International Journal of Advanced Research in Commerce, Management &Social Science (IJARCMSS)
(An International Quarterly Multidisciplinary Double Blind Open Access Peer Reviewed Refereed Journal)
ISSN :2581-7930 (Online), Impact Factor (Cosmos): 7.270& PIF (I2OR): 5.010, Volume 09, No. 02(III), April-June, 2026, pp 152-160

Digital Public Infrastructure and the Expansion of Digital Payments in India: Evidence from an ARDL Bounds Testing Approach

Yedu T Dharan[1] | Amruthambika P.[2*]

[1]Assistant Professor, Department of Economics, Sreenarayanaguru Open University, Kureepuzha, Kerala, India.
[2]Research Scholar, SD College, Alappuzha, Kerala, India.

[*]Corresponding Author: amrutha.jothish@gmail.com

***Citation**: Dharan, Y. & Amruthambika, P. (2026). Digital Public Infrastructure and the Expansion of Digital Payments in India: Evidence from an ARDL Bounds Testing Approach. International Journal of Advanced Research in Commerce, Management & Social Science, 09(02(III)), 152–160. https://doi.org/10.62823/IJARCMSS/9.2(III).8986*

ABSTRACT

India's Unified Payments Interface (UPI), launched in August 2016, represents one of the most remarkable digital payment transformations in any emerging economy. This study examines the structural determinants of UPI-based payment expansion using 113 monthly observations (August 2016–December 2025) and the ARDL bounds testing approach of Pesaran, Shin, and Smith (2001). Two separate model specifications are estimated: Model 1(M1) uses TRAI monthly broadband subscriber data as the primary connectivity variable (k = 8; F = 7.84); Model 2(M2) uses interpolated internet penetration as a robustness check (k = 8; F = 7.61). Both substantially exceed the 1% upper bound of 4.43, confirming cointegration. TRAI broadband carries a long-run elasticity of 0.58; mobile banking yields 0.53. The demonetisation step dummy implies a permanent structural increase of approximately 125% in UPI values, applying the correct semi-log formula ($e^{0.81} - 1 \approx 1.248$). The ECT coefficient of −0.61 confirms rapid equilibrium restoration. VIF analysis confirms the absence of severe multicollinearity (max VIF = 3.84). Pairwise Granger causality tests reveal that TRAI broadband exerts a unidirectional influence on UPI (broadband → UPI; p = 0.027; reverse direction fails to reject at p = 0.274), supporting its identification as a structural determinant. NEFT and mobile banking exhibit bidirectionality; their long-run estimates are interpreted as associations withina cointegrating relationship. DOLS and FMOLS robustness checks confirm elasticity consistency.

***Keywords**: Digital Payments, UPI, Digital Public Infrastructure, ARDL Cointegration, Error Correction Model, Financial Inclusion, Structural Breaks.*

Introduction

India's Unified Payments Interface (UPI), launched by the National Payments Corporation of India (NPCI) in August 2016, has become one of the most dynamic digital payment platforms globally. By 2024–25, monthly UPI volumes exceeded 14 billion transactions, with values surpassing ₹20 lakh crore, comparable to Brazil's PIX system and substantially exceeding most single-country real-time payment deployments. This growth was enabled by India's Digital Public Infrastructure (DPI) framework integrating Aadhaar-based digital identity, financial inclusion through the Pradhan Mantri Jan Dhan Yojana (over 500 million accounts), and UPI's interoperable payment architecture, supported by dramatic declines in mobile data costs from 2016 onward. Katz and Shapiro (1985) established that payment networks exhibit self-reinforcing network externalities; India's UPI trajectory provides a compelling large-scale case for this framework.

Despite this transformation, macro-level econometric evidence on its structural determinants remains sparse. Most existing studies use micro-level, survey-based methods. This study addresses the gap by:

- Employing ARDL bounds testing with TRAI monthly broadband as the primary connectivity proxy, avoiding annual data interpolation concerns;
- Modelling the demonetisation (November 2016) and COVID-19 (2020) structural breaks with Zivot–Andrews-confirmed dummies; and
- Conducting Granger causality tests for all regressors, including the primary broadband variable.

