NNPA with CE directs that higher problem loans lead to lower bank efficiency [7, 19, 20]. Higher COD and Net NPA also negatively impact the banks' technical efficiency, indicating that they hinder cost reduction and constrain banks from efficiently converting inputs into earnings. CAR also exhibits negative relation with both CE and TE scores, even though the coefficient is statistically insignificant. Banks with high CAR are considered safe and more likely to meet financial obligation, making CAR an important variable for financial sustainability of banks. This variable, however, is associated with lower profitability of banks in accordance with the risk-return trade-off theory (Hersugondo *et.* al, 2021). ROA and RoE positively impact CE of Indian commercial banks. Since banks listed in the stock market are under pressure to provide high returns to shareholders, RoE induces positive impact on cost efficiency scores of the banks. On the other hand, ROA directly impacts the output variable of our model i.e., interest earnings and is therefore expected to improve banks' TE. Our results show that it has a significant positive impact on banks' CE in line with Berger and Mester [11] and Chen and Lin [17].

6 Conclusion

This paper employs a dynamic panel data estimation approach on bank-level cost and technical efficiency estimates for the period 2011–2018, to capture the impact of payment technology innovation on banking sector efficiency. We find that intensified use of digital payment technologies (viz NEFT, cards, ATMs and PoS machines) makes good business sense for the banks, by helping them improve the cost efficiency of their operations. Interestingly, we are unable to establish a significant effect of digital payment technology use on the technical efficiency of banking operations, hinting that payments technology enhances efficiency of banks by helping them reduce their expenditure on inputs rather than the quantity of inputs directly. We augment the banking efficiency literature by establishing persistence or stickiness of both cost and technical efficiency, indicating that empirical analysis of the industry in the future should consider the dynamic aspect of DEA-derived efficiency measures. While innovations in the payment system demonstrably provide customers with easy, convenient, and hassle-free access to banking services, lead to effective financial intermediation, and risk management, our paper establishes empirical backing for the fact that adoption of these technologies is also a good business decision.

Appendix

See Tables 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13.

[3] The variable takes value one for financial year 2016–2017 (the year of withdrawal of specified bank notes as legal tender in India) onwards and zero for all preceding years.

Table 3 Variables description for cost and technical efficiency calculation. Source: Author's calculations

Variables		Description
Inputs		
1	Loanable funds	Deposits + borrowing
2	Fixed assets	Fixed assets
3	Total employees	Calculated using business per employee ratio Business = Deposits + Advances Number of Employees = Business/Business per employee
Outputs		
1	Net interest income	Interest earned – Interest Spent
2	Non-interest income	Other Income
Prices		
1	Price of loanable fund	(Interest on deposit + interest on borrowing)/Loanable fund
2	Price of fixed assets	(Rent, taxes and lighting + Printing and stationer + depreciation + repair + Insurance)/Value of FA
3	Price of total employees	Payment & provision to employees/ Total Employees

Table 4 Summary statistics of input and output variables for DEA. Source: Author's calculations

Years	Statistics	Fixed assets	Loanable funds	Total employees	Other income	Net Interest income
2011	Mean	12,971	1,633,432	24,785	34,211	52,044
	SD	13,015	2,000,331	38,781	64,078	69,685
	Min	589	59,379	1462	852	1930
	Max	54,665	11,700,000	239,376	354,609	423,421
2012	Mean	14,452	1,888,267	25,664	38,757	57,734
	SD	14,352	2,321,719	38,937	76,145	72,848
	Min	943	110,779	1991	946	2656
	Max	70,050	13,700,000	238,201	446,007	430,955
2013	Mean	17,426	2,167,107	27,444	20,630	61,343
	SD	18,338	2,694,922	40,388	28,223	82,522
	Min	1169	134,688	2592	186	2801
	Max	80,022	15,800,000	244,817	158,246	491,230
2014	Mean	18,472	2,385,322	28,183	22,637	65,271
	SD	19,656	3,035,049	39,205	27,747	88,376
	Min	1273	133,230	2229	671	2988
	Max	93,292	17,800,000	233,130	143,515	519,650
2015	Mean	25,839	2,593,027	29,052	24,303	69,897
	SD	26,110	3,422,939	38,759	28,969	92,655
	Min	1564	116,056	2190	1047	2954
	Max	103,893	20,500,000	226,394	160,368	531,618
2016	Mean	34,350	2,791,291	29,866	31,043	74,087
	SD	67,226	3,888,531	38,989	35,054	101,485
	Min	1544	114,389	2005	2036	3136
	Max	429,189	23,600,000	222,650	185,529	573,258
2017	Mean	33,730	3,165,763	31,423	32,997	84,000
	SD	63,001	4,940,190	46,324	40,040	125,417
	Min	1403	113,118	1853	1254	3848
	Max	399,923	30,700,000	277,918	225,759	724,996
2018	Mean	35,385	3,407,067	3138	42,130	98,391
	SD	62,244	5,354,891	4579	64,759	153,261
	Min	1384	108,037	174	527	3468
	Max	391,976	33,100,000	27,156	367,749	883,489

