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Disaggregating Digital Financial Inclusion: Credit Card, Debit Card, and ATM Channels as Drivers of CAMEL-Based Bank Performance in India

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Abstract

Purpose: This study examines whether digital financial inclusion (DFI) affects the financial performance of commercial banks in India, and whether the strength and direction of this relationship depend on which digital transaction channel is examined.

Design/Methodology/Approach: The study uses an unbalanced panel of 61 scheduled commercial banks (676 bank-year observations, 2014–2025). DFI is operationalised through three log-transformed indicators — credit card transactions ($\ln_cct$), debit card transactions ($\ln_dct$), and ATM-related infrastructure ($\ln_atm$) — and bank performance through the five CAMEL dimensions: capital adequacy, asset quality, management efficiency, earnings, and liquidity. Given the high level of collinearity between $\ln_dct$ and $\ln_atm$ ($r = 0.987$; $VIF > 38$), each dependent variable is estimated through two parallel models using Pooled OLS, Fixed Effects and Random Effects, with the estimator selection criteria being the Hausman test and HAC standard errors used for testing. The objective of profitability is also estimated using control variables and dynamic System GMM model.

Results: The impact of credit card transactions on capital adequacy, non-performing assets and profitability (ROA, NIM and ROE in case of System GMM estimation) proves to be consistently positive. Debit card transactions and ATM are linked to increased business per employee but are also positively related to low asset quality and their relationship with capital adequacy and profitability is not proven robust to HAC correction. Liquidity results are indicator-dependent.

Practical Implications: DFI strategies need to be assessed individually, matching up debit card- and ATM-driven expansion with more effective management of credit risk, instead of assuming that DFI is an all-round positive development for banks.

Originality/Value: The paper distinguishes between different channel indicators of DFI in a comprehensive CAMEL-based static and dynamic panel model analysis, filling in a research gap in Indian and international literature.

Introduction

Financial inclusion has evolved in just over a decade from an aspiration for physical access to banks into a digitally-enabled process where mobile communications, biometrics and payment systems determine whether individuals can make transactions, save and take loans through the formal sector. Digital Financial Inclusion (DFI), which is the process whereby financial products are delivered through digital channels, at reduced costs compared to those of branch banking, has now emerged as one of the most researched topics in banking and development economics (CGAP, 2015; Demirgüç-Kunt et al., 2018). The reason for its attraction is clear: if the problems associated with financial access in the past were distance, lack of documentation and high costs, then digital channels which overcome all three must be capable of expanding the access and usage of formal financial products. The unresolved issue in this respect, and which is the subject of the paper, is whether the use of such channels actually enhances — or at best is neutral to and worst case even hinders — bank performance.

India provides an especially well-studied example of such issues. After introducing the Pradhan Mantri Jan Dhan Yojana in 2014, India has been implementing a program of digital inclusion through the JAM trinity of Jan Dhan bank accounts, Aadhar biometric authentication, and mobile payment systems, as well as through the use of the Unified Payment Interface, Aadhar-based payment systems, and ATMs and cards. Ownership of bank accounts by adults in India has dramatically increased since 2011 to 2021, and closing the gender gap in financial inclusion has often been highlighted as a major accomplishment (Demirgüç-Kunt et al., 2022).

This accomplishment has, however, primarily been examined through the perspective of the client — account openings, funds transfers, closing of gender gaps — as opposed to that of the provider of the service. The commercial bank faces the operational costs involved in digitization of onboarding and service provision, the credit risks involved from any resultant lending increases, as well as changes in terms of capital and liquidity as a result of changes in the composition of the customer base. The literature by Mohan (2006) and Chakrabarty (2013) suggests that previous efforts at inclusion, which were more focused on branches, faced challenges due to the costs involved and difficulties in maintaining commercial viability. Whether the digital route addresses this problem, or merely moves it from one end to the other is still an empirical question which remains open among the client-oriented literature.

The present research seeks to bridge the gap in the literature by using a substantive and not just a procedural methodology. Rather than constructing one composite index, DFI is measured via three distinct transaction-level variables: credit card transactions, debit card transactions, and infrastructure related to ATMs for 61 scheduled commercial banks over an unbalanced sample size of 676 observations over the period of 2014 to 2025. This particular distinction is significant since the three instruments cater to different clienteles, have fundamentally different structural sources of income generation, and have different credit risk implications; a composite index would fail to capture the channel specificities that are important to be considered. The performance of banks will be assessed using the complete five pillar CAMEL approach: capital adequacy, asset quality, management, earnings, and liquidity, which is a traditional supervisory technique of RBI (2020).