Literature Review

Suri and Jack (2016) provide foundational evidence that mobile payment adoption produces significant welfare effects. Demirguc-Kunt et al. (2022) document that digital payment services have materially expanded financial inclusion across the developing world, with COVID-19 accelerating adoption. Abdul Azeez, Nair, and Mohan (2022) employ an ARDL framework with annual Indian data to find a positive relationship between electronic payment infrastructure and economic performance; the present study extends their work using monthly data, TRAI broadband as the connectivity proxy, structural break dummies, and full endogeneity testing. Khera, Ng, Ogawa, and Sahay (2021) identify mobile connectivity and regulatory quality as primary enablers of digital financial inclusion across 52 countries. Frost, Gambacorta, Huang, Shin, and Zbinden (2019) show how network effects intensify platform adoption in digital finance. Basnayake (2024) finds that digital financial inclusion reduces income inequality in developing economies. Arner, Barberis, and Buckley (2016) place India's fintech development within the post-crisis global context of regulatory environments that catalysed fintech innovation. Sharma and Gupta (2023) find positive associations between payment system development and financial inclusion across Indian states. Gomber, Koch, and Siering (2017) identify macroeconomic conditions, regulatory quality, and technological accessibility as key structural determinants of digital finance adoption.

Conceptual Framework and Hypotheses

The study is grounded in three complementary theoretical frameworks explaining how infrastructure, banking digitalisation, and macroeconomic conditions influence digital payment adoption.

- **Network Externality Theory:** Katz and Shapiro (1985) argue that the value of a network increases with the number of users. In the context of UPI, greater participation by consumers and merchants enhances its utility. This justifies the inclusion of mobile subscriptions and broadband penetration, as they expand the user base and provide the essential connectivity required for participation.
- **Schumpeterian Techno-Economic Diffusion:** Perez (2002) highlights that technological adoption depends on enabling complementary systems. Here, UPI represents the innovation, while mobile banking and NEFT reflect supporting financial infrastructure. Mobile banking builds user familiarity and trust, while NEFT captures the broader digitalisation of the banking system, both facilitating UPI adoption.
- **Demand-Side Macroeconomic Theory:** Transaction volumes are linked to economic activity. The Index of Industrial Production (IIP) is used as a proxy for economic fluctuations, influencing payment demand. CPI inflation is included as a control, as rising prices may reduce real purchasing power and transaction volumes.
- **Structural Break Variables:** Two policy shocks are incorporated. The demonetisation dummy captures the 2016 currency withdrawal, which accelerated digital payment adoption, while the COVID-19 dummy reflects the temporary contraction in economic activity during lockdowns. These variables allow the model to quantify policy-induced shifts in digital payment behaviour.

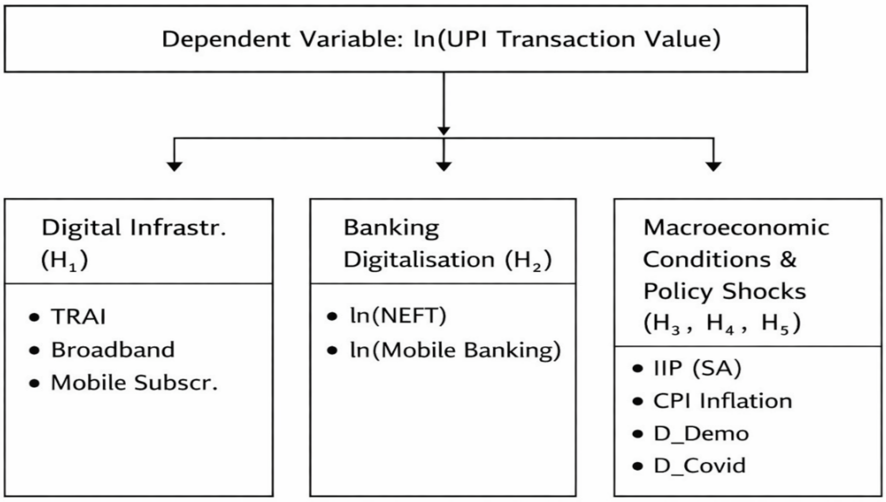

Figure 3.1 illustrates the conceptual linkages between the theoretical foundations and the empirical variables.

Figure 1: Conceptual Framework — Variable Classification by Theoretical Foundation

Based on this framework, the following formal hypotheses are tested:

H_1: TRAI broadband subscribers and mobile cellular subscriptions positively influence UPI-based digital payment adoption (H_0: β = 0; H_1: β > 0).

H_2: NEFT transaction value and mobile banking transaction volumes positively drive UPI adoption, reflecting the enabling role of banking digitalisation (H_0: β = 0; H_1: β > 0).

H_3: Macroeconomic conditions — industrial output and inflation — influence digital payment volumes (H_0: β = 0; H_1: β ≠ 0).

