The Post-Pandemic Investor Surge and UPI Growth: A Structural Break Analysis of India's Retail Equity Ecosystem

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Abstract. Policy discourse on India's digital finance transformation rests on a near-universal assumption: the Unified Payments Interface (UPI), now the world's largest real-time payment system, is pulling households into formal capital markets, and further expanding UPI will continue to deepen retail equity participation. This paper formally tests that assumption and finds that the data invert it.

Using 103 monthly observations from May 2017 to December 2025, a Toda-Yamamoto modified Wald procedure and an ARDL bounds testing approach are deployed jointly, with Nifty 50 returns as a market-performance control and a COVID-19 regime dummy whose validity is verified through Chow, CUSUM, and Bai-Perron procedures. The two series share strong post-pandemic co-movement but are linked by an asymmetric causal channel: new demat openings Granger-cause UPI volume at the one-percent level, while UPI volume does not Granger-cause demat openings at any lag length tested. Variance decomposition reinforces the direction; demat shocks explain nearly half of UPI variance at a two-year horizon, while UPI shocks explain under two percent of demat variance at any horizon.

Three implications follow. The supply-side framing of digital finance, in which payment infrastructure leads to capital market entry, is not borne out; the demand-pull theory of financial innovation provides the better fit. The relationship is essentially a post-pandemic phenomenon, suggesting COVID-19 activated the mechanism rather than disturbing it. The policy assumption that further UPI penetration will broaden retail equity participation by itself is left without empirical support; deepening capital market participation will require interventions at the equity entry margin.

Keywords: UPI, Demat, Toda-Yamamoto causality, ARDL Bounds Testing, COVID-19, India.

1. Introduction

India runs the world's largest real-time payments system. Nearly 46 percent of global real-time transaction volumes pass through Indian rails (ACI Worldwide, 2024), and the Unified Payments Interface (UPI) was processing over 21 billion transactions a month by December 2025 (NPCI, 2025). The country's retail capital market has scaled in parallel. Monthly new demat account openings have risen from about 1.3 lakh in 2017 to a peak of 87.8 lakh in the post-pandemic period, and the cumulative demat base

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now exceeds 170 million (CDSL and NSDL, 2025). The two trajectories have placed India at the centre of the empirical literature on digitalisation, financial inclusion, and household capital market participation (Demirgüç-Kunt et al., 2022; D'Silva et al., 2019).

How are the two series related? The dominant reading treats digital payments as the cause and capital market entry as the effect. Payment access lowers transaction frictions, pulls savers into investment products, and progressively converts cash-only households into formal market participants. On that account, monthly UPI volume should temporally precede growth in new demat openings.

The demand-pull theory of financial innovation suggests the reverse. Silber (1983) argued that financial activity intensifies in response to user demand, not the other way around. Applied to the present case, every new equity investor generates a stream of digital payment transactions: brokerage funding, SIP AutoPay mandates, dividend receipts, and SEBI-mandated UPI IPO applications. Causation, on this reading, runs from equity participation to payment volume rather than from payment to participation.

These views predict the temporal sequence in opposite directions, and the Indian empirical literature has not adjudicated between them. The work that exists is descriptive or cross-sectional, neither of which can identify lead-lag structure. The gap matters because the two readings imply different policy levers. If the financial-inclusion view is correct, expanding UPI should help broaden capital market access. If the demand-pull view is correct, payment infrastructure follows rather than leads, and deepening capital markets requires investor-side interventions. The Reserve Bank of India and the Securities and Exchange Board of India both operate on the supply-side framing in their current outreach. That framing has never been empirically tested for India.

This paper tests it. We have three objectives: to establish whether UPI transaction volume and new demat openings share a stable long-run relationship; to identify the direction of causality between them with appropriate controls for market performance; and to test whether the COVID-19 pandemic constitutes a statistically significant structural break in the relationship and, if so, characterize the regime shift.

Section 2 reviews literature. Section 3 describes the data, the unit root properties of the series, and the estimation framework. Section 4 presents the results and section 5 concludes.

2. Literature Review

2.1 Theoretical Underpinning

Two strands of theory speak to the relationship between digital payment infrastructure and equity market participation in opposing directions. The financial-inclusion perspective, developed prominently in the Global Findex tradition (Demirgüç-Kunt et al., 2022), treats access to digital payments as a prerequisite for households to engage with the formal financial system. Payment access reduces transaction costs, formalises savings, and is expected to spill over into investment behaviour, with capital market participation following the diffusion of digital payment use (Allen et al., 2016; Demirgüç-Kunt et al., 2022). Under this view, the causal arrow runs from payment infrastructure to capital market entry.