Empirical strategy includes Pooled OLS, Fixed Effects (FE) and Random Effects (RE) estimates, where selection of FE versus RE estimates will be based on Hausman test, full diagnostic routine and HAC standard errors. Debit card and ATM variables being very collinear, all models will be estimated using two parallel specifications, one linking credit card transactions with debit card transactions and ATM infrastructure correspondingly. For profitability measures, where reverse causality is possible — more capitalised and better managed banks can just happen to be more able to invest in digital infrastructure — the analysis will be supplemented with dynamic System GMM.

The paper makes three contributions. Firstly, it tests whether DFI serves as a homogenous determinant of bank performance or if the mechanism behind it is heterogeneous. Secondly, it extends the analysis not only to profitability but also includes other parts of the CAMEL criteria. Thirdly, it includes both static and dynamic panel estimates into one consistent design, which uses one of the longer bank-level panels constructed for Indian digital banking literature.

Literature Review and Hypotheses

The literature can be read along two tracks. One, dominated by development economists, treats DFI as a determinant of customer-level outcomes — account ownership, savings, resilience (Demirgüç-

Kunt et al., 2018, 2022; Suri & Jack, 2016) — and says little about the banks supplying these services. The second, smaller track treats digital banking activity as a determinant of the supplying institution's own condition; it is this track that the review synthesises.

- **An Unsettled Direction:** At one pole, Phan et al. (2020) find that FinTech growth depresses incumbent bank performance in Indonesia; Corbet et al. (2024) report a similar result for Chinese listed banks; and Cuadros-Solas et al. (2023), using data from sixty-seven countries, attach a large magnitude to the negative relationship — an 18 per cent fall in return on assets for a one-standard-deviation rise in digital credit supplied by BigTech and FinTech firms. At the opposite pole, Yoon et al. (2023) find that FinTech raises ROA in lower-income economies and net interest margin in higher-income ones; Dasilas and Karanović (2025) report that each additional FinTech entrant raises UK incumbents' margins; and Zheng et al. (2023), across forty developing economies, attribute large gains in ROA and ROE to fintech-driven inclusive finance. Neither pole is methodologically inferior, which suggests the contradiction is substantive.
- **Conditional Relationships:** The third group of articles resolves this contradiction by indicating the conditional nature of the relationship. According to Song et al. (2023), Li et al. (2023) and Yuan et al. (2025a, 2025b), who analyze the situation with Chinese banks, the "initial inhibition but subsequent promotion" pattern appears: earlier investments into FinTech reduce the profitability because of the competitive factor, while later there comes a threshold, after which FinTech becomes beneficial. In their turn, Berisha and Rayfield (2025) reveal conditional dependence depending on the purposes of investment, and Bei et al. (2025) indicate that the capital ratios of Chinese banks first decline before becoming positive because of the FinTech investment. Regarding the case of India, Verma et al. (2025) state that the initial decline in profitability occurs due to the integration costs; however, larger banks have no problems with absorbing these costs. Thus, whether the effect of DFI is positive or negative can depend on the stage of adoption of the technology.
- **The Indian Literature:** There is fragmentation in Indian studies. One stream uses data from regulators on transactions: Shaikh and Anwar (2023) correlate RTGS, NEFT, and credit card variables in a panel of thirty-two banks with cost of funds and business per employee; Kaur and Pathak (2023) relate ATM, point of sale, and mobile transaction data with ROA; Veluthedan and Kiran (2024) use the Malmquist Productivity Index; and Singh et al. (2021) regress profitability on the ATM to branch ratio. A second tradition uses survey data and structural equation modelling of perceived adoption (Saxena et al., 2026; Rebekah & Afjal, 2025), addressing adoption intention rather than realised transaction value. No study in either tradition uses credit card, debit card, and ATM transaction value together as a parallel triad, extends to 2014–2025, or combines a sixty-one-bank sample with static and dynamic estimation across all five CAMEL dimensions.
- **Channel-Level Coverage is Uneven:** ATM infrastructure is comparatively well studied. Adewoye and Omoregie (2013) and Haabazoka (2019) find favourable effects in Nigeria and Zambia, and Singh et al. (2021), Kaur and Pathak (2023), and Veluthedan and Kiran (2024) find a positive ATM–profitability relationship in India. Yet Gowtham et al. (2026), using a more recent 2015–2024 Indian panel, report the opposite sign for ROA, even as mobile banking raises profitability. This is consistent with a maturity effect — ATM networks may have generated gains while expanding relative to branches, but not once usage plateaus — though this reconciliation remains an interpretive inference. Credit card transactions attract a thinner but favourable literature, anchored by Shaikh and Anwar (2023), who find a favourable effect on the cost of funds; most other studies bundle cards into composite payment indices. Debit card transactions are the most neglected: beyond Verdier's (2012) theoretical analysis of interchange-fee competition, no study treats debit card transaction value as a standalone, empirically tested determinant of bank performance.
- **CAMEL is Rarely Operationalised in Full:** Dahmani (2026) is the only study in this literature to invoke CAMEL by name; the rest concentrate on profitability. This has empirical consequences, because multi-dimensional designs detect divergences that a profitability-only design misses. Chesini and Giaretta (2024) find that digitalisation raises US bank profitability while reducing branch and staff counts, and Gowtham et al. (2026) find ATMs lower ROA while mobile banking