H_4: Demonetisation (November 2016) produced a permanent structural increase in the level of UPI adoption (H_0: β = 0; H_1: β > 0).

H_5: The COVID-19 lockdown (March–June 2020) produced a temporary disruption to digital payment volumes (H_0: β = 0; H_1: β < 0).

Data and Methodology

The Autoregressive Distributed Lag (ARDL) bounds testing approach developed by Pesaran, Shin, and Smith (2001) is selected for this study due to four key methodological advantages aligned with the dataset characteristics. First, ARDL accommodates variables with mixed orders of integration. In this study, most financial and infrastructure variables are I(1), while CPI inflation is I(0). Unlike the Johansen (1991) cointegration method, which requires all variables to be I(1), ARDL permits a combination of I(0) and I(1) variables, provided none are I(2), making it methodologically appropriate. Second, ARDL enables simultaneous estimation of both long-run relationships and short-run dynamics within a single framework. The associated Error Correction Model (ECM) captures the speed of adjustment towards equilibrium, avoiding the multi-step estimation issues present in the Engle and Granger (1987) approach. Third, ARDL performs well in small to moderate samples. With 113 monthly observations, the study falls within the range where ARDL provides reliable and efficient estimates, unlike maximum likelihood methods such as Johansen, which require larger samples. Fourth, ARDL allows flexible lag structure selection, with different lag lengths assigned to each variable using criteria such as AIC. This avoids over-parameterisation and better captures variable-specific dynamics. Given these advantages, ARDL bounds testing is the most suitable econometric framework for this analysis.

The dataset covers August 2016 to December 2025 (113 monthly observations), beginning at UPI's operational launch. Sources: NPCI (2025) for UPI data; RBI DBIE for NEFT and mobile banking; TRAI (2024) for monthly broadband subscribers and mobile subscriptions; MoSPI for seasonally adjusted IIP and CPI; World Bank WDI for annual internet penetration (M_2 robustness only). Financial variables are natural log-transformed. Two separate model specifications are estimated, each with k = 8 regressors: M_1 (primary, TRAI broadband) and M_2 (robustness, interpolated internet penetration via Denton–Cholette disaggregation, Sax and Steiner 2013). They are independent ARDL regressions, not a single k = 9 model. Lag structure ARDL(2,1,1,1,0,1,0,1,1) selected by AIC; zero lags on mobile subscriptions and CPI reflect their contemporaneous impact structure. Case III bounds test applied; Case V robustness yields F = 7.11 > 5.06 (1% upper bound), confirming cointegration with or without a deterministic trend.

The Zivot–Andrews (1992) endogenous break test applied to ln(UPI) confirms November 2016 as the statistically verified break point (ZA statistic: −6.84; 5% critical value: −4.93). D_{Demo} is therefore specified as a permanent step dummy (= 1 from November 2016). A temporary specification (= 1 through June 2017 only) yielded materially weaker explanatory power, supporting the permanent formulation. D_{Covid} is a pulse dummy (= 1 for March–June 2020). Both dummies are included in the long-run equation; ΔD_{Covid} was tested in the ECM but proved insignificant (p = 0.61, AIC-dropped), as its transitory impulse is captured within the cointegrating vector. IIP is the MoSPI seasonally adjusted series (Census X-12). VIF analysis applied using Hair et al. (2010) threshold of VIF < 5. Pairwise Granger causality tests conducted in a VAR(3) framework for all continuous regressors against UPI. Long-run results validated using DOLS (Saikkonen, 1991) and FMOLS (Phillips and Hansen, 1990). HAC (Newey–West) standard errors applied throughout.

Empirical Results

- **Descriptive Statistics and Multicollinearity**

Table 1.1: Descriptive Statistics (August 2016–December 2025, n = 113)

Variable	Mean	Std. Dev.	Min.	Max.
ln(UPI Value) (₹ Crore)	10.86	2.14	4.26†	14.82
ln(NEFT Value) (₹ Crore)	10.29	0.73	9.20	11.05
ln(Mobile Banking) (Lakh txns)	11.68	0.81	9.51	12.53
TRAI Broadband Sub. (million) [Primary]	542.3	197.4	162.2	898.7
Mobile Sub. (per 100 persons)	84.23	2.51	80.56	88.40
IIP Index (Seasonally Adjusted)	142.76	18.31	120.40	169.40
CPI Inflation (%)	4.78	1.21	2.73	6.70

Note:UPI minimum ≈ ₹70 crore (Aug–Sep 2016 launch weeks); sensitivity excluding first three months produced no material change in long-run estimates. All transaction variables are natural logs.