The demand-pull theory of financial innovation, articulated by Silber (1983), offers the opposite reading. Innovation in financial products and services responds to unmet user demand rather than creating it. Applied to India, each new equity investor requires a stream of digital payment transactions for brokerage funding, SIP AutoPay mandates, ASBA-UPI IPO applications, and dividend receipts; aggregate UPI volume responds endogenously to the inflow of demat account holders. The two perspectives are observationally equivalent in cross-section but generate opposite predictions in time series, which is the analytical leverage exploited here.

2.2 Digital Payments and Equity Market Participation

The empirical literature on the UPI-demat link has largely worked from the financial-inclusion premise rather than testing it. Shahid (2022) document the rapid diffusion of UPI in India during and after the COVID-19 lockdown using a Diffusion of Innovation framework. The most direct international counterpart is Hong et al. (2025), who use Chinese household data and exploit the exogenous penetration of QRPay in Shenzhen to provide causal evidence that digital payment adoption raises participation and risk-taking in mutual fund investments through the lowering of psychological and informational barriers; their finding establishes the financial-inclusion direction in a major emerging-market setting and serves as the natural benchmark against which the Indian time-series evidence is read. The most proximate cross-sectional Indian study is Fatima and Chakraborty (2025), who show that mobile payment proficiency is positively associated with stock market participation after controlling for Nifty 50 returns. While valuable in establishing positive association, cross-sectional and survey designs cannot identify temporal direction, since payment proficiency and equity participation are observed contemporaneously.

Two strands of evidence point towards the alternative reading. The fintech-ecosystem framing of Lee and Shin (2018) emphasises that payment infrastructure and capital market activity co-evolve as mutually reinforcing components of a digital financial system. Talwar et al. (2021), surveying Indian retail investors during COVID-19, identify financial-attitude dimensions including precautionary-savings orientation as significant predictors of pandemic-period trading; the surge in retail investor entry, on their reading, is driven primarily by attitudinal and market-opportunity factors rather than infrastructure-side variables. Using NSE proprietary data, the Economic and Political Weekly (2023) similarly documents that retail equity-market entry through both direct and indirect channels picked up meaningfully during the pandemic, with retail risk-taking rising with market performance. Despite this growing descriptive work, no formal causality test on the UPI-demat variable pair has been conducted.

The choice of monthly UPI transaction volume as the digital payment proxy follows the NPCI-anchored Indian fintech literature (Shahid, 2022; Aurazo and Gasmi, 2024). The choice of monthly new demat account openings as the equity participation proxy is consistent with the SEBI Annual Report tradition of treating demat openings as the formal entry point into Indian capital markets, and with the Indian retail-investor literature that uses demat-account-based measures (Talwar et al., 2021). Nifty 50 monthly returns are used as a market-performance control following Fatima and Chakraborty (2025).

2.3 COVID-19 as a Defining Event

The COVID-19 pandemic is widely treated in the Indian financial literature as a structural inflection point. Shahid (2022) document a step-change in UPI adoption during lockdown, attributable to the shift from cash to digital transactions. Talwar et al. (2021) record a parallel step-change on the equity side, with retail trading activity rising sharply from March 2020 onwards. These two transformations were simultaneous, but the literature has not examined whether the relationship between them changed across the pandemic break. Moizz and Akhtar (2024) employ ARDL and Bai-Perron procedures on Indian stock market data and identify March 2020 as a statistically significant breakpoint, providing direct methodological precedent. Any specification that pools the pre- and post-pandemic periods without accommodating a regime shift is therefore liable to be misspecified.

2.4 Methodological Literature and the Research Gap

The methodological choices of this study are anchored in two empirical traditions. The ARDL bounds testing procedure of Pesaran et al. (2001) is selected for its ability to accommodate mixed I(0)/I(1) regressors without integration-order pre-testing and has been applied to Indian financial time series by Srivastava and Varshney (2022) and Bhavsar and Samanta (2022). The Toda-Yamamoto (1995) modified Wald procedure for Granger non-causality is selected for robustness to mixed integration properties, an essential feature given the unit root behaviour documented in Section 3.2 and has been applied to Indian financial series by Prabheesh (2020) and Prabheesh et al. (2023).