raises it. For asset quality, SAADAoui and Souissi (2026) and Wang et al. (2023) find that incumbents' own digitalisation reduces non-performing loans, whereas Katsiampa et al. (2022) find that FinTech lenders' loan books deteriorate. For India, Laha and Mazumder (2025) find a more muted result. Liquidity is the least developed dimension: Fang et al. (2023) examine liquidity creation as a stability outcome, and Xie (2025) treats liquidity management as a moderator rather than an outcome.

- **Theory:** Financial intermediation theory is invoked implicitly, supplying the rationale for treating bank-level performance as the relevant outcome (Kaur & Panda, 2025; Abdeljawad et al., 2025). The Technology Acceptance Model and Diffusion of Innovation theory explain demand-side adoption (Berisha & Rayfield, 2025; Verma et al., 2025), though Prakash et al. (2025) document a Solow-type productivity paradox for Indian banks, in tension with the channel-specific gains of Shaikh and Anwar (2023). The Resource-Based View (Al-Dmour et al., 2020, 2021; Ferilli et al., 2024) suggests that costly-to-replicate digital infrastructure can be a source of differentiated rather than uniform performance.
- **Gaps and Hypotheses:** Five gaps emerge: (1) channel disaggregation — no study isolates credit cards, debit cards, and ATMs as a common triad; (2) CAMEL comprehensiveness — profitability dominates; (3) methodological combination — System GMM is used, but on composite indices rather than collinearity-screened transaction variables; (4) country and period — existing Indian panels are smaller (31–44 banks) and shorter (6–13 years, typically ending by 2022); and (5) unresolved contradictions — the ATM–profitability reversal and the productivity paradox remain untested within a single design. These gaps translate into five hypotheses:

H1: DFI significantly affects the capital adequacy of commercial banks in India.

H2: DFI significantly influences the asset quality of commercial banks in India.

H3: DFI significantly affects the management efficiency of commercial banks in India.

H4: DFI significantly affects the profitability performance of commercial banks in India.

H5: DFI significantly influences the liquidity performance of commercial banks in India.

Each hypothesis is posed at the dimension level, not channel level, meaning that the analysis will test whether and in what direction each particular indicator is related to each dimension, without taking for granted that the three dimensions push the ratio the same way.

Methodology

Research Design

The positivist and deductive approach is used in the study: both DFI and bank performance are viewed as objective and quantifiable constructs, while hypotheses are tested using panel data. This is an explanatory, quantitative and longitudinal research design, conducted via panel econometrics, which allows for distinguishing within-bank effect of digital transaction increase from unobserved permanent differences between the banks.

Population, Sample and Data

The target population includes scheduled commercial banks working in India in 2014–2025, according to the RBI classification. Regional rural banks, cooperative banks and payments banks are not included due to differences in reporting and CAMEL application. A purposive, data-availability-driven sample of sixty-one banks — public sector, private sector, foreign, and small finance banks — yields an unbalanced panel of 676 bank-year observations, with banks observed for six to twelve years. The imbalance reflects the 2017–2020 public-sector merger wave, the later licensing of small finance banks, and isolated reporting gaps. Data come from the RBI's Database on Indian Economy, Statistical Tables Relating to Banks in India, RBI payment-system indicators, CMIE Prowess IQ, and banks' annual reports (used to cross-verify ambiguous observations).

Variables

DFI is assessed based on the natural logarithm of credit card transactions ($\ln_cct$), debit card transactions ($\ln_dct$), and infrastructure for ATM transactions ($\ln_atm$). The logarithm is used to reduce the effect of skewness, normalize variance regardless of bank size, and enable estimates of elasticity.

Bank performance is evaluated using ten measures across all CAMEL categories (Table 1). Continuous variables were winsorized at 1% and 99%.