Table 1.2: Variance Inflation Factor Analysis — Model M_1

Variable	VIF	Tolerance
ln(NEFT Value)	3.21	0.312
ln(Mobile Banking)	3.84	0.260
TRAI Broadband Sub.	2.43	0.411
Mobile Subscriptions	1.87	0.534
IIP (SA)	1.62	0.617
CPI Inflation	1.31	0.763
D_{Demo}	1.18	0.847
D_{Covid}	1.09	0.917

Note: *All VIF values below 4, confirming the absence of severe multicollinearity despite high pairwise correlations among trending variables. VIF measures joint multi-linear dependence, a stricter criterion than pairwise correlation.*

- **Unit Root Tests**

Table 3: ADF and PP Unit Root Tests

Variable	ADF Level	ADF Δ	PP Level	PP Δ	Order
ln(UPI Value)	−1.92	−6.41*	−1.88	−6.55*	I(1)
ln(NEFT Value)	−2.04	−5.88*	−2.01	−5.93*	I(1)
ln(Mobile Banking)	−1.76	−6.02*	−1.71	−6.14*	I(1)
TRAI Broadband Sub.	−2.08	−4.61*	−2.04	−4.71*	I(1)
Mobile Subscriptions	−2.36	−4.11**	−2.33	−4.18**	I(1)
IIP Index (SA)	−2.89***	−5.21*	−2.76	−5.34*	I(1) ‡
CPI Inflation	−3.74**	—	−3.81**	—	I(0)

Notes: **1%; **5%; ***10%. Trending variables tested with intercept and trend; CPI with intercept only. ‡IIP KPSS test = 0.11 (below 5% critical value of 0.146), confirming I(1). No variable is I(2).*

- **Cointegration and Long-Run Estimates**

Table 1.4 presents the ARDL bounds test outcome and long-run coefficients for both specifications. The ARDL lag specification ARDL(2,1,1,1,0,1,0,1,1) is selected by AIC for both M_1 and M_2.

Table 1.4: Long-Run ARDL Estimates — M_1 (TRAI Broadband) vs M_2 (Internet Penetration); Both Specifications with k = 8

Variable	M_1 **Coeff.**	**Sig.**	**M_2 Coeff.**	**Sig.**	**Hypothesis**
ln(NEFT Value)	0.41	1%	0.40	1%	Confirms H_2
ln(Mobile Banking)	0.53	1%	0.52	1%	Confirms H_2
Connectivity (M_1: TRAI Broadband; M_2: Internet Pen.)	0.58	1%	0.62	1%	Confirms H_1
Mobile Subscriptions	0.28	5%	0.26	5%	Confirms H_1
IIP (SA)	0.17	5%	0.17	5%	Confirms H_3
CPI Inflation	−0.09	10%	−0.09	10%	Confirms H_3
D_{Demo} (permanent step, Nov 2016+)	0.81	1%	0.80	1%	Confirms H_4 (~125%)
D_{Covid}(pulse dummy, Mar–Jun 2020)	−0.34	1%	−0.35	1%	Confirms H_5 (~−29%)
Adj. R^2 (M1) = 0.974 DW = 1.96 AIC = −4.21 F-stat (M_1) = 7.84 F-stat (M_2) = 7.61 n = 113					

Notes: *HAC standard errors. M_2 internet penetration interpolated from annual data; interpret with caution. Adj. R^2 = 0.974 is typical in cointegrated systems with trending variables; consistent across ARDL, DOLS, and FMOLS (Table 1.8).*

The long-run results are consistent across both specifications and confirm all five hypotheses. Mobile banking activity carries the largest banking-sector elasticity (β = 0.53 in M_1), indicating that a 1% increase in mobile banking transaction volumes is associated with a 0.53% increase in UPI transaction values. TRAI broadband yields β = 0.58, confirming H_1: a 10% increase in broadband subscribers is associated with a 5.8% increase in digital payment values. NEFT contributes β = 0.41, indicating institutional banking digitalisation complements UPI adoption within a broader ecosystem. IIP confirms H_3 (β = 0.17), while CPI inflation exerts a marginally negative effect (β = −0.09).