This paper's contribution is the targeted application of two well-established Indian-finance procedures to a question on which they have not yet been deployed: the temporal direction of causation between digital payment volume and equity market entry, embedded within a formally specified COVID-19 structural break, and read against the financial-inclusion and demand-pull accounts. The argument is that the descriptive consensus on the UPI-demat relationship has run ahead of the time-series evidence, and that closing this gap reveals a direction of causation that the policy framing has assumed away.

3. Data And Methodology

3.1 Data

The dataset comprises 103 monthly observations from May 2017 to December 2025; January 2020 is excluded because the negative net demat addition reported by CDSL and NSDL in that month yields an undefined natural logarithm. The two endogenous variables are the natural logarithm of monthly UPI transaction volume in millions, sourced from NPCI (denoted ln_upi), and the natural logarithm of monthly new demat account openings in lakh, sourced from CDSL and NSDL combined (denoted ln_demat); both proxy choices follow Shahid (2022) and Talwar et al. (2021). A demat account is a multi-asset depository account holding equities, mutual funds, ETFs, bonds, and government securities, so new openings proxy formal entry into the broader investment ecosystem, with equities the dominant but not exclusive holding category. The first exogenous control is the monthly Nifty 50 return, included to absorb market-performance-driven entry following Fatima and Chakraborty (2025). The second is a binary COVID-19 dummy taking the value of one from April 2020 onwards, the first full month of national lockdown following the WHO pandemic declaration in March 2020 (WHO, 2020). All series are used in raw form without seasonal adjustment, since the augmented VAR with six lags absorbs intra-annual seasonal patterns.

Table 1. Descriptive Statistics

Variable	N	Mean	SD	Min	Max	Skewness	Kurtosis
UPI Volume (Mn)	103	6,441.13	6,576.12	9.36	21,634.67	0.814	2.311
ln(UPI Volume)	103	7.780	1.882	2.236	9.982	-1.049	3.659
New Demat Accts (Lakh)	103	18.32	14.23	1.31	87.78	1.206	6.719
ln(New Demat Accts)	103	2.505	1.008	0.268	4.475	-0.441	1.757

Nifty Return (%)	103	1.139	4.731	-23.25	14.68	-1.008	8.775

Note. Sample: May 2017 to December 2025 (n = 103). January 2020 excluded due to negative net demat additions. UPI volume sourced from NPCI; demat additions from CDSL and NSDL; Nifty 50 returns computed from NSE monthly closing prices.

3.2 Unit Root Tests

All variables are tested for integration order using ADF, Phillips-Perron, and KPSS procedures, with constant-only and constant-with-trend specifications; the Zivot and Andrews (2002) endogenous-break test is additionally applied to ln_upi, where the conventional tests yield conflicting results.

Under ADF and PP tests with deterministic trend, ln_upi rejects the unit root null at conventional levels (ADF $\tau = -5.69$ with trend), but the KPSS test rejects the stationarity null. This conflict is symptomatic of a series containing a one-time level shift: trend-augmented ADF and PP tests can over-reject the unit root null in the presence of a structural break, while the KPSS statistic is itself sensitive to permanent level shifts. The Zivot-Andrew's procedure, which permits a single endogenously determined break, rejects the unit root null at the 1 percent level in all three specifications, with statistics of -7.08 (intercept-break), -8.22 (trend-break), and -8.15 (both) against 5 percent critical values of -4.80, -4.42, and -5.08, identifying August 2020 as the endogenous break date. Under the standard ZA decision rule, ln_upi is best characterised as trend-stationary around a one-time level shift, I(0) with a structural break, rather than a pure I(1) process. Because ADF, PP, and ZA agree in rejecting the unit root null while KPSS points the other way, the integration order of ln_upi cannot be classified unambiguously and is best treated as borderline I(0)/I(1). The remaining series are unambiguous: ln_demat is I(1) and nifty_return is I(0).