Table 5 Summary statistics for controls. Source: Author's calculations

Years	Statistics	NPA	Return on advances	Cost of deposits	CAR	No of branches	Return on equity	Asset share[a]
2011	Mean	1.04	11.16	6.72	13.86	1861	14.38	2.44
	SD	0.68	1.30	1.13	2.42	2469	6.81	2.99
	Min	0.05	8.67	3.21	9.49	49	− 14.70	0.09
	Max	3.09	14.23	8.40	23.20	14,821	24.91	17.58
2012	Mean	1.46	11.22	7.00	13.56	2025	13.85	2.44
	SD	0.97	1.35	1.06	2.11	2599	5.64	3.02
	Min	0.01	8.40	3.85	11.02	49	0.35	0.15
	Max	3.36	14.13	8.74	18.74	15,513	24.81	17.93
2013	Mean	1.93	10.92	6.86	12.65	2235	8.98	2.44
	SD	1.42	1.39	1.12	2.45	2759	10.38	3.04
	Min	0.05	7.69	3.85	8.67	50	− 33.54	0.15
	Max	7.18	13.35	8.42	18.83	16,359	25.02	17.87
2014	Mean	2.29	10.64	6.79	12.57	2443	8.44	2.44
	SD	1.56	1.23	1.06	2.12	2928	8.85	3.14
	Min	0.12	7.47	4.26	9.59	50	− 33.07	0.13
	Max	6.22	12.85	8.17	17.17	17,199	21.33	18.55
2015	Mean	4.08	10.21	6.46	12.44	2598	1.28	2.44
	SD	3.02	1.24	0.96	2.20	2997	13.14	3.26
	Min	0.28	7.34	3.93	7.51	50	− 34.01	0.10
	Max	11.89	13.49	7.86	16.64	17,578	19.94	19.64
2016	Mean	5.08	9.55	5.88	12.95	2712	3.05	2.44
	SD	3.90	1.15	0.85	2.20	3089	11.59	3.43
	Min	0.18	7.18	3.24	10.26	36	− 26.98	0.10
	Max	13.99	11.54	7.07	18.76	18,146	18.58	20.87
2017	Mean	6.09	8.91	5.25	13.01	2933	− 8.02	2.44
	SD	4.72	1.11	0.71	2.84	3937	19.37	3.82
	Min	0.28	7.03	2.64	8.69	26	− 46.63	0.08
	Max	16.69	11.03	6.28	18.48	24,492	17.87	23.71
2018	Mean	4.38	9.01	5.22	13.22	2937	− 11.35	2.44
	SD	2.90	0.98	0.72	3.01	3811	27.60	3.80
	Min	0.19	7.48	2.64	2.00	26	− 103.27	0.08
	Max	10.81	11.02	6.72	17.89	23,560	17.94	23.40

[a]Asset share is calculated by dividing total assets of individual banks with aggregate total assets of all 41 banks, multiplied by 100

Table 6 Summary statistics for digital payment variables. Source: Author's calculations

