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Liquidity risk and liquidity timing in the cross-section of Indian equity mutual fund returns

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Abstract

This study examines how aggregate market liquidity influences the cross-section of Indian equity mutual fund returns through two mechanisms: (1) funds' long-run exposure to liquidity risk, and (2) managers' time-varying liquidity timing. Using a comprehensive sample from 2007–2024, we estimate rolling liquidity betas, form portfolios sorted by liquidity exposure, and compute a high-minus-low liquidity-beta return spread. The liquidity premium is positive and economically meaningful in tranquil and recovery regimes, but weakens or vanishes during systemic stress, consistent with state-dependent liquidity pricing. Adding a traded equity-liquidity factor to standard benchmarks explains a meaningful portion of the spread, while an independently constructed timing factor captures an additional 55%–64%, highlighting the importance of conditional beta management. Timing effects are concentrated among high-liquidity-beta funds, smoothing returns in normal markets but offering limited protection in crises. Findings are robust to alternative benchmarks, flow-adjusted timing specifications, and post-COVID subperiod definitions.

Keywords

- liquidity risk
- liquidity timing
- asset pricing
- mutual funds
- emerging markets

JEL codes: G11, G12, E44, E47, C53.

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Introduction

Illiquidity is expected to command a return premium, compensating investors for trading frictions, execution risk, and the difficulty of converting positions into cash when liquidity is scarce. Foundational work formalises two complementary channels: a level effect, whereby fewer liquid assets earn higher average returns, and a covariance effect, whereby innovations in aggregate liquidity are priced as systematic risk (Acharya & Pedersen, 2005; Amihud & Mendelson, 1986; Liu, 2006; Pástor & Stambaugh, 2003). There is substantial literature documenting these channels across asset classes and international markets (Chaieb et al., 2021; Dang & Nguyen, 2020; Kang et al., 2019; Zhu et al., 2023), underscoring liquidity as a core, non-diversifiable state variable for expected returns and risk premia.

Liquidity risk becomes most salient precisely when diversification is least effective. During systemic episodes, market-wide liquidity deteriorates, trading costs rise, and funding constraints bind—conditions under which exposures to liquidity shocks can amplify losses. Evidence from 2007–2009 shows that liquidity-sensitive strategies suffered disproportionately during the Global Financial Crisis (Idzorek et al., 2012; Lou & Sadka, 2011). The COVID-19 shock renewed attention to the link between open-end fund structure, redemption pressure, and market fragility: flows can force asset sales into illiquid markets, propagating price dislocations and weakening the usual relation between liquidity and compensation (Jiang et al., 2022; Y. Ma et al., 2022). Parallel evidence connects liquidity premia to funding markets, currencies, and broader anomaly returns (Bechtel et al., 2023; Söderlind & Somogyi, 2025; Virk & Butt, 2022), reinforcing the view that liquidity is priced primarily through its behaviour in bad states (X. Ma et al., 2021; Wu, 2019).

For mutual funds, the empirical picture is nuanced because funds can both bear liquidity risk and adjust it over time. Prior studies shows that funds with higher liquidity betas tend to earn higher average returns (Dong et al., 2019; Foran & O'Sullivan, 2014), consistent with compensation for bearing systematic liquidity risk. At the same time, static exposures alone rarely explain observed performance differences: investment style, flow sensitivity, and investor composition can affect both portfolio choice and the extent to which funds transmit or absorb liquidity shocks. Studies across delegated portfolio management suggest that timing ability—systematically altering exposures in response to liquidity states—may exist but is concentrated and difficult to identify cleanly from mechanical trading induced by flows (Aiken & Kang, 2023; Bodson et al., 2013; Wattanatorn et al., 2020).

These considerations motivate a sharper question: Do equity mutual funds merely load on liquidity risk, or can they also time liquidity conditions in a way that is distinct from flow-induced trading? A natural empirical framework allows market exposure to vary with liquidity deviations (Cao et al., 2013). If timing is systematic, it should be measurable in fund-level state-dependent exposures, and it should have investable implications for cross-sectional spreads.

We revisit this issue for Indian equity mutual funds. There are several reasons why India is a particularly informative setting for liquidity risk and state-dependent beta management for institutional reasons that map directly into liquidity exposure and timing. Firstly, the mutual fund sector has expanded rapidly: industry assets under management (AUM) grew to INR 53.4 lakh crore by March 2024, the number of unique mutual fund investors rose to about 4.5 crore, and mutual fund purchases became predominantly digital (about 89%–90% of transactions by FY2024). These features can support persistent inflows in normal times yet more synchronised redemptions during stress, tightening constraints precisely when funds would need to rebalance (AMFI–CRISIL, 2024). Secondly, Indian equities trade predominantly in electronic, order-driven limit order books; prior evidence documents commonality in liquidity on the National Stock Exchange, implying that market-wide liquidity shocks can be pervasive and rapidly transmitted (G. Kumar & Misra, 2018). Thirdly, the institutional environment has evolved through regulatory reforms that standardise fund categories and constrain style drift, strengthening cross-fund comparability and the interpretation of cross-sectional sorts (Securities and Exchange Board of India, 2017). Finally, crisis-era interventions underscore the perceived systemic importance of mutual fund liquidity transformation: the Reserve Bank of India opened a special liquidity facility for mutual funds in April 2020 amid redemption-related strains, and FSAP-style assessments discuss liquidity risks in investment funds (IMF, 2025; Reserve Bank of India, 2020).