Table 2. Unit Root Test Summary

Variable	Test	Specification	Statistic	CV (5%)	Decision
ln(UPI) (Level)	ADF	Trend	-5.689	-3.43	See ZA below
ln (UPI) (Level)	KPSS	Trend	Reject H_0	—	Non-stationary
ln(UPI) (Level)	Zivot-Andrews	Intercept	-7.078	-4.80	Stationary with break (Aug-2020)
ln(Demat) (Level)	ADF	Trend	-1.518	-3.43	Non-stationary
ln(Demat) (1st Diff)	ADF	Trend	-8.795	-3.43	Stationary, I(1)

Nifty Return (Level)	ADF	Trend	-7.963	-3.43	Stationary, I(0)

Note. ADF = Augmented Dickey-Fuller; KPSS = Kwiatkowski-Phillips-Schmidt-Shin; ZA = Zivot and Andrews (2002). Critical values at the 5% level. ln(UPI) shows conflicting results: the ADF and PP tests on the level series, and the break-augmented Zivot-Andrews test, all reject the unit root null, while the KPSS test rejects stationarity. The integration order is therefore borderline I(0)/I(1) and is treated conservatively in the estimation framework. PP tests confirm I(1) for ln(Demat) and I(0) for Nifty Return.

This integration profile shapes the choice of estimation methodology. With ln_demat I(1), nifty_return I(0), and ln_upi borderline I(0)/I(1), standard Granger causality is invalid in the presence of integration, and Johansen requires uniform integration order. The Toda-Yamamoto modified Wald procedure (asymptotically chi-squared distributed regardless of integration properties) and the ARDL bounds procedure (accommodating mixed I(0)/I(1) regressors) are uniquely suited to this configuration and address both the causality and the long-run questions without requiring a definitive prior classification of ln_upi.

3.3 Estimation Framework and Hypotheses

The Toda-Yamamoto and ARDL procedures are jointly selected because each is constructed for the configuration of these data present. Neither requires the integration order of ln_upi to be resolved, and both absorb the COVID-19 break through dummy specification rather than discarding the post-2020 sample. The empirical strategy is organised around four formal hypotheses:

- H1: Monthly UPI transaction volume Granger causes monthly new demat account openings.
- H2: Monthly new demat account openings Granger-cause monthly UPI transaction volume.
- H3: A stable long-run relationship exists between monthly UPI transaction volume and monthly new demat account openings.
- H4: The COVID-19 pandemic constitutes a statistically significant structural break in the UPI-demat relationship.

H1 and H2 are tested using the Toda-Yamamoto procedure; H3 using the ARDL bounds test; H4 using the Chow F-test, supplemented by CUSUM and Bai-Perron diagnostics.

Toda-Yamamoto Granger non-causality test. Following Toda and Yamamoto (1995), an augmented VAR of order ($p + d_{max}$) is estimated, where p is the optimal lag length (AIC) and $d_{max} = 1$ is the maximum integration order in the system. With $Y_t = (ln\_upi_t, ln\_demat_t)'$ and $X_t = (nifty\_return_t, covid_t)'$, the system is

$$Y_t = c + \sum_{i=1}^{p+dmax} A_i Y_{t-i} + BX_t + \varepsilon_t \quad (1)$$

where c is a vector of intercepts, A_i are 2 × 2 coefficient matrices, B is the coefficient matrix on the exogenous regressors, and ε_t is the innovation vector. A standard Wald test is applied to the first p coefficient matrices only, with the additional d_{max} lags treated as auxiliary regressors. The Wald statistic is asymptotically chi-squared with p degrees of freedom regardless of integration or cointegration properties. AIC selects p = 6, giving an augmented VAR of order 7.

ARDL bounds test for cointegration. Following Pesaran et al. (2001), a conditional ARDL error-correction representation for ln_demat with ln_upi as the regressor of interest is:

$$\Delta ln\_demat_t = \alpha + \sum_{i=1}^{p} \beta_i \, \Delta ln\_demat_{t-i} + \sum_{j=0}^{q} \gamma_j \, \Delta ln\_upi_{t-j} + \theta_1 \, ln\_demat_{t-1} + \theta_2 \, ln\_upi_{t-1} + \varphi_1 \, nifty\_return_t + \varphi_2 \, covid_t + \varepsilon_t \quad (2)$$

where Δ denotes first-difference. The null of no level relationship, H_0: $\theta_1 = \theta_2 = 0$, is tested via an F-statistic compared against the I(0) and I(1) critical bounds tabulated by Pesaran et al. (2001); an F-statistic exceeding the upper bound confirms a level relationship regardless of regressor integration orders. The BIC selects ARDL(2,0). The procedure has been applied in the Indian setting by Srivastava and Varshney (2022) and Bhavsar and Samanta (2022).