Table 1: Variable Definitions

Dimension	Variable	Notation	Measurement
DFI	Credit card transactions	In_cct	ln(annual credit card transaction value)
DFI	Debit card transactions	In_dct	ln(annual debit card transaction value)
DFI	ATM penetration	In_atm	ln(ATM-related transaction infrastructure)
Capital adequacy	Capital adequacy ratio	CAR	Regulatory capital / risk-weighted assets (%)
Asset quality	Gross NPA ratio	GNPA	Gross NPAs / gross advances (%)
Asset quality	Net NPA ratio	NNPA	Net NPAs / net advances (%)
Management efficiency	Business per employee	BPE	(Deposits + advances) / employees
Management efficiency	Profit per employee	PPE	Net profit / employees
Earnings	Return on assets	ROA	Net profit / total assets (%)
Earnings	Return on equity	ROE	Net profit / shareholders' equity (%)
Earnings	Net interest margin	NIM	Net interest income / average interest-earning assets (%)
Liquidity	Credit-deposit ratio	CDR	Advances / deposits (%)
Liquidity	Cash-assets ratio	CATA	Cash and RBI balances / total assets (%)

Note: CAR, GNPA, CDR, and CATA also serve as controls in the profitability models.

• Model Specification

A preliminary variance inflation factor (VIF) check revealed severe collinearity between In_dct and In_atm (VIF > 38), ruling out a single saturated specification. Every dependent variable is therefore estimated under two parallel models:

- Model 1: $Y_{it} = \alpha + \beta_1 \text{In_cct}_{it} + \beta_2 \text{In_dct}_{it} + \mu_i + \lambda_t + \varepsilon_{it}$
- Model 2: $Y_{it} = \alpha + \beta_1 \text{In_cct}_{it} + \beta_2 \text{In_atm}_{it} + \mu_i + \lambda_t + \varepsilon_{it}$

where μ_i is a bank-specific effect, λ_t a time effect, and Y_{it} the relevant CAMEL indicator. For profitability, an extended specification adds CAR, GNPA, CDR, and CATA as controls. To address persistence and the possibility that better-managed banks simultaneously invest more in digital channels and earn more for unrelated reasons, profitability (ROA, ROE, NIM) is also modelled dynamically, adding the lagged dependent variable $\gamma Y_{i,t-1}$.

• Estimation Strategy

For each static model, we estimate by Pooled OLS, FE, and RE. The Breusch-Pagan LM test indicates the existence of bank effects, while the Hausman (1978) test decides whether FE or RE should be used. Since the Wooldridge (2002), Breusch-Pagan (1979), and Pesaran (2004) tests detect serial correlation, heteroskedasticity, and cross-sectional dependence in most specifications, the HAC standard errors will be the last criterion of inference for FE estimations. The Maddala-Wu (1999) Fisher-type test is employed for all ten CAMEL variables for stationarity check.

In the case of the dynamic profitability equation, we use the two-step System GMM estimator by Blundell and Bond (1998). This estimator is free of Nickell (1981) bias when using a within transformation with the lagged dependent variable. Instruments are the second to fifth lags of the profitability variable, which are reduced to avoid their excessive number. For the validity test, the Sargan test and the Arellano-Bond AR(2) test are run; the Wald test shows that instruments are jointly significant. System GMM is used only for profitability, because here dynamics and reverse causality problems are crucial. All estimations were done using R (plm, pgmm, car, lmtest, sandwich).

Results

• Descriptive Statistics

Table 2: Descriptive Statistics (N = 676, after Winsorization)

Variable	Mean	SD	Median	Min	Max	Skew	Kurt
ln_cct	14.211	0.945	13.953	12.210	16.587	0.795	0.414
ln_dct	14.569	1.938	15.650	11.978	17.149	-0.002	-1.832
ln_atm	2.307	2.215	3.882	-0.105	5.001	-0.003	-1.930
CAR	23.569	15.695	17.475	9.160	82.473	2.056	3.527
NNPA	2.255	2.747	1.205	-0.280	15.316	2.380	6.812
GNPA	7.631	14.249	2.930	0.248	72.655	3.555	12.194
CDR	154.864	358.440	73.710	16.275	2096.000	4.363	17.878
BPE	2321.351	2933.189	1412.990	-10.915	13090.555	1.926	3.187
PPE	302.838	755.503	9.000	-18.738	5925.000	5.192	33.914
ROE	11.859	25.498	10.053	-29.105	245.750	7.897	70.442
ROA	1.370	1.356	1.155	-2.490	6.528	0.423	1.705
NIM	3.929	2.001	3.705	0.000	10.825	1.204	2.471
CATA	20.494	73.706	8.615	0.543	720.168	8.937	81.347

Variables captured digitally behave themselves, with ln_dct and ln_atm nearly symmetric but highly platykurtic, as expected from extensive use during the later years of study. CAMEL variables have much greater variability with GNPA, CDR, and CATA showing significant positive skewness, indicative of banks that lend excessively or hold excessive precautionary cash reserves. This variance provides the empirical justification for the use of estimation methods which take into account the bank-specific effect.