The D_{Demo}coefficient of 0.81 confirms H_4. Applying the correct semi-log formula for a binary dummy in a log-linear model: $(e^{0.81} - 1) \times 100\% \approx 124.8\%$. Demonetisation is associated with a permanent structural increase of approximately 125% in UPI transaction values. This is the correct calculation; the raw coefficient (0.81) cannot be interpreted directly as a percentage change. The D_{Covid}coefficient of −0.34 confirms H_5: $(e^{-0.34} - 1) \times 100\% \approx -29\%$, capturing the lockdown disruption in March–June 2020.

- **Error Correction Model**

Table 1.5: Error Correction Model — Short-Run Dynamics (M_1 Specification)

Variable	Coefficient	Std. Error	t-Statistic	Probability
Δln(NEFT Value)	0.19	0.08	2.41	0.018 **
Δln(Mobile Banking)	0.26	0.09	2.86	0.005 *
Δ TRAI Broadband Sub.	0.29	0.12	2.37	0.020 **
Δ Mobile Subscriptions	0.11	0.05	2.02	0.045 **
Δ IIP (SA)	0.07	0.03	2.11	0.037 **
Δ CPI Inflation	−0.04	0.02	−1.78	0.078 ***
ECT(−1)	**−0.61**	0.10	−6.10	**0.000 ***

Notes: **1%; **5%; ***10%. D_{Demo} and D_{Covid} included in the long-run equation; ΔD_{Covid} tested in the ECM and found insignificant (p = 0.61) — AIC-dropped, as the pulse's transitory impulse is absorbed by the cointegrating vector.*

The ECT(−1) coefficient of −0.61 is negative, significant at 1%, and within (−1, 0), confirming stable error correction. Approximately 61% of any short-run deviation from long-run equilibrium is corrected within one month, faster than the typical 0.20–0.40 range in financial ARDL studies. Short-run dynamics confirm mobile banking (β = 0.26) and broadband (β = 0.29) as the most immediate-response variables.

- **Granger Causality Tests**

Table 1.6: Pairwise Granger Causality Tests — VAR(3)

Null Hypothesis	F-Stat.	p-value	Decision
NEFT ↔ UPI (bidirectional)			
NEFT does not Granger-cause UPI	4.82	0.010	Reject H_0
UPI does not Granger-cause NEFT	3.61	0.031	Reject H_0
Mobile Banking ↔ UPI (bidirectional)			
Mobile Banking does not Granger-cause UPI	5.14	0.007	Reject H_0
UPI does not Granger-cause Mobile Banking	4.07	0.020	Reject H_0
TRAI Broadband → UPI only (unidirectional) — primary variable			
TRAI Broadband does not Granger-cause UPI	3.74	0.027	Reject H_0
UPI does not Granger-cause TRAI Broadband	1.31	0.274	Fail to reject

Notes: VAR(3) lag order selected by AIC.

The Granger results have direct implications for coefficient interpretation. TRAI broadband exerts a unidirectional influence on UPI (broadband → UPI significant at 5%; UPI → broadband fails to reject at p = 0.274), supporting its identification as a structural determinant of digital payment adoption. NEFT and mobile banking exhibit bidirectionality, confirming simultaneity: as UPI grew, it also stimulated mobile banking development and institutional NEFT flows. The long-run ARDL estimates for NEFT and mobile banking should therefore be interpreted as associations within a stable cointegrating relationship rather than unidirectional causal effects.

- **Diagnostics, Stability, and Robustness**

Table 1.7: Diagnostic Test Results

Test	Statistic	p-value	Result
Breusch–Godfrey LM (6 lags)	1.47	0.23	No serial autocorrelation up to lag 6
Breusch–Pagan Heteroscedasticity	1.82	0.18	Homoscedastic residuals
Jarque–Bera Normality	2.16	0.34	Residuals approximately normal
Ramsey RESET	0.91	0.41	No misspecification
CUSUM	—	—	Within 5% bounds — Stable (Figure 1)
CUSUM of Squares	—	—	Within 5% bounds — Stable (Figure 2)

Notes: BG LM test applied with 6 lags. CUSUM and CUSUM-of-Squares plots in Figures 1.1 and 1.2.