Structural break testing. The Chow (1960) F-test compares the residual sum of squares of the pooled specification with that of two sub-period specifications at the pre-specified break date of April 2020:

$$F = [(RSS_R - RSS_U) / k] / [RSS_U / (n - 2k)] \quad (3)$$

where RSS_R and RSS_U are restricted (pooled) and unrestricted (sub-period) residual sums of squares, k is the number of estimated parameters, and n is the total number of observations. The Chow test is supplemented by CUSUM and MOSUM diagnostics and by the Bai and Perron (2003) procedure for endogenous detection of multiple breaks. Sub-period OLS regressions are estimated for the pre-COVID (n = 34, May 2017 to March 2020, January 2020 excluded) and post-COVID (n = 69, April 2020 to December 2025) periods, following Moizz and Akhtar (2024).

4. Results And Discussion

4.1 Toda-Yamamoto Granger Causality

Table 3A presents the Toda-Yamamoto results at the optimal lag specification. The null that UPI does not Granger-cause demat openings (H1) cannot be rejected: $\chi^2 = 4.96$ with six degrees of freedom yields p = 0.55, comfortably above any conventional threshold. H1 is not supported. The result is robust across lag specifications p = 1 to 6 (Table 3B), with H1 p-values consistently above 0.50. In contrast, the null that demat openings do not Granger-cause UPI volume (H2) is rejected at the 1 percent level, with $\chi^2 = 24.12$, $p = 0.0005$. H2 is supported, and the support strengthens monotonically with lag length, reaching 1 percent significance at p = 5 and 6 and 5 percent significance from p = 2 onwards.

Table 3A. Toda-Yamamoto Granger Causality Results

Direction	Lag (p)	χ^2	df	p-value	Decision
UPI does not cause Demat (H1)	6	4.955	6	0.5496	Not rejected
Demat does not cause UPI (H2)	6	24.122	6	0.0005***	Rejected at 1%

*Note. VAR order p = 6 (AIC), augmented by d_max = 1; p_aug = 7. Exogenous regressors: Nifty 50 monthly returns and COVID-19 regime dummy. Wald test applied to the first p lag matrices only. *** p < 0.01.*

Table 3B. Sensitivity Analysis: Toda-Yamamoto Results Across Lag Specifications

p	H1: χ^2	H1: p-value	H2: χ^2	H2: p-value	H2 Decision
1	0.271	0.6025	0.733	0.3918	Not rejected
2	0.515	0.7728	10.216	0.0060***	Rejected at 1%
3	1.104	0.7762	9.660	0.0217**	Rejected at 5%
4	1.403	0.8437	11.731	0.0195**	Rejected at 5%
5	2.639	0.7554	17.646	0.0034***	Rejected at 1%
6	4.955	0.5496	24.122	0.0005***	Rejected at 1%

*Note. H1: UPI does not Granger-cause Demat. H2: Demat does not Granger-cause UPI. ** p < 0.05; *** p < 0.01. H1 is not rejected at any lag specification.*

This asymmetry maps onto the demand-pull interpretation set out in Section 2.1. Each new demat account generates a recurrent stream of digital payment transactions: brokerage funding, monthly SIP AutoPay mandates, dividend receipts, and (post-2019) UPI-routed IPO applications under SEBI's ASBA-UPI rule. UPI flow therefore responds endogenously to the stock of equity investors, while the reverse channel UPI use leading households into equity investment is not detectable in monthly aggregate data once Nifty 50 returns and the COVID regime are controlled for. The pattern is consistent with the fintech-ecosystem framing of Lee and Shin (2018) and with the post-pandemic Indian retail-investor evidence in Talwar et al. (2021).

A diagnostic caveat applies. The augmented VAR exhibits residual serial correlation (Portmanteau $p < 0.001$) that could not be cleared by extension of lag length or inclusion of structural-break dummies, a known limitation of TY inference on monthly Indian financial series. The asymptotic chi-squared distribution does not require white-noise residuals for consistency. Two further considerations mitigate the concern: the companion-form eigenvalues of the augmented VAR all lie within or on the unit circle with no explosive roots, the appropriate stability criterion for a system with possibly integrated components; and the asymmetric causation finding is independently corroborated by the IRF and FEVD evidence in Section 4.4. Newey-West HAC corrections are applied to the ARDL estimates in Section 4.2 but are not applicable to the modified Wald statistic, which uses the asymptotic chi-squared distribution by construction.