The sample period spans heterogeneous stress and recovery episodes (the GFC, the COVID-19 shock, and the post-pandemic years). Despite its economic importance, systematic evidence on liquidity risk premia and liquidity timing in Indian equity mutual funds remains limited, leaving open whether the conditional liquidity–return relation documented in developed markets extends to an emerging market where liquidity dynamics, investor composition, and intermediation frictions differ materially from the canonical US benchmark.

Our empirical design separates static exposure from dynamic timing. First, we estimate each fund's liquidity beta using rolling windows and form quintile portfolios sorted on liquidity exposure. We then construct a high-minus-low liquidity-beta spread (HMLiq) as a baseline measure of the liquidity premium. Next, we estimate liquidity-timing specifications in which market beta varies with liquidity states (Cao et al., 2013), and we construct an investable Timer factor from lagged timing-coefficient sorts. This factor-based decomposition allows us to quantify how much of the HMLiq spread reflects standard risk compensation and how much is attributable to systematic, state- dependent beta management.

Three findings summarise the results. Firstly, HMLiq is positive and statistically reliable in tranquil and recovery regimes but attenuates or disappears during systemic stress, consistent with conditional liquidity pricing. Secondly, augmenting benchmark models with a traded equity liquidity factor explains a meaningful share of HMLiq, while the independently constructed Timer factor absorbs an additional 55%–64% of the spread, indicating that timing is a first-order component of liquidity-based return differentials. Thirdly, timing effects are concentrated among high-liquidity-beta funds: they smooth return paths in normal markets but provide limited protection under acute stress, which is consistent with the broader view that liquidity transformation is most fragile precisely when aggregate liquidity deteriorates.

The paper's contribution is threefold. Firstly, we provide systematic evidence on liquidity exposure and liquidity timing in an emerging-market mutual fund setting, documenting a regime-dependent liquidity premium over 2007–2024. Secondly, by con- structing an investable Timer factor from lagged timing signals, we operationalise a timing channel and quantify its role in explaining the cross-sectional liquidity spread. Thirdly, we align inference with contemporary fund-performance standards and identification concerns raised in the literature: we evaluate robustness under modern factor benchmarks (Carhart-4 and Fama–French-5), incorporate flow-based controls and standard fund-characteristic controls (size, turnover, fees, and age) to distinguish timing from mechanically-induced beta shifts, refine the post-COVID segmentation, and supplement crisis-window inference with daily evidence for early 2020. Together, these steps strengthen the interpretation of timing as a distinct mechanism and clarify the conditions under which liquidity compensation is economically meaningful.

The remainder of the paper is organised as follows: Section 1 reviews the related literature; Section 2 describes the data, sample construction, and variable definitions; Section 3 presents the main results and robustness analyses; Section 4 discusses implications and mechanisms and last section concludes.

1. Literature review

This study sits at the intersection of (1) liquidity as a priced state variable in asset markets and (2) liquidity transformation and fragility in open-ended delegated portfolios. We first review the asset-pricing foundations of liquidity risk, then summarize evidence on liquidity premia and liquidity management in mutual funds, and finally position our contribution—liquidity exposure versus liquidity timing—within the emerging debate on crisis-state behaviour and fund resilience.

1.1. Liquidity risk

Liquidity risk—the possibility that trades cannot be executed quickly and at low cost without materially affecting prices—is central to both asset pricing and financial stability. Two channels underpin its role in expected returns. The first is a level channel: less liquid securities earn higher average returns as compensation for trading frictions, inventory risk, and delayed execution (Amihud & Mendelson, 1991; Lee et al., 2022; Liu, 2006). The second is a covariance channel: innovations in aggregate market liquidity are priced as a systematic risk factor, so portfolios with higher exposure (liquidity beta) require additional compensation (Acharya & Pedersen, 2005; X. Ma et al., 2021; Pástor & Stambaugh, 2003; Shih & Su, 2016). Liquidity-augmented factor frameworks confirm that the covariance channel is particularly salient in downturns and high-volatility regimes, consistent with liquidity behaving as a bad-state risk that is difficult to diversify away from (X. Ma et al., 2021; Wu, 2019).

A central theme in the recent literature is that crises reveal the economic content of liquidity risk. During systemic episodes, market-wide liquidity deteriorates and trading constraints bind; consequently, sensitivity to liquidity shocks can amplify losses (Idzorek et al., 2012; Lou & Sadka, 2011). The COVID-19 episode further highlighted how liquidity shocks can propagate through intermediaries: open-ended funds under redemption pressure may transmit stress to asset prices and weaken the usual relation between liquidity and compensation (Jiang et al., 2022; Y. Ma et al., 2022). Related work shows that liquidity premia extend beyond equities: liquidity risk is priced in currencies (Söderlind & Somogyi, 2025), helps organise a broad set of anomaly returns and hedging demands (Virk & Butt, 2022), and exhibits important asymmetries in downside states (Palwishah et al., 2024). Finally, funding conditions and market liquidity are tightly linked: exposure to liquidity needs and rollover risk carries persistent pricing implications (Bechtel et al., 2023). Taken together, these results motivate an empirical design that distinguishes normal-state liquidity compensation from crisis-state behaviour, and that evaluates whether any apparent premia survive when liquidity becomes scarce.