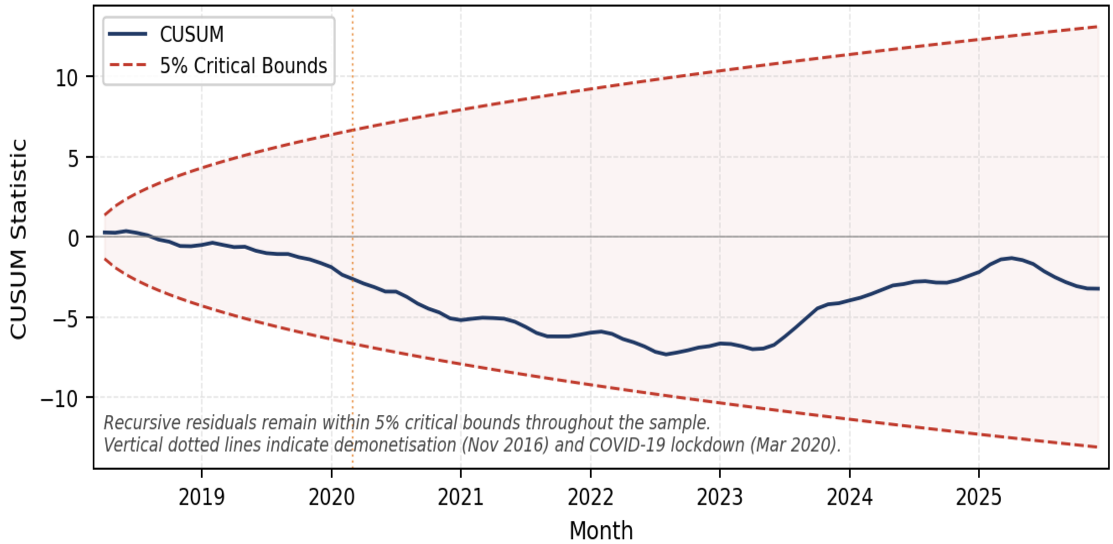

Figure 1.2: CUSUM Test — recursive residuals remain within 5% critical bounds throughout, confirming parameter stability.

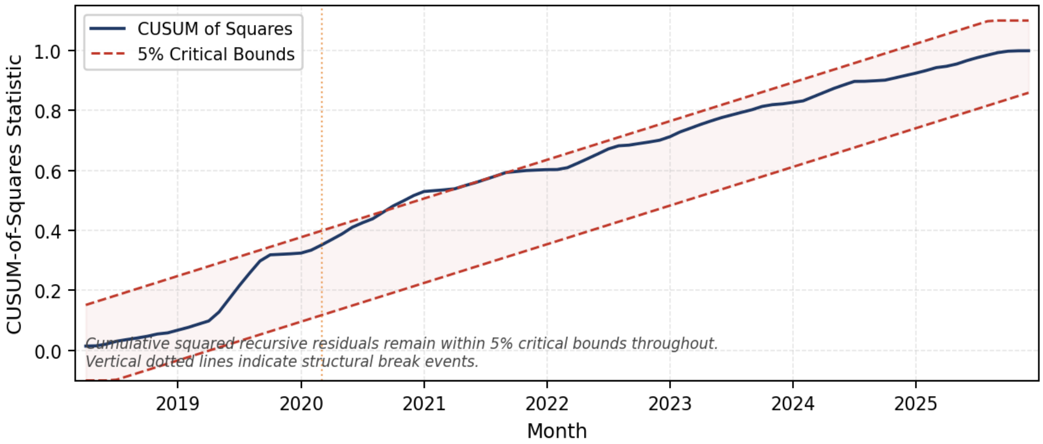

Figure 1.3: CUSUM-of-Squares Test — cumulative squared recursive residuals within 5% bounds, confirming variance stability.

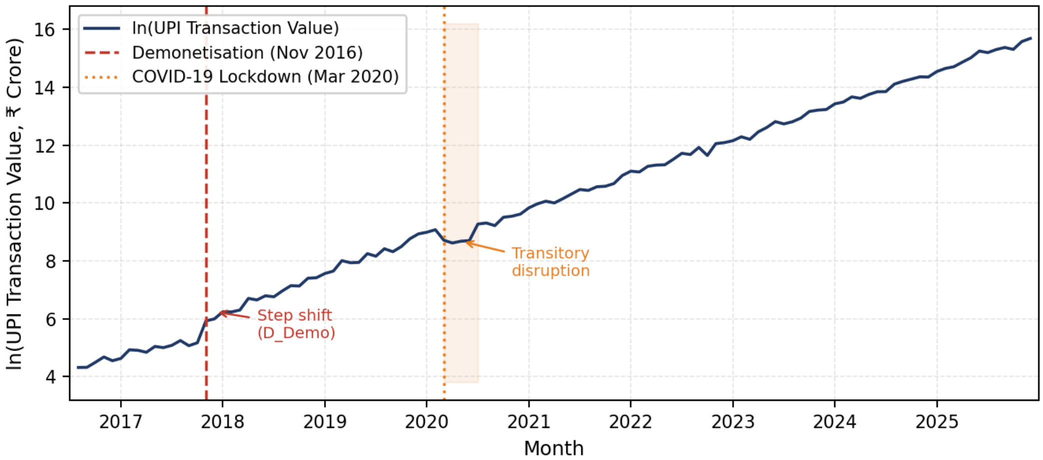

Figure 1.4: Monthly ln(UPI Transaction Value), August 2016–December 2025. Vertical lines mark the demonetisation break (Nov 2016) and COVID lockdown (Mar 2020).