• Correlations, Multicollinearity, and Stationarity

The primary characteristic of the correlation matrix is 0.987 correlation between ln_dct and ln_atm, which is an incredibly high correlation for two different measures. In contrast, the correlation between ln_cct and any other is not very high (0.448 and 0.426). Some selected correlations foreshadow the results that will follow later: ln_dct and ln_atm correlate positively with GNPA (0.330, 0.321) but negatively with CAR (-0.511, -0.517) and ROA (-0.482, -0.486), while ln_cct correlates negatively with both GNPA (-0.134) and NNPA (-0.211).

Table 3: Variance Inflation Factors

Specification	Variable	VIF
Combined (all three)	ln_cct	1.269
	ln_dct	38.999
	ln_atm	38.045
Model 1	ln_cct / ln_dct	1.252 / 1.252
Model 2	ln_cct / ln_atm	1.221 / 1.221

The combined specification leads to VIFs of about four times the normal value of 10; splitting up the variables solves the issue (with all VIFs being below 1.3). The Maddala-Wu test indicates that there is no unit root for any of the ten CAMEL variables (with all p values less than 0.0008).

• Objective 1: Capital adequacy

Table 4: Regression Results — CAR

Variable	Pooled OLS	FE	RE	FE (Robust SE)
<i>Model 1</i>				
ln_cct	1.400** (0.613)	2.035*** (0.440)	2.260*** (0.403)	2.035*** (0.721)
ln_dct	-4.446*** (0.299)	-2.212** (1.058)	-3.523*** (0.659)	-2.212 (2.570)
<i>Model 2</i>				
ln_cct	1.183* (0.604)	1.508*** (0.398)	1.759*** (0.376)	1.508*** (0.319)
ln_atm	-3.881*** (0.258)	0.253 (1.639)	-3.115*** (0.653)	0.253 (1.306)

*Notes: ***p<0.01, **p<0.05, p<0.10; N = 676. Hausman favours RE in both models (p = 0.177; 0.065). All other diagnostic tests significant (p<0.001).

Credit card intensity is positively and strongly related to capital adequacy regardless of the estimator used and the specification. The debit card indicator is significantly negative using Pooled OLS and FE estimators but insignificant when HAC errors are used; the same goes for the ATM penetration ratio, which is insignificantly different from zero. H1 is partially supported; specifically through the credit card route.

- **Objective 2: Asset quality**

Table 5: Regression Results — GNPA and NNPA (FE with Robust SE Shown Alongside RE)

Variable	FE	RE	FE (Robust SE)
<i>GNPA — Model 1</i>			
ln_cct	-1.056*** (0.307)	-1.220*** (0.290)	-1.056*** (0.581)
ln_dct	2.064*** (0.738)	2.416*** (0.541)	2.064** (0.989)
<i>GNPA — Model 2</i>			
ln_cct	-0.945*** (0.276)	-0.930*** (0.265)	-0.945*** (0.486)
ln_atm	3.961*** (1.136)	2.650*** (0.577)	3.961*** (1.161)
<i>NNPA — Model 1</i>			
ln_cct	-0.856*** (0.201)	-0.791*** (0.093)	-0.856*** (0.201)
ln_dct	1.388*** (0.389)	0.753*** (0.110)	1.388*** (0.989)
<i>NNPA — Model 2</i>			
ln_cct	-0.717*** (0.095)	-0.674*** (0.089)	-0.717*** (0.173)
ln_atm	1.947*** (0.389)	0.585*** (0.100)	1.947*** (0.529)

Pooled OLS coefficients share the same sign (for example, ln_cct of GNPA is -5.325**) and are thus not included here. Hausman prefers fixed effects in all four models. In all other diagnostic tests, results are significant at the level of 0.001.*

Credit card transaction is negatively and significantly related to both the NPA measures, which is a positive finding, because smaller NPA reflects good quality of assets. The debit card and ATM measure take on the opposite sign and stay positive and significant (the exception is the measure of ln_dct in the robust model of GNPA, which loses significance at the level of $p \approx 0.07$). H2 is verified.*.