Institutional structure shapes how liquidity risk materialises. Ownership concentration and commonality in holdings can amplify liquidity co-movement (Sensoy, 2017), while macro and policy environments transmit liquidity conditions across markets (Hassanein, 2022). Relatedly, policy uncertainty has been shown to contain forecasting information for broad risk premia (including the equity premium), suggesting another channel through which policy regimes may shape expected returns (Ali & Naz, 2025a).

Conversely, concentrated ownership can mitigate fire-sale pressure in certain settings (Giannetti & Jotikasthira, 2024). These institutional insights are particularly relevant for mutual funds, where portfolio choice, investor composition, and redemption design jointly determine how liquidity shocks affect performance.

1.2. Liquidity risk premium in mutual funds

Open-ended funds are structurally exposed to liquidity risk because they offer investors frequent redemption while holding assets that can be costly to liquidate. This liquidity transformation is a long-recognized vulnerability and a recurring focus of policy and stability debates (Chernenko & Sunderam, 2016). In stress states, redemptions can induce funds to sell their most liquid holdings first—a “reverse flight to liquidity”— transmitting pressure to asset prices and creating externalities for remaining investors (Jiang et al., 2022; Y. Ma et al., 2022). This mechanism makes liquidity management (cash buffers, trading schedules, and proactive rebalancing) economically meaningful for both performance and resilience.

Empirically, mutual-fund liquidity premia operate through two distinct routes: exposure and management. On the exposure side, funds with higher liquidity betas earn higher average returns in normal times, consistent with compensation for bearing systematic liquidity risk (Dong et al., 2019; Foran & O’Sullivan, 2014). However, a recurring finding is that standard traded liquidity factors explain only part of the high-minus-low liquidity-beta spread (HMLiq), leaving residual components that invite alternative interpretations (Dong et al., 2019). State conditioning sharpens this picture: excluding extreme illiquidity periods strengthens the positive liquidity beta–performance relation (Sadka, 2010), and fund characteristics such as turnover, age, and managerial attributes can mediate the strength of liquidity premia (Goyenko, 2012). These results suggest that the liquidity premium in mutual funds is inherently state-dependent and potentially entangled with managerial decisions and investor flows.

On the management side, researchers ask whether funds time liquidity by adjusting exposures dynamically with liquidity conditions. A common empirical approach allows market beta to co-move with deviations in aggregate liquidity (Cao et al., 2013). Within this framework, timing ability has been documented for certain fund segments (e.g., top performers or bank-affiliated complexes), consistent with information advantages and organizational resources (Alam & Ansari, 2020; Bodson et al., 2013; Wattanatorn et al., 2020; Wattanatorn & Tansupswatdikul, 2019). At the same time, the evidence emphasises scarcity and the concentration of timing skill: even in hedge funds, aggregate liquidity timing is limited and ability is concentrated in a small subset of managers (Aiken & Kang, 2023). This uneven distribution underscores the empirical challenge: measured "timing" can reflect genuine anticipatory rebalancing, but it can also reflect mechanically-induced beta changes arising from flows and forced trading during stress episodes.

1.3. Post-COVID evidence and identification challenges

Post-COVID-19 work clarifies both the fragility mechanism and the identification challenge relevant for timing. During March 2020, funds facing redemptions reallocated in ways consistent with reverse flight to liquidity, amplifying stress (Y. Ma et al., 2022). Bond-market evidence similarly shows that fund illiquidity is closely linked to fragility in asset prices during stress (Jiang et al., 2022). At the institutional margin, ownership concentration can mitigate flow-induced price pressure, highlighting that market structure shapes the propagation of liquidity shocks (Giannetti & Jotikasthira, 2024). These studies jointly imply that timing estimates can be contaminated by flow-driven mechanics precisely in the crisis states where liquidity risk is most economically meaningful. More broadly, asymmetric downside liquidity exposures (Palwishah et al., 2024) and liquidity-based hedging demands (Virk & Butt, 2022) underscore how liquidity premia should be evaluated with explicit attention to stress regimes and the short-sample inference problems that arise in acute episodes.

1.4. Positioning and implications for our study

The literature yields two robust messages that directly motivate our design. Firstly, liquidity compensation is conditional: it is most informative when evaluated across regimes rather than averaged across the full sample. This regime dependence echoes conditional asset-pricing and return-predictability evidence in which betas and premia vary with observable state variables (Ali, 2021). Secondly, mutual funds are not passive carriers of liquidity risk—observed spreads can reflect both static exposure and dynamic management, and crisis-period behaviour may be confounded by flows and forced trading.

Our study contributes to these debates in three ways. (1) We provide systematic evidence on liquidity premia and liquidity timing for Indian equity mutual funds over 2007–2024, an economically important emerging-market setting, where institutional frictions and liquidity dynamics may differ from developed markets. (2) Building on the state-dependent beta framework (Cao et al., 2013), we separate exposure from timing by pairing liquidity-beta sorted portfolios (HMLiq) with an investable timing factor (Timer) constructed from lagged timing signals, enabling a transparent decomposition of the cross-sectional spread. (3) We interpret the results through the lens of the recent fragility literature (Jiang et al., 2022; Y. Ma et al., 2022) and the evidence that timing skill is scarce and concentrated (Aiken & Kang, 2023; S. Kumar et al., 2023), motivating robustness and identification checks that distinguish timing from flow-driven mechanics and emphasise regime-specific inference. Prior Indian evidence remains limited and mixed (Alam & Ansari, 2020); extending the analysis through 2024 and explicitly separating exposure from timing helps clarify when liquidity risk is compensated, how much of the spread reflects dynamic beta management, and why systemic stress remains difficult to hedge.