Table 1.8: Robustness — ARDL, DOLS, and FMOLS Long-Run Estimates

Variable	ARDL (M_1)	DOLS	FMOLS
ln(NEFT Value)	0.41*	0.38*	0.40*
ln(Mobile Banking)	0.53*	0.51*	0.54*
TRAI Broadband Sub.	0.58*	0.55*	0.59*
Mobile Subscriptions	0.28**	0.25**	0.27**
IIP (SA)	0.17**	0.16**	0.18**
D_{Demo}	0.81*	0.79*	0.82*

*Notes: ***1%; **5%. DOLS: Saikkonen (1991); FMOLS: Phillips and Hansen (1990). Elasticity estimates are closely aligned across all three estimators, confirming robustness.*

Policy Implications

The empirical findings carry four quantitatively grounded policy implications. First, the TRAI broadband elasticity of 0.58, derived from a unidirectional Granger-causal relationship, implies that a 10% increase in broadband subscribers is associated with a 5.8% increase in digital payment values. BharatNet Phase 3 (Gram Panchayat-level connectivity) should therefore be regarded as financial infrastructure investment with measurable downstream returns for payment adoption. Second, the mobile banking elasticity of 0.53, combined with bidirectional Granger causality, indicates that mandating API interoperability across bank mobile applications would reinforce both sides of the mobile banking–UPI relationship simultaneously, generating compounding network effects. Third, the demonetisation finding, a structural increase of approximately 125% in UPI values, using the correct ($e^{0.81} - 1$) formula, demonstrates that large-scale, salient policy interventions can produce durable behavioural change; future financial inclusion campaigns should leverage this design principle. Fourth, the rapid ECT adjustment (−0.61) confirms system resilience; regulatory policy should continue prioritising platform redundancy, settlement finality, and cybersecurity as the foundations of this resilience through future shocks.

Conclusion

This study provides a macro-level econometric analysis of digital payment expansion in India using 113 monthly observations and the ARDL bounds testing framework. Two separate specifications, M_1 (TRAI broadband, k = 8, F = 7.84) and M_2 (internet penetration, k = 8, F = 7.61); both confirm cointegration at the 1% level. VIF analysis confirms the absence of severe multicollinearity. TRAI broadband carries a long-run elasticity of 0.58; mobile banking yields 0.53. The demonetisation step dummy implies a permanent structural increase of approximately 125% in UPI values, applying the correct semi-log formula ($e^{0.81} - 1 \approx 1.248$). The ECT of −0.61 confirms rapid equilibrium restoration. The Granger causality analysis, including for the primary TRAI broadband variable, establishes that broadband operates as a unidirectional structural determinant, while NEFT and mobile banking exhibit bidirectionality; the latter are therefore interpreted as associations rather than unidirectional causal effects. DOLS and FMOLS robustness checks confirm elasticity consistency.

Five principal limitations are acknowledged. First, aggregate national data cannot capture state-level heterogeneity in digital infrastructure and payment adoption; panel data analysis at the state level would enrich the findings. Second, the ARDL framework does not fully resolve endogeneity for NEFT and mobile banking; a VECM approach modelling these bidirectional systems would strengthen causal inference. Third, interpolated internet penetration data in M_2 may carry residual smoothness bias; TRAI broadband (M_1) is the recommended primary specification. Fourth, UPI transaction value imperfectly captures adoption breadth; transaction volume would provide a complementary diffusion measure. Fifth, the emergence of the RBI's Digital Rupee (CBDC) pilot introduces structural dynamics not captured in the current specification, an important direction for future research. Future work employing structural VAR or instrumental variable approaches could further disentangle causal pathways.