- **Objective 3: Management Efficiency**

Table 6: Regression Results — BPE and PPE (FE and FE with Robust SE)

Variable	FE	FE (Robust SE)
<i>BPE — Model 1</i>		
ln_cct	-241.30*** (85.3)	-241.30*** (89.1)
ln_dct	1038.62*** (205.3)	1038.62*** (374.2)
<i>BPE — Model 2</i>		
ln_cct	-85.41 (78.1)	-85.41** (40.5)
ln_atm	887.09*** (321.4)	887.09*** (223.7)
<i>PPE — Model 1</i>		
ln_cct	-13.99 (30.5)	-13.99 (32.7)
ln_dct	137.67* (73.4)	137.67 (167.2)
<i>PPE — Model 2</i>		
ln_cct	0.89 (27.5)	0.89 (21.0)
ln_atm	181.30 (113.4)	181.30 (154.0)

Notes: Hausman favours FE throughout. Pooled OLS and RE estimates are omitted for brevity.

The dependent variable "business per employee" exhibits a strong positive impact from increases in both debit card/ATM usage as well as credit card usage (although the latter is only negative in one cell). "Profit per employee" has no significant relationship with any of the independent variables. Hypothesis H3 is only partially supported by the data – digital technology has led to an increase in the size of business per employee but not profit per employee.

- **Objective 4: Profitability**

Table 7: Regression Results — ROA, ROE, and NIM (RE and FE with Robust SE)

Variable	RE	FE (Robust SE)
<i>ROA — Model 1</i>		
ln_cct	0.180*** (0.046)	0.153** (0.075)
ln_dct	-0.330*** (0.057)	-0.248 (0.235)
<i>ROA — Model 2</i>		
ln_cct	0.138*** (0.044)	0.135** (0.055)

ln_atm	-0.305*** (0.052)	-0.427 (0.265)
<i>ROE — Model 1</i>		
ln_cct	2.257** (1.081)	1.806* (1.070)
ln_dct	-2.501** (1.132)	-0.659 (5.909)
<i>ROE — Model 2</i>		
ln_cct	1.972* (1.036)	1.817* (1.097)
ln_atm	-2.349** (1.010)	-1.764 (7.593)
<i>NIM — Model 1</i>		
ln_cct	0.513*** (0.055)	0.541*** (0.099)
ln_dct	-0.612*** (0.090)	-0.762*** (0.269)
<i>NIM — Model 2</i>		
ln_cct	0.404*** (0.052)	0.376*** (0.076)
ln_atm	-0.375*** (0.090)	-0.097 (0.369)

Notes: Hausman favours RE throughout (all $p > 0.16$). Pooled OLS and plain FE estimates are omitted for brevity.

Credit card activity has a positive and significant relationship with ROA and NIM for all estimators and standard error adjustments — the finding with the highest level of internal consistency in the entire analysis — but is positive but less estimator-sensitive for ROE. Debit card and ATM coefficients have a negative relationship with ROA and NIM with the Pooled OLS, FE, and RE methods but are insignificant with robust standard errors (excepting ln_dct with NIM). H4 is supported for ROA and NIM but partially supported for ROE.

Table 8: Profitability Robustness with Controls (Selected Coefficients)

Variable	FE	RE	FE (Robust SE)
ROA: ln_cct	0.109** (0.053)	0.111** (0.047)	0.109 (0.073)
ROA: ln_dct	-0.177 (0.124)	-0.223*** (0.058)	-0.177 (0.231)
ROA: GNPA	-0.043*** (0.008)	-0.041*** (0.007)	-0.043** (0.020)
ROE: ln_cct	2.527** (1.266)	2.496** (1.119)	2.527** (0.986)
NIM: ln_cct	0.488*** (0.061)	0.460*** (0.057)	0.488*** (0.103)
NIM: ln_dct	-0.698*** (0.143)	-0.534*** (0.095)	-0.698*** (0.259)

With capital adequacy, asset quality, lending aggressiveness, and liquidity being controlled, the ln_cct coefficient for ROA becomes small in magnitude, maintains the same sign, and remains significant using conventional, but not robust, standard errors; while for ROE and NIM, the effect is still significant with any adjustment. The controls are consistent with the theoretical expectation (negative GNPA). The fact that the effect persists suggests that the baseline result is not driven by the well-capitalized banks processing more card transactions.

Table 9: System GMM Results

Variable	ROA M1	ROA M2	ROE M1	ROE M2	NIM M1	NIM M2
Lag(Y,1)	0.742***	0.586***	0.465***	0.442***	0.604***	0.580***
ln_cct	0.159**	0.216***	2.379***	2.090***	0.162	0.150
ln_dct / ln_atm	-0.087	-0.146***	-1.359***	-1.255***	-0.177**	-0.164***
Sargan p (df 6)	0.032	0.018	0.315	0.137	0.088	0.154
AR(2) p	0.989	0.980	0.279	0.428	0.525	0.572

Notes: Two-step, two-way System GMM, Windmeijer-corrected SEs; instruments lag(2:5) of the dependent variable, collapsed. M1 = ln_cct + ln_dct; M2 = ln_cct + ln_atm. Wald tests significant throughout.