Year	Statistics	Credit cards	Debit cards	NEFT	ATM	PoS
2011	Mean	7.28	122	4.99	1,911	14,545
	Std. Dev	18.50	313	7.76	3,653	44,517
	Min	0	0.51	0.04	44	0
	Max	79.30	1,920	35.09	21,313	192,084
2012	Mean	9.23	130	8.75	2,370	17,856
	Std. Dev	23.60	343	13.29	4,317	52,849
	Min	0	0.95	0.09	128	0
	Max	107	2,170	64.32	23,823	214,203
2013	Mean	12	150	14.66	3,090	23,464
	Std. Dev	31.80	407	22.55	5,783	64,681
	Min	0	1.82	0.28	144	0
	Max	161	2,590	122.90	34,155	264,119
2014	Mean	14.40	175	20.63	3,980	25,599
	Std. Dev	38.70	482	31.79	7,369	67,388
	Min	0	2.64	0.78	139	0
	Max	198	3,080	179.23	45,206	270,922
2015	Mean	18.40	208	27.21	4,421	29,325
	Std. Dev	48.80	575	43.87	7,791	71,859
	Min	0	3.95	0.91	125	0
	Max	251	3,690	253.86	47,705	266,504
2016	Mean	25.30	246	34.47	4,738	40,063
	Std. Dev	65.60	672	50.86	8,188	92,522
	Min	0.00	5.52	1.18	110	0
	Max	333.00	4,310	271.81	49,977	367,334
2017	Mean	32.90	289	43.75	5,035	69,722
	Std. Dev	82.10	795	67.00	9,473	143,113
	Min	0.00	7.70	1.47	98	0
	Max	405.00	5,110	368.00	59,080	624,171
2018	Mean	41.30	343	51.25	4,928	82,226
	Std. Dev	99.80	928	75.63	9,416	161,290
	Min	0.00	9.57	1.79	90	0
	Max	486.00	5,970	401.69	58,973	582,451

Table 7 Ownership wise statistics of mean of TE and CE scores. Source: Author's calculations

	TE				CE			
	Foreign	Private	Public	All Banks	Foreign	Private	Public	All Banks
Average	0.975	0.811	0.590	0.710	0.892	0.676	0.372	0.536
S.D	0.039	0.063	0.066	0.045	0.070	0.067	0.027	0.022
Min	0.882	0.703	0.527	0.652	0.774	0.550	0.342	0.496
Max	1.000	0.878	0.716	0.804	1.000	0.755	0.409	0.561

Table 8 Summary statistics for public sector banks scores

Year	Obs	TE				CE			
		Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
2011	21	0.631	0.170	0.392	1	0.409	0.182	0.227	1
2012	21	0.577	0.195	0.303	1	0.408	0.180	0.266	1
2013	21	0.716	0.191	0.393	1	0.380	0.183	0.235	1
2014	21	0.638	0.161	0.342	1	0.374	0.177	0.214	1
2015	21	0.541	0.145	0.332	1	0.354	0.167	0.218	1
2016	21	0.527	0.157	0.308	1	0.343	0.174	0.190	1
2017	21	0.536	0.163	0.284	1	0.342	0.174	0.201	1
2018	21	0.557	0.134	0.409	1	0.361	0.167	0.234	1

Table 9 Summary statistics for private sector banks scores

Year	Obs	TE				CE			
		Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
2011	17	0.726	0.220	0.334	1	0.550	0.187	0.302	1
2012	17	0.703	0.207	0.436	1	0.656	0.200	0.356	1
2013	17	0.878	0.147	0.601	1	0.698	0.235	0.386	1
2014	17	0.818	0.183	0.505	1	0.696	0.230	0.412	1
2015	17	0.849	0.152	0.613	1	0.755	0.215	0.440	1
2016	17	0.829	0.197	0.437	1	0.724	0.227	0.431	1
2017	17	0.837	0.187	0.503	1	0.716	0.230	0.444	1
2018	17	0.851	0.200	0.421	1	0.614	0.251	0.321	1

Table 10 Summary statistics for foreign banks scores

Year	Obs	TE				CE			
		Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
2011	3	1	0	1	1	0.968	0.056	0.904	1
2012	3	0.882	0.204	0.647	1	1	0.000	1	1
2013	3	1.000	0.000	1	1	0.872	0.141	0.721	1
2014	3	0.988	0.021	0.963	1	0.891	0.189	0.672	1
2015	3	0.983	0.029	0.950	1	0.909	0.157	0.728	1
2016	3	0.982	0.031	0.947	1	0.867	0.127	0.747	1
2017	3	1	0	1	1	0.852	0.133	0.742	1
2018	3	0.966	0.057	0.900	1	0.774	0.198	0.627	1

Table 11 Impact of individual digital parameters on CE. Source: Author's calculations