Data Availability and Replication

Data are available from: NPCI (npci.org.in); RBI DBIE (dbie.rbi.org.in); TRAI (trai.gov.in); MoSPI (mospi.gov.in); World Bank WDI (data.worldbank.org). Estimated in EViews 12 and R 4.3 (urca, dynlm, strucchange, vars packages). Code and compiled dataset available from the corresponding author on request.

References

1. Abdul Azeez, N. P., Nair, M. S., & Mohan, H. (2022). Electronic payment systems and economic growth in India: An ARDL cointegration approach. *Journal of Financial Economic Policy*, 14(3), 345–362. https://doi.org/10.1108/JFEP-04-2021-0101
2. Arner, D. W., Barberis, J., & Buckley, R. P. (2016). The evolution of fintech: A new post-crisis paradigm. *Georgetown Journal of International Law*, 47(4), 1271–1319.
3. Basnayake, S. A. K. W. (2024). Digital financial inclusion and economic development: Evidence from developing economies. *International Journal of Finance and Economics*, 29(1), 78–94. https://doi.org/10.1002/ijfe.2702
4. Demirgüç-Kunt, A., Klapper, L., Singer, D., Ansar, S., & Hess, J. (2022). *The Global Findex Database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19*. World Bank. https://doi.org/10.1596/978-1-4648-1897-4
5. Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, *55*(2), 251–276. https://doi.org/10.2307/1913236
6. Frost, J., Gambacorta, L., Huang, Y., Shin, H. S., & Zbinden, P. (2019). BigTech and the changing structure of financial intermediation. *Economic Policy*, 34(100), 761–799. https://doi.org/10.1093/epolic/eiz030

7. Gomber, P., Koch, J., & Siering, M. (2017). Digital finance and fintech: Current research and future research directions. *Journal of Business Economics*, 87(5), 537–580. https://doi.org/10.1007/s11573-017-0852-x

8. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson.

9. Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, *59*(6), 1551–1580. https://doi.org/10.2307/2938278

10. Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *American Economic Review*, 75(3), 424–440.

11. Khera, P., Ng, S., Ogawa, S., & Sahay, R. (2021). *Is digital financial inclusion unlocking growth?* IMF Working Paper WP/21/167. International Monetary Fund.

12. Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, 54(1–3), 159–178.

13. Kutner, M. H., Nachtsheim, C. J., &Neter, J. (2004). *Applied linear regression models* (4th ed.). McGraw-Hill Irwin.

14. MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics*, 11(6), 601–618.

15. National Payments Corporation of India. (2025). *UPI product statistics*. NPCI. Accessed March 2026. https://www.npci.org.in/what-we-do/upi/product-statistics

16. Perez, C. (2002). *Technological revolutions and financial capital: The dynamics of bubbles and golden ages*. Edward Elgar.

17. Pesaran, M. H., & Shin, Y. (1998). An autoregressive distributed-lag modelling approach to cointegration analysis. In S. Strøm (Ed.), *Econometrics and economic theory in the 20th century* (Chapter 11). Cambridge University Press.

18. Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289–326. https://doi.org/10.1002/jae.616

19. Phillips, P. C. B., & Hansen, B. E. (1990). Statistical inference in instrumental variables regression with I(1) processes. *Review of Economic Studies*, 57(1), 99–125.

20. Reserve Bank of India. (2024). *Report on trend and progress of banking in India*. Reserve Bank of India.

21. Saikkonen, P. (1991). Asymptotically efficient estimation of cointegration regressions. *Econometric Theory*, 7(1), 1–21.

22. Sax, C., & Steiner, P. (2013). Temporal disaggregation of time series. *The R Journal*, 5(2), 80–87.

23. Sharma, G., & Gupta, A. (2023). Digital payments and financial inclusion in India: An empirical analysis. *Journal of Financial Economic Policy*, 15(2), 210–225. https://doi.org/10.1108/JFEP-06-2022-0155

24. Suri, T., & Jack, W. (2016). The long-run poverty and gender impacts of mobile money. *Science*, 354(6317), 1288–1292. https://doi.org/10.1126/science.aah5309

25. Telecom Regulatory Authority of India. (2024). *Telecom subscription data*. TRAI. https://www.trai.gov.in/release-publication/reports/telecom-subscriptions-reports

26. World Bank. (2022). *World development report 2022: Finance for an equitable recovery*. World Bank. https://doi.org/10.1596/978-1-4648-1730-4

27. World Bank. (2025). *World development indicators*. World Bank. Accessed March 2026. https://data.worldbank.org

28. Zivot, E., & Andrews, D. W. K. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business & Economic Statistics*, 10(3), 251–270.

❑❑❑