2. Variables, data, and methods

2.1. Liquidity risk measures

India-specific RM, SMB, and HML factors are obtained from the Indian Finance Database (IFD). The risk-free rate $R_{f,t}$ is the 1-month Treasury bill yield, converted to a simple monthly rate from the quoted annualised value. Market excess return is defined as $R_{m,t} - R_{f,t}$. All series extend through December 2024 to match the fund sample window.

For stock j on day d, Amihud illiquidity is:

$$ILLIQ_{j,d} = \frac{|R_{j,d}|}{Dvol_{j,d}}$$

where $R_{j,d}$ is the daily return and $Dvol_{j,d}$ is rupee trading value. Monthly $ILLIQ_{j,t}$ is the average across trading days in month *t*. We exclude zero-return/zero-volume days, winsorise each month's cross-section at the 1st/99th percentiles, and require at least 15 valid trading days. Aggregate market liquidity is then:

$$AML_t = \frac{1}{N_t}\sum_{j=1}^{N_t} ILLIQ_{j,t}$$

where N_t is the number of eligible broad-index constituents in month t. Constituents are updated monthly to reflect membership changes.

Because liquidity is persistent, the priced component is the unexpected innovation. We estimate:

$$AML_t = a + b\,AML_{t-1} + e_t, \qquad InnAML_t \equiv \hat{e}_t$$

and define $InnAML_t$ as the innovation in aggregate market liquidity. For comparability across subperiods, $InnAML_t$ is standardised to mean zero and unit variance.

Following Lou and Sadka (2011), the liquidity beta of fund i is estimated from:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}\,(R_{m,t} - R_{f,t}) + \beta_{2,i}\,InnAML_t + \epsilon_{i,t} \tag{1}$$

We estimate $\beta_{2,i}$ using a rolling 24-month window and sort funds each January into quintiles by their most recent $\beta_{2,i}$: PoF1 (highest liquidity beta) through PoF5 (lowest). Quintile portfolios are equally weighted, held for 12 months, and rebalanced annually. The liquidity premium at the fund level is captured by PoF1–PoF5 ("HMLiq"), a zero-investment portfolio that isolates compensation for exposure to liquidity innovations.

2.2. Liquidity timing and flows

To test for liquidity timing, we allow market beta to vary with deviations of aggregate liquidity from its recent mean (Cao et al., 2013):

$$\beta_{m,i} = \beta_{0m,i} + \gamma_{m,i}(Liq_{m,t} - \overline{Liq_m}) \tag{2}$$

where $Liq_{m,t}$ is the aggregate liquidity state and $\overline{Liq_m}$ is its rolling mean (36 months). Substituting (2) into a standard factor benchmark yields:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \left[\beta_{0m,i} + \gamma_{m,i}(Liq_{m,t} - \overline{Liq_m})\right] \\ (R_{m,t} - R_{f,t}) + \beta_{s,i}SMB_t + \beta_{v,i}HML_t + \epsilon_{i,t} \end{aligned} \tag{3}$$

the coefficient $\gamma_{m,i}$ measures liquidity timing: $\gamma_{m,i} > 0$ indicates that the fund raises (lowers) its market exposure when liquidity is above (below) trend.

To address the concern that measured timing may reflect mechanically-induced beta changes arising from flows, we compute net flows using the standard AUM decomposition:

$$Net\ Flow_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1}(1 + R_{i,t})}{AUM_{i,t-1}}$$

Appendix C in the Supplementary material augments the timing regressions with flow interactions and outflow-state terms to separate timing from flow-driven trading pressure. In addition, Appendix G in the Supplementary material examines whether estimated liquidity exposure and timing are systematically explained by standard fund characteristics (size, turnover, expense ratios, and age) using panel regressions with fund and month fixed effects and conditional double-sorts.

2.3. Mutual funds data

Our empirical analysis uses a comprehensive panel of actively managed Indian equity mutual funds from November 2007 through December 2024. This horizon spans multiple liquidity environments and market regimes, enabling regime-specific inference on both liquidity risk exposure and liquidity timing. For consistency across the paper, we define the following subperiods: Nov 2007–Dec 2024, Nov 2007–May 2009, Jun 2009–Dec 2019, Jan 2020–Jun 2020, and Jul 2020–Dec 2024. Because the post-pandemic era contains heterogeneous phases, we further split Jul 2020–Dec 2024 into finer subperiods in Appendix D in the Supplementary Material.

Fund-level data are obtained from Morningstar India, supplemented with disclosures from the Association of Mutual Funds in India (AMFI) and fund fact sheets for cross-validation of classifications and share-class attributes. The sample includes actively managed equity open-ended funds and excludes index funds, ETFs, sector/thematic funds, funds-of-funds, and closed-end products. For each fund, we collect total-return NAVs, assets under management (AUM), and available fund characteristics (e.g., expense ratios and portfolio attributes when disclosed). In addition, we compute fund flows using the standard AUM-based flow decomposition described below; flows play an explicit role in the robustness and identification checks in Appendix C in the Supplementary material.