4.2 ARDL Bounds Test for a Long-Run Level Relationship

The ARDL (2,0) specification selected by the Bayesian information criterion yields a bounds-test F-statistic of 6.97 ($p = 0.0015$), which lies above the 1 percent upper critical bound of 5.61. Hypothesis H3 is therefore supported: a stable long-run level relationship exists between UPI transaction volume and new demat account openings, conditional on the inclusion of Nifty 50 returns and the COVID regime dummy. The implied error-correction coefficient, computed as ($1 - \beta_1 - \beta_2$) from the lagged dependent-variable coefficients of the conditional ARDL representation, equals -0.363 and is statistically significant at the 1 percent level (the underlying lagged level coefficients carry p-values of 0.001 and 0.001 respectively). The negative sign confirms the expected restoring force: roughly 36 percent of any short-run deviation from long-run equilibrium is corrected within one month, consistent with a stable, mean-reverting long-run relationship.

Table 4. ARDL Bounds Test for a Long-Run Level Relationship

Model	F-stat	p-value	CV I(0) 1%	CV I(1) 1%	LR UPI Coef	Decision
ARDL(2,0)	6.972	0.0015	4.29	5.61	-0.114 (ns)	Level relationship at 1%

Note. Table CI(iii), k = 1. LR UPI Coef = long-run coefficient on ln(UPI); ns = not significant (p = 0.354). COVID-19 dummy long-run coefficient = 0.606 (p = 0.0002). Implied error-correction coefficient = -0.363 (significant at 1%), computed from lagged dependent-variable coefficients in the conditional ARDL representation. All results robust to Newey-West HAC correction.

The long-run coefficient on ln_upi is small, negative, and statistically insignificant ($\beta = -0.114$, $p = 0.354$), apparently in tension with a stable long-run level relationship. The structural-break analysis below indicates that the long-run relationship is dominated by the COVID-19 regime shift rather than by UPI's own trend. The COVID dummy enters with a large and highly significant coefficient (0.606, $p < 0.001$), absorbing the bulk of the level shift. The PSS framework explicitly accommodates deterministic regime variables of this kind (Case III of Table CI in PSS 2001, with unrestricted intercept and no trend); the bounds-test F-statistics remains valid in their presence. The result should therefore be read as a stable long-run level relationship conditional on the COVID-19 level shift. The result is robust to Newey-West HAC standard errors and aligns with Srivastava and Varshney (2022) and Bhavsar and Samanta (2022).

4.3 COVID-19 Structural Break

Table 5 reports the structural-break diagnostics. The Chow F-statistic at the pre-specified April 2020 break is 25.38 ($p < 0.001$), comfortably rejecting the null of parameter stability. H4 is therefore supported. CUSUM and MOSUM independently confirm parameter instability ($p = 0.005$ and $p = 0.010$). The Bai and Perron (2003) procedure identifies June 2019 and April 2022 as additional data-driven breakpoints. The June 2019 break is interpretable considering SEBI's UPI-routed retail IPO mechanism (SEBI, 2018), operational from January 2019 but requiring several months of broker, registrar, and SCSB system integration before retail UPI-ASBA volumes reached the threshold of detectability in monthly aggregate data. The April 2022 break corresponds to the post-pandemic monetary tightening cycle.

Table 5. Structural Break Tests and Sub-Period Analysis

Test	Break Date	F / Statistic	p-value	Decision
Chow Test	April 2020	F = 25.384	< 0.001***	Break confirmed
CUSUM	Full sample	—	0.005***	Instability
MOSUM	Full sample	—	0.010**	Instability
Bai-Perron	Jun-2019, Apr-2022	—	—	2 structural breaks

Table 6. Sub-Period OLS Regression Results

Period	UPI Coefficient	R^2	n
Pre-COVID (to Mar-2020)	0.055 (ns)	0.068	34
Post-COVID (Apr-2020 onwards)	1.187***	0.587	69

*Note. Chow test pre-specified at April 2020 (first full lockdown month). CUSUM and MOSUM from OLS-based fluctuation tests. Bai-Perron (2003) multiple breakpoint estimates are data-driven. Sub-period regressions include Nifty 50 return as control. ns = not significant; ** p < 0.05; *** p < 0.01.*