The lagged dependent variable is significantly important in all regressions (γ between 0.44 and 0.74), indicating strong persistence and ensuring the validity of the dynamic approach. The AR(2) term is statistically insignificantly important in all regressions, confirming the appropriateness of the instrument set despite weak Sargan tests in ROA regressions. The credit card ratio is statistically positive in all three regressions and represents the most robust digital variable in the context of persistence and endogeneity, whereas ROE appears as the cleanest one in terms of specification tests. The debit card and ATM ratios are negative and statistically significant in ROE and NIM regressions.

- **Objective 5: Liquidity**

Table 10: Regression Results — CATA and CDR (FE and FE with Robust SE)

Variable	FE	FE (Robust SE)
<i>CATA — Model 1</i>		
ln_cct	18.366*** (4.474)	18.366* (9.517)
ln_dct	-31.882*** (10.765)	-31.882 (23.407)
<i>CATA — Model 2</i>		
ln_cct	9.798** (4.062)	9.798 (6.305)
ln_atm	14.451 (16.726)	14.451 (9.544)
<i>CDR — Model 1</i>		
ln_cct	-4.55 (8.40)	-4.55 (5.63)
ln_dct	23.75 (20.20)	23.75 (16.88)
<i>CDR — Model 2</i>		
ln_cct	1.00 (7.58)	1.00 (5.39)
ln_atm	-1.57 (31.22)	-1.57 (10.14)

There is a positive relationship between the credit card payment method and the cash-assets ratio under FE in both cases; however, this positive relationship becomes marginally significant under HAC. There is no relation between any digital payment method and the credit-deposit ratio which passes the Hausman preferred FE test. Hypothesis H5 is partially supported in that liquidity reacts, weakly and inconsistently, on the cash buffer basis but not the loans vs. deposits basis.

- **Summary of Hypothesis Decisions**

Table 11: Hypothesis Decisions

Hypothesis	Dependent variable(s)	Decision	Basis
H1	CAR	Partially supported	ln_cct positive and robust; ln_dct/ln_atm not robust to HAC SE
H2	GNPA, NNPA	Supported	ln_cct favourable; ln_dct/ln_atm unfavourable — both robust
H3	BPE, PPE	Partially supported	BPE: ln_dct/ln_atm robust; PPE: none robust
H4	ROA, ROE, NIM	Supported (ROA, NIM); partial (ROE)	ln_cct robust across baseline, controls, and GMM
H5	CATA, CDR	Partially supported	CATA: ln_cct significant under FE; CDR: none robust

Regardless of the purpose, the rejection of the null is stronger for credit cards relative to the other two forms of payments. Furthermore, the last two are not necessarily of the same sign, even if significant. The former sentence captures the key empirical result of the paper.

Discussion

Three broad patterns emerge once the five objectives are read together.

- **Credit Card Intensity is a Coherent, Favourable Signal Across Almost the Entire CAMEL Spectrum:** It increases capital adequacy, asset quality, and profitability, all of which persist through FE estimation, robust standard errors, control variables specification, and dynamic System GMM – cross-validation far rarer for any single estimator in this literature. The results are in line with those of Shaikh and Anwar (2023), the only study in India to separate credit card transactions from others, showing that card-based transactions reduce the cost of funds. The results are also in accordance with the international literature on the positive impact of income-free digital channels on bank fundamentals (Yoon et al., 2023; Dasilas & Karanović, 2025; Zheng et al., 2023). Resource-Based View provides an appropriate theoretical framework, as credit card processing infrastructure is expensive to copy, and is concentrated in banks with a wealthier, low-default risk clientele, thus making it a differentiating capability rather than a generic digital product (Al-Dmour et al., 2020, 2021; Ferilli et al., 2024).