Market-wide liquidity measures are constructed from daily stock-level trading data for constituents of a broad Indian equity index (BSE 500 constituents), using daily prices and trading value to compute Amihud-style illiquidity at the stock level and then aggregating to the market level. This construction ensures that the liquidity state is derived bottom-up (stock → market) and is consistent across regimes.

The initial sample contains 546 share classes. We impose the following screens: (1) the fund must be an open-ended, actively managed equity fund; (2) at least 80% of assets must be allocated to domestic Indian equities; (3) at least 36 consecutive months of return history are required to support rolling-window exposure estimation and annual portfolio formation; and (4) funds must satisfy a minimum AUM screen at formation to mitigate return distortions and imprecise beta estimates associated with very small funds.

The baseline AUM screen sets a minimum of USD 5 million (converted from INR using month-end exchange rates), following the methodology outlined by

Kacperczyk et al. (2008). Because the appropriate cutoff can be market-dependent, we do not rely on this threshold mechanically: Appendix A in the Supplementary Material replicates the full analysis under alternative minimum-AUM screens and distribution-based cutoffs (excluding the bottom tail of the Indian AUM distribution) and shows that the main conclusions are not driven by small-fund behaviour.

Where multiple share classes exist for a given portfolio, we consolidate at the portfolio level by retaining the oldest unhedged accumulation class to avoid overweighting fund families with multiple fee variants. Funds enter the panel once they satisfy history requirements and remain until termination/merger when data are available. This design mitigates mechanical survivorship effects and ensures that portfolio formation reflects the information set available at each formation date.

All NAVs and distributions are recorded in INR. Monthly returns are calculated from end-of-month total-return NAVs with reinvested distributions. Total-return series are net of ongoing expense ratios and management fees, and gross of front/back loads. Factors and state variables (market, SMB, HML, and liquidity) are aligned to the same calendar month.

We benchmark the fund universe to the BSE 500 index and report descriptive statis- tics for funds and the benchmark across standard horizons and for the COVID/post-COVID period. Table 1 summarises return and risk characteristics for the final sample of 208 funds.

We drop months with missing NAVs, reinvest distributions, remove data errors (e.g., non-positive NAVs), and winsorise monthly returns at the 0.5% and 99.5% tails. For stock-level liquidity inputs, we require at least 15 valid trading days per month for inclusion in monthly illiquidity measures.

2.4. Estimation and robustness checks

Funds are sorted each January using rolling-window estimates, and quintile portfolios are held from February to the following January. We compute monthly returns for PoF1–PoF5 and HMLiq and evaluate performance using CAPM, FF3F, and liquidity/timing-augmented models.

Time-series regressions report heteroskedasticity- and autocorrelation-consistent Newey–West statistics. For spread portfolios and overlapping formation procedures, HAC corrections are applied analogously.

The empirical design is complemented by a set of robustness checks that map directly to the main identification concerns, presented and discussed in the Supplementary material. Appendix A reports alternative minimum-AUM screens and value-weighted portfolio results. Appendix B reports modern benchmark models (Carhart-4 and FF5) with liquidity and Timer augmenta-

Table 1. Descriptive statistics of Indian equity funds and BSE 500 (Nov 2007–Dec 2024; subperiods and horizons)

	1 year		5 years		10 years		COVID & post-COVID (2020–2024)	
	Funds	BSE500	Funds	BSE500	Funds	BSE500	Funds	BSE500
Return analysis								
Total return (%)	7.28	8.97	101.75	119.99	244.34	214.01	68.42	72.15
Annualized mean return (%)	11.54	14.19	14.15	26.04	21.81	20.61	13.72	14.95
Annualized mean excess return (%)	–2.29	–1.16	–9.24	–1.11	–2.91	–2.31	–1.85	–1.12
Risk								
Annualised standard deviation (%)	12.76	13.47	16.88	17.39	18.62	19.75	19.25	20.11
Annualised downside risk (%)	8.19	8.72	12.14	12.49	14.35	14.21	13.81	13.95
Annualised tracking error (%)	2.04		2.23		2.49		2.62	
Risk/return								
Sharpe measure	0.12	0.24	0.54	0.59	0.91	0.83	0.58	0.61
Jensen alpha (%)	–1.60	–0.88	1.13				0.97	
Information ratio	–0.81	–0.42	0.80	0.28			0.74	0.31
Treynor measure	0.02	0.03	0.09	0.12	0.28	0.26	0.19	0.21
Correlation	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99

Notes: Descriptive statistics are based on 208 actively managed Indian equity funds benchmarked against the BSE 500. Returns are INR total returns (net of ongoing fees and gross of loads). Standard horizons (1y, 5y, 10y) are complemented by COVID and post-COVID performance (2020–2024).

Source: own work.

tions. Appendix C implements flow-adjusted timing specifications. Appendix D refines the post-COVID segmentation. Appendix E reports Timer diagnostics (correlations, VIFs, and orthogonalized Timer). Appendix F assesses sensitivity to rolling-window length and supplements crisis-window inference using daily evidence for Jan–Jun 2020. Appendix G adds fund-characteristic controls (size, turnover, expense ratios, age) and conditional double-sorts to assess whether liquidity exposure and timing estimates are mechanically explained by fund type rather than discretionary beta management.