The sub-period analysis (Table 6) quantifies the regime shift directly. In the pre-COVID period ($n = 34$), the OLS coefficient on ln_upi explaining ln_demat is statistically insignificant ($\beta = 0.055$, $R^2 = 0.068$). In the post-COVID period ($n = 69$), it rises to $\beta = 1.187$ with $R^2 = 0.587$. The UPI-demat nexus is essentially a post-pandemic phenomenon: the simultaneous bull-market recovery, digital onboarding revolution at zero-commission brokers, and maturation of the UPI ecosystem combined post-April 2020 to produce the relationship that the full-sample TY and ARDL results detect. This reading aligns with Talwar et al. (2021), Shahid (2022), and Moizz and Akhtar (2024).

4.4 Forecast Error Variance Decomposition and Impulse Responses

Orthogonalised FEVD and generalised impulse response functions provide an independent check on the asymmetric causality finding (Table 7 and Figure 1). The FEVD uses a Cholesky decomposition with ln_upi ordered first, which constrains the contemporaneous response of demat to a UPI shock at horizon one to zero by construction; this ordering is conservative for our argument since it gives UPI the contemporaneous advantage. At a 24-month horizon, shocks to UPI explain only 1.44 percent of demat variance, with the share never exceeding 1.9 percent, the equity series is effectively exogenous to UPI shocks. By contrast, demat shocks explain a growing share of UPI variance, rising from negligible at horizon one to 23.05 percent at horizon 12 and 48.20 percent at horizon 24. The generalised impulse responses (Figure 1), under the ordering-invariant framework, show the same pattern: the response of demat to a UPI shock oscillates around zero with confidence intervals that include zero throughout, while the response of UPI to a demat shock rises monotonically from horizon two and stabilises at a positive level outside the zero band by month twelve. The agreement between the ordering-dependent FEVD and ordering-invariant GIRF confirms the asymmetry is not an artefact of any particular Cholesky ordering. Table 8 presents the hypothesis status summary.

Table 7. Orthogonalised Forecast Error Variance Decomposition (Selected Horizons)

Horizon (months)	**Variance of ln_demat explained by ln_upi (%)**	**Variance of ln_upi explained by ln_demat (%)**
1	0.00	0.00
6	1.49	8.03
12	1.22	23.05
18	1.29	38.72
24	1.44	48.20

Note. Orthogonalised forecast error variance decomposition based on a Cholesky factorisation of the residual covariance matrix from the augmented VAR of order seven, with ln_upi ordered first. The horizon-one zero in both off-diagonal cells is a structural feature of the Cholesky decomposition rather than an empirical finding. The asymmetry between the two columns is the central feature: shocks to UPI explain a negligible fraction of demat variance at every horizon, while shocks to demat explain an increasing and substantial fraction of UPI variance.

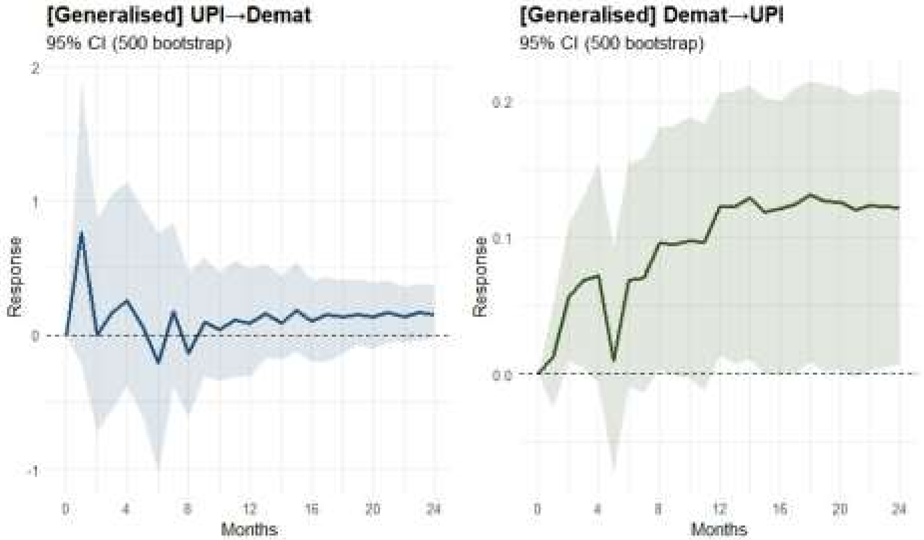

Fig 1. Generalised Impulse Response Functions, 95% Bootstrap Confidence Intervals

Note. Generalised IRFs from the augmented VAR of order seven, with 95 percent bootstrap confidence intervals from 500 replications. Left panel: response of ln_demat to a unit shock in ln_upi. Right panel: response of ln_upi to a unit shock in ln_demat. The horizontal axis is months.