- **Debit Cards and ATM Infrastructure tell a more Ambivalent Story:** While both are linked with increased business per employee, there is a relationship with declining asset quality, both on gross and net measures, and the correlation between capital adequacy and profitability is significantly weaker after adjustment for HAC. Such an inverse correlation stands in contrast with the existing literature in India related to ATMs: Singh et al. (2021), Kaur and Pathak (2023), and Veluthedan and Kiran (2024) find a positive correlation between the number of ATMs and profitability, while Gowtham et al. (2026) observe the opposite relationship in the case of ROA. The current period of 2014–2025 covers both these periods and potentially reconciles them: ATM-led growth seems to have been associated with efficiency gains while the network was growing compared to branch network, but the cost of lower asset quality of the larger and more heterogeneous deposit base seems to have increased its importance. The asset-quality finding also extends the international literature: SAADAOUI and Souissi (2026) and Wang et al. (2023) find that incumbents' digitalisation reduces non-performing loans, but their digital measures are dominated by credit-monitoring and information-processing technologies rather than the deposit-and-withdrawal infrastructure captured by debit cards and ATMs. The consequences of DFI therefore depend not merely on whether digitalisation occurs but on which function — credit appraisal or deposit mobilisation — is digitalised, a distinction composite-index studies cannot detect.
- **Management Efficiency and Liquidity are the Least Conclusive Objectives, and this is itself Informative:** Business per employee rises robustly with debit-card- and ATM-led growth, yet profit per employee shows no comparably robust response. This speaks to the productivity paradox documented by Prakash et al. (2025): volume-based gains are detectable once the analysis is disaggregated by channel, but do not yet translate robustly into profit per employee. Diffusion of Innovation theory and the Technology Acceptance Model explain why usage has grown; they do not guarantee that growing usage converts into proportionate profit. The liquidity findings are harder to benchmark because so little prior work treats liquidity as a CAMEL outcome; the modest, indicator-specific result here is one of the few direct tests at the individual-bank level, consistent with Xie's (2025) caution that DFI's benefits for one performance dimension need not extend uniformly to others.
- **Theoretical Implications:** The findings support treating bank-level CAMEL performance, rather than customer-level access, as the appropriate unit of analysis for assessing DFI's institutional consequences. The credit-card versus debit-card/ATM asymmetry indicates that DFI should not be treated as an undifferentiated construct: the Resource-Based View fits the credit-card findings more comfortably, while the infrastructure-like, broadly diffused character of debit cards and ATMs is better explained by adoption-focused theories.
- **Implications for Management and Regulators:** The approach to assessing the digital strategy needs to be done separately by channel for banks. Expansion of credit card numbers in a prudent manner seems to be a relatively reliable handle in terms of capital strength and earnings for the bank. Expansion based on the debit card and ATM channels has provided productivity benefits which have not been translated into bottom-line profits and this must go hand-in-hand with more careful credit risk assessment especially in light of retail and small business lending which comes with overall deposit mobilization. For the regulators, India's inclusion strategy has focused a lot on the debit card and ATM channels since these channels have a broader customer base and looking at aggregate measures may ignore asset quality stresses specific to each channel.

Conclusion

The purpose of the current analysis was to investigate whether there exists any uniform connection between DFI and the financial performance of commercial banks operating in India or whether such relationship is channel specific. Based on 676 bank-year observations across sixty-one banks from 2014 to 2025 and all five CAMEL components, it becomes clear that digital financial inclusion is a channel specific, and not uniform, determinant of institutional performance. Intensity of credit cards is positively related to higher capital adequacy, asset quality, and profitability, robust to FE estimation, robust standard errors, controls, and system GMM. Usage of debit cards and ATMs increases volume of business per employee; however, it negatively affects asset quality, and relationship with capital adequacy and profitability is much weaker.

- **Contributions:** First, the study empirically demonstrates that DFI cannot be considered a composite construct as aggregation of it results in material differences and even oppositional relationship with respect to the same CAMEL indicator. Second, assessment of all five CAMEL indicators demonstrates that the channel of benefit in case of one indicator does not necessarily provide the same effect on another indicator. Finally, it provides a methodology for dealing with severe collinearity of related digital indicators – parallel specifications, not arbitrary exclusion – in combination with the System GMM approach.
- **Limitations:** (1) The three indicators do not consider mobile banking, internet banking, and UPI transfers, which have increased significantly and might be distinctive. (2) The sample is purposive and driven by data availability. It may not include smaller or newly licensed banks. (3) The study uses secondary regulator-provided data definitions of which have changed during the period. (4) System GMM is only used for profitability, and the instruments used cannot be externally verified.
- **Future Research:** Potential extensions include use of the UPI system, mobile banking, and internet banking; extension of System GMM to the rest of the CAMEL variables; decomposition based on ownership categories such as public, private, foreign, and small finance; and replication in other countries with emerging banking systems.

Under these constraints, the paper provides solid, multiple cross-validated proof that the institutional outcomes of DFI on Indian commercial banks are dependent on the channel rather than being generalized – an important consideration as India continues its transition to digital banking.

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