3. Results and analysis

This section evaluates whether exposure to innovations in aggregate market liquidity is compensated in Indian equity mutual fund returns and whether such compensation is state-dependent. Quintile portfolios (PoFs) are formed each January by sorting funds on their *ex ante* liquidity betas from (1) estimated over the prior 24 months; portfolios are equally weighted, held for 12 months, and rebalanced annually. By construction, PoF1 has the highest liquidity beta (greatest exposure to liquidity innovations), while PoF5 has the lowest (often negative) exposure.

Period labels are harmonised across text and tables using Nov 2007–Dec 2024, Nov 2007–May 2009, Jun 2009–Dec 2019, Jan 2020–Jun 2020, and Jul 2020–Dec 2024. Because the post-pandemic era contains heterogeneous phases, Appendix D in the Supplementary material further refines Jul 2020–Dec 2024 into finer subperiods. Inference in the acute COVID window (Jan 2020–Jun 2020) is inherently noisy due to the short sample; Appendix F in the Supplementary material therefore supplements monthly results with daily evidence and rolling-window sensitivity.

3.1. Descriptive properties and the liquidity-beta premium

Table 2 reports average monthly returns and ex-post liquidity betas for the PoFs across subperiods. Three patterns are central. Firstly, liquidity betas decline monotonically from PoF1 to PoF5 in each subperiod, confirming that the preformation sort generates portfolios with ordered liquidity exposure. This monotonicity is a necessary diagnostic for interpreting PoF spreads as related to systematic liquidity risk rather than a sorting artifact. Secondly, in longer samples such as Jun 2009–Dec 2019 and Jul 2020–Dec 2024, average returns are higher for the high-liquidity-beta portfolios relative to the low-liquidity-beta portfolios, consistent with a positive liquidity premium outside acute stress. Thirdly, in short crisis windows, the cross-sectional return ordering is less stable and estimates are less precise, consistent with the view

Table 2. Mean returns of portfolios sorted by liquidity-innovation exposure

	PoF1	PoF2	PoF3	PoF4	PoF5
Panel A: Nov 2007–Dec 2024					
Mean	0.717	0.625	0.445	0.383	0.215
Standard deviation	4.030	3.660	3.380	3.080	2.350
Alpha	0.593	0.491	0.460	0.402	0.175
Liquidity beta	0.950	0.750	0.440	–0.150	–0.370
Panel B: Jun 2009–Dec 2019					
Mean	0.540	0.517	0.480	0.390	0.318
Standard deviation	3.050	2.930	2.690	2.350	2.030
Alpha	0.454	0.370	0.315	0.225	0.178
Liquidity beta	0.870	0.700	0.370	–0.090	–0.290
Panel C: Nov 2007–May 2009					
Mean	1.254	0.974	0.676	0.334	0.021
Standard deviation	6.580	5.840	5.050	4.880	4.470
Alpha	1.020	0.730	0.440	0.080	–0.110
Liquidity beta	1.170	0.980	0.620	–0.110	–0.430
Panel D: Jan 2020–Jun 2020					
Mean	0.310	0.280	0.240	0.190	0.150
Standard deviation	7.200	6.950	6.500	6.300	6.100
Alpha	0.200	0.170	0.150	0.120	0.080
Liquidity beta	1.300	1.050	0.780	0.200	–0.100
Panel E: Jul 2020–Dec 2024					
Mean	0.480	0.460	0.430	0.390	0.350
Standard deviation	3.600	3.400	3.200	2.900	2.700
Alpha	0.350	0.310	0.280	0.220	0.180
Liquidity beta	0.920	0.740	0.410	–0.050	–0.220

Notes: Funds are sorted each January into five equally weighted quintile portfolios (PoF1 = highest, PoF5 = lowest liquidity beta) using the prior 24 months of estimates from (1). The table reports average monthly returns (%) and ex post liquidity betas by subperiod. Market excess return is $R_{m,t} - R_{f,t}$; the liquidity factor is the innovation in aggregate market liquidity ($InnAMLt$).

Source: own work.

that liquidity compensation is conditional and may compress when common shocks dominate and market functioning deteriorates.

Taken together, the descriptive evidence is consistent with conditional liquidity pricing: bearing liquidity-innovation exposure is associated with economically meaningful return differences in normal and recovery regimes, while acute stress episodes attenuate or eliminate the premium. Subsequent sub-sections evaluate whether these differences are absorbed by traded liquidity risk (exposure) and whether a separate timing channel contributes to the spread (management).

3.2. Fund-level liquidity risk premium (HMLiq)

We summarise the fund-level liquidity premium as the high-minus-low return spread (PoF1−PoF5), denoted HMLiq. Table 3 reports the mean monthly spread, its volatility and HAC *t*-statistic, the correlation between PoF1 and PoF5, and the intercept/slope from regressing PoF1 on PoF5.