Variables	(1) lnCE	(2) lnCE	(3) lnCE	(4) lnCE	(5) lnCE
L.lnCE	0.545*** (0.134)	0.498*** (0.154)	0.543*** (0.138)	0.552*** (0.136)	0.557*** (0.132)
Constant	− 0.587** (0.295)	− 0.592** (0.297)	− 0.597** (0.301)	− 0.587** (0.297)	− 0.554** (0.282)
NEFTTransactions	− 0.000123 (0.000505)				
No. of ATMs		1.57e-05 (2.17e-05)			
No. of PoS			3.00e-07 (3.52e-07)		
CC transaction volume				− 4.40e-10 (4.24e-10)	
DC transaction volume					− 1.83e-11 (4.16e-11)
Net NPA	− 0.0130* (0.00790)	− 0.0158* (0.00916)	− 0.0148* (0.00834)	− 0.0132* (0.00793)	-0.0131 (0.00809)
Cost on Deposits	− 0.0978** (0.0400)	− 0.104** (0.0441)	− 0.0894** (0.0412)	− 0.102** (0.0399)	− 0.0993** (0.0404)
Log of asset share	− 0.157** (0.0727)	− 0.166** (0.0747)	− 0.155** (0.0785)	− 0.161** (0.0727)	− 0.145** (0.0704)
No. of branches	2.53e-05 (3.18e-05)	3.06e-06 (3.19e-05)	2.16e-05 (3.85e-05)	3.10e-05 (3.06e-05)	1.97e-05 (2.50e-05)
Return on Advances	0.0798** (0.0365)	0.0807** (0.0381)	0.0742** (0.0371)	0.0822** (0.0363)	0.0793** (0.0366)
Return on Equity	0.00101 (0.000826)	0.00129 (0.000872)	0.000992 (0.000866)	0.00111 (0.000819)	0.000982 (0.000826)
Capital adequacy Ratio	0.00708 (0.00913)	0.00707 (0.00943)	0.00786 (0.00993)	0.00712 (0.00903)	0.00728 (0.00908)
Observations	287	287	287	287	287
Number of banks	41	41	41	41	41

Standard errors in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 12 Results with demonetisation. Source: Author's calculations

Variables	(1) lnCE	(2) lnTE
L.lnCE	0.465*** (0.135)	
L.lnTE		0.337*** (0.0729)
Constant	– 0.347 (0.307)	0.233 (0.282)
Digital Index	0.00727* (0.00393)	0.00160 (0.00415)
Net NPA	– 0.0183** (0.00823)	– 0.0393*** (0.00912)
Cost on Deposits	– 0.120*** (0.0457)	– 0.116* (0.0650)
Log of asset shares	– 0.231*** (0.0593)	– 0.148 (0.115)
No. of branches	2.80e-05** (1.28e-05)	3.64e-05 (3.43e-05)
Return on Advances	0.0654* (0.0353)	0.0439 (0.0421)
Return on Equity	0.000967 (0.00104)	0.000643 (0.00151)
Capital Adequacy Ratio	0.00318 (0.0104)	– 0.00927 (0.0131)
Demonetisation dummy	– 0.0661** (0.0320)	– 0.0225 (0.0301)
Observations	287	287
Number of banks	41	41

Standard errors in parentheses

***p < 0.01, **p < 0.05, *p < 0.1

Table 13 Results with square of asset share. Source: Author's calculations

Variables	(1) lnCE
L.lnCE	0.487*** (0.172)
Constant	– 0.507* (0.278)
Digital Index	0.00584 (0.00436)
Net NPA	– 0.0160** (0.00793)
Cost on Deposits	– 0.103** (0.0435)
Log of asset shares	– 0.182** (0.0815)
Log of square of asset shares	0.00148 (0.0608)
No. of branches	2.95e-05 (3.43e-05)
Return on Advances	0.0728** (0.0364)
Return on Equity	0.00144* (0.000802)
Capital Adequacy Ratio	0.00162 (0.00882)
Observations	287
Number of banks	41

Standard errors in parentheses

***p < 0.01, **p < 0.05, *p < 0.1

Data availability Banks' balance sheet data were accessed from the Reserve Bank of India's (RBI) 'Statistical Tables Relating to Banks in India'. Data on number of bank branches were from the RBI's Branch Banking Statistics'. Both are annual publications available on the RBI website (https://rbi.org.in/Scripts/publications.aspx). Data on payment systems (NEFT, ATM, PoS and Cards) are from the monthly Data Releases titled 'Bankwise Volumes in NEFT/RTGS/Mobile Transactions/Internet Banking Transactions' (https://rbi.org.in/scripts/NEFTView.aspx) and Bankwise ATM/PoS/Card Statistics (https://rbi.org.in/scripts/ATMView.aspx) available on the RBI website.

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