Table 8. Hypothesis Status Summary

H	Statement	Procedure	Outcome
H1	UPI Granger causes new demat openings	Toda-Yamamoto modified Wald test	Not supported (χ^2 = 4.96, p = 0.55)
H2	New demat openings Granger-cause UPI	Toda-Yamamoto modified Wald test	Supported at 1% (χ^2 = 24.12, p = 0.0005)
H3	Long-run level relationship	ARDL bounds test	Supported at 1% (F = 6.97, p = 0.0015)
H4	COVID-19 is a structural break	Chow + CUSUM + Bai-Perron	Supported at 1% (Chow F = 25.38, p < 0.001)

5. Conclusion

This paper has shown that the conventional supply-side reading of the UPI-demat relationship cannot be sustained against time-series evidence. Working with monthly data from May 2017 to December 2025, formal causality testing and structural-break analysis converge on a single direction of causation. It runs from new equity market entry to digital payment volume, not the reverse. The result holds across all lag specifications. It is corroborated by IRF and variance decomposition analysis and is robust to market-performance controls and a verified COVID-19 regime variable.

Three interpretations follow. The variance-decomposition asymmetry, in which demat shocks come to explain nearly half of UPI variance at long horizons while UPI shocks never exceed two percent of demat variance, is too stark to be read as a partial effect. The equity series is effectively exogenous to the payment series in monthly aggregate data. The pre- and post-COVID sub-period regressions show that the relationship is essentially a post-pandemic phenomenon. COVID-19 looks to have activated the channel between equity entry and payment activity rather than disturbing one that already existed. And the ARDL long-run coefficient on UPI is small and statistically insignificant, with the COVID dummy absorbing the bulk of the level shift. The long-run relationship is best read as conditional on the structural-break component.

The practical implications follow from the direction of causation, subject to the limits of the aggregate time-series design. The widespread assumption that further expanding digital payment penetration will, by itself, broaden equity market participation does not find support here. Policy initiatives at SEBI and the RBI may find greater traction if directed at the equity entry margin itself: investor education, simplified KYC and onboarding, lower investment minimums, and continued development of zero-commission discount brokerage. Supply-side initiatives that target UPI penetration are unlikely to translate automatically into capital market deepening, although a complementary household-level role cannot be ruled out.

Three caveats apply. First, the demat series is a multi-asset entry indicator covering equities, mutual funds, ETFs, bonds, and government securities. Equities are the dominant but not exclusive holding category, so the demand-pull mechanism is tested at the level of formal market entry rather than equity-only entry. Second, the augmented VAR retains some residual autocorrelation, which is why we report IRF and FEVD results alongside the Wald inference rather than as a substitute. Third, the aggregate UPI series conflates investment-related and consumption-related payments, so the data are consistent with the demand-pull mechanism without isolating it from co-trending factors such as smartphone diffusion and 4G coverage. The COVID dummy and Nifty 50 returns absorb part, but not all of this confound. Monthly controls for internet penetration and household income would sharpen the specification, but they are not yet available at monthly frequency for India.

Three open questions follow. First, what is the precise mechanism through which new investors generate UPI demand? Disaggregated UPI flows by transaction purpose, where they become available from NPCI, would arbitrate between the investment-channel reading and the unmeasured-third factor reading. Second, is the demand-pull direction a general feature of digitalising emerging-market financial systems, or an artefact of the Indian institutional configuration? Comparative work with Brazil's Pix, Kenya's M-Pesa, and Peru's Yape (Aurazo and Gasmi, 2024) is needed to test the boundary conditions. Third, what does the direction imply for the design of financial inclusion programmes? If payment infrastructure is endogenous to capital market participation rather than its precondition, then the conventional sequencing of inclusion policy may need to be reversed for at least some segments. Household-level panel data with instrumental variable identification (Fatima and Chakraborty, 2025) would allow a sharper micro-level test. The aggregate time series cannot answer these questions, but it does establish the empirical fact that demands them.

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