Table 3. Fund-level liquidity risk premium (HMLiq = PoF1−PoF5)

	Nov 2007–Dec 2024	Jun 2009–Dec 2019	Nov 2007–May 2009	Jan 2020–Jun 2020	Jul 2020–Dec 2024
Mean	0.480	0.470	0.520	0.120	0.310
Standard deviation	2.680	2.570	2.980	3.900	2.400
t-statistic (HAC)	2.680	2.050	0.920	0.420	2.030
Correlation	0.930	0.920	0.980	0.950	0.910
Cumulative	17.520	59.400	15.720	1.800	11.160
Alpha (PoF1 on PoF5)	0.480	0.470	0.520	0.100	0.280
t-statistic (HAC)	3.940	2.440	1.130	0.390	2.100
Beta (PoF1 on PoF5)	0.940	0.940	1.130	1.200	0.960

Notes: Funds are sorted each January by liquidity beta (prior 24 months). The table reports monthly high-minus-low (HMLiq) spreads. Cumulative is the arithmetic sum of monthly spreads.

Source: own work.

HMLiq is positive in the aggregate sample and is most reliably estimated in the longer normal and recovery subperiods. In crisis windows, estimates are weaker and less stable, consistent with conditional liquidity pricing and the dominance of common shocks during systemic stress. The high correlation between PoF1 and PoF5 (ρ typically above 0.90) indicates that HMLiq isolates a comparatively subtle component of expected returns, reinforcing the role of factor attribution and disciplined inference.

Because the Indian mutual fund cross-section includes a long tail of small funds, Appendix A in the Supplementary material replicates the full pipeline under alternative minimum-AUM screens and distribution-based cutoffs, and compares equal-weighted to value-weighted portfolios. These checks ensure that the HMLiq pattern is not driven by an arbitrary AUM threshold or by small-fund behaviour.

3.3. Risk-adjusted performance with a traded liquidity factor

We next assess whether HMLiq reflects compensation for exposure to a traded stock-level liquidity factor or residual performance beyond such exposure. Table 4 reports alphas for each quintile portfolio and for HMLiq under CAPM and FF3F, as well as liquidity-augmented variants that add the traded liquidity factor (Liq). A decline in the HMLiq alpha after adding Liq indicates that traded liquidity risk explains part of the spread.

Adding Liq attenuates HMLiq in the aggregate sample and in normal/recovery regimes, indicating that a nontrivial component of the liquidity-beta spread is attributable to traded liquidity exposure. Crisis-period estimates are less stable and statistically weaker, consistent with the broader evidence that liquidity premia are not reliably earned under systemic stress.

Because mutual-fund performance evaluation commonly controls for Momentum and (in newer frameworks) Profitability and Investment, Appendix B in the Supplementary material re-estimates HMLiq alphas under Carhart-4 and Fama–French-5, each optionally augmented with Liq and Timer. Richer benchmarks attenuate alphas but preserve the paper's central regime-dependent conclusions.

Table 4. Risk-adjusted performance of liquidity-beta sorted portfolios of funds (Nov 2007–Dec 2024, subperiods)

Model	Port1	Port2	Port3	Port4	Port5	HMLiq	Liq.
Panel A: Nov 2007–Dec 2024							
CAPM	0.396	0.272	0.153	0.064	0.015	0.381	–
	(1.440)	(1.000)	(0.620)	(0.250)	(0.050)	(2.210)	–
CAPM+Liq.	0.304	0.213	0.129	0.041	0.032	0.272	0.562
	(1.110)	(0.780)	(0.510)	(0.160)	(0.060)	(1.380)	(3.880)
FF3F	0.398	0.278	0.158	0.067	0.024	0.359	–
	(1.490)	(1.030)	(0.640)	(0.260)	(0.080)	(2.320)	–
FF3F+Liq.	0.322	0.232	0.137	0.046	0.037	0.285	0.470
	(1.200)	(0.860)	(0.550)	(0.170)	(0.120)	(1.380)	(3.380)

Model	Port1	Port2	Port3	Port4	Port5	HMLiq	Liq.
Panel B: Jun 2009–Dec 2019							
CAPM	0.484	0.314	0.196	0.107	–0.014	0.498	–
	(3.940)	(3.090)	(2.970)	(1.580)	(0.150)	(3.050)	–
CAPM+Liq.	0.373	0.248	0.190	0.119	0.014	0.359	0.612
	(3.150)	(2.700)	(2.800)	(1.700)	(0.150)	(2.260)	(3.850)
FF3F	0.454	0.301	0.188	0.104	–0.012	0.466	–
	(4.020)	(3.360)	(2.830)	(1.530)	(0.130)	(3.100)	–
FF3F+Liq.	0.376	0.268	0.183	0.108	0.003	0.373	0.418
	(3.340)	(3.160)	(2.670)	(1.530)	(0.030)	(2.470)	(2.630)
Panel C: Nov 2007–May 2009							
CAPM	–0.456	–0.486	–0.628	–0.622	–0.692	0.236	–
	(–0.230)	(–0.240)	(–0.340)	(–0.320)	(–0.350)	(0.540)	–
CAPM+Liq.	–0.409	–0.440	–0.589	–0.583	–0.655	0.246	0.189
	(–0.200)	(–0.220)	(–0.320)	(–0.290)	(–0.330)	(0.550)	(–0.750)
FF3F	0.712	0.751	0.555	0.605	0.571	0.141	–
	(0.310)	(0.320)	(0.260)	(0.270)	(0.260)	(0.283)	–
FF3F+Liq.	1.115	1.148	0.995	0.955	0.910	0.205	0.206
	(0.490)	(0.500)	(0.400)	(0.430)	(0.410)	(0.433)	(0.780)
Panel D: Jan 2020–Jun 2020							
CAPM	–0.892	–0.754	–0.643	–0.611	–0.585	–0.307	–
	(–0.420)	(–0.360)	(–0.310)	(–0.300)	(–0.280)	(–0.520)	–
CAPM+Liq.	–0.801	–0.692	–0.601	–0.567	–0.542	–0.259	0.128
	(–0.380)	(–0.330)	(–0.300)	(–0.280)	(–0.260)	(–0.490)	(0.840)
FF3F	–0.741	–0.628	–0.539	–0.502	–0.478	–0.263	–
	(–0.350)	(–0.300)	(–0.260)	(–0.240)	(–0.230)	(–0.480)	–
FF3F+Liq.	–0.653	–0.571	–0.496	–0.461	–0.438	–0.215	0.102
	(–0.310)	(–0.280)	(–0.240)	(–0.230)	(–0.210)	(–0.430)	(0.690)
Panel E: Jul 2020–Dec 2024							
CAPM	0.512	0.344	0.229	0.118	0.021	0.491	–
	(2.340)	(1.980)	(1.640)	(1.120)	(0.190)	(2.270)	–
CAPM+Liq.	0.417	0.283	0.207	0.097	0.038	0.329	0.391
	(2.010)	(1.750)	(1.480)	(0.990)	(0.270)	(2.020)	(2.610)
FF3F	0.485	0.331	0.218	0.115	0.019	0.466	–
	(2.420)	(2.030)	(1.570)	(1.140)	(0.180)	(2.210)	–
FF3F+Liq.	0.392	0.278	0.196	0.098	0.036	0.307	0.342
	(1.950)	(1.690)	(1.410)	(1.010)	(0.250)	(2.010)	(2.210)

Notes: Average monthly alphas (%) for quintile portfolios (PoF1 highest to PoF5 lowest liquidity beta) and the high-minus-low spread (PoF1−PoF5).

Source: own work.

3.4. Timing ability of liquidity-beta sorted funds

The preceding evidence indicates that traded liquidity risk explains a meaningful fraction of *HMLiq*, yet a residual component remains in normal and recovery regimes. A natural presumption is that part of this residual reflects state-dependent beta management (liquidity timing). We test this mechanism in two complementary ways: (1) estimating timing coefficients in the state-dependent beta specification (3), and (2) constructing an investable Timer factor from lagged timing-coefficient sorts and using it to decompose *HMLiq*.

3.4.1. Liquidity timing coefficients

We estimate the liquidity-timing specification in (3) for each liquidity-beta quintile (PoF1– PoF5). The timing coefficient $\gamma_{m,i}$ multiplies the interaction $(Liq_{m,t} - Liq_m)(R_{m,t} - R_{f,t})$; $\gamma_{m,i} > 0$ indicates that a portfolio scales market exposure up (down) when liquidity is above (below) trend, consistent with liquidity-state-dependent beta management. Results are reported in Table 5.

Table 5. Liquidity timing in liquidity–beta sorted portfolios

	α_i	$\beta_{0m,i}$	$\beta_{s,i}$	$\beta_{v,i}$	$\gamma_{m,i}$	Adj R^2
Panel A: Nov 2007–Dec 2024						
PoF1	0.246 (2.21)	0.875 (30.27)	0.173 (5.83)	–0.025 (–1.07)	0.020 (3.31)	0.957
PoF2	0.167 (1.96)	0.907 (48.51)	0.134 (4.59)	0.022 (1.02)	0.000 (0.00)	0.975
PoF3	0.061 (0.94)	0.842 (27.81)	0.130 (3.89)	–0.030 (–1.04)	0.020 (1.62)	0.968
PoF4	0.019 (0.26)	0.861 (32.56)	0.200 (5.20)	–0.040 (–0.94)	–0.040 (–0.94)	0.946
PoF5	–0.023 (–0.17)	0.810 (13.61)	0.019 (0.55)	0.045 (1.55)	0.017 (0.94)	0.925
Panel B: Jun 2009–Dec 2019						
PoF1	0.316 (2.93)	0.813 (25.54)	0.172 (6.25)	0.012 (0.51)	0.113 (2.43)	0.914
PoF2	0.190 (2.21)	0.967 (37.30)	0.132 (7.26)	0.032 (1.64)	–0.019 (–0.49)	0.961
PoF3	0.061 (1.05)	0.944 (45.58)	0.013 (0.93)	–0.005 (–0.35)	–0.014 (–0.45)	0.973
PoF4	0.019 (0.43)	0.949 (40.63)	–0.025 (–1.76)	–0.012 (–0.73)	–0.046 (–1.63)	0.972
PoF5	–0.029 (–0.32)	1.087 (32.49)	–0.040 (–2.01)	–0.012 (–0.67)	–0.046 (–1.16)	0.964

	α_i	$\beta_{0m,i}$	$\beta_{s,i}$	$\beta_{v,i}$	$\gamma_{m,i}$	Adj R^2
Panel C: Nov 2007–May 2009						
PoF1	–0.158 (–0.48)	0.893 (27.45)	0.182 (2.06)	–0.057 (–1.03)	0.033 (3.88)	0.986
PoF2	–0.015 (–0.05)	0.891 (43.89)	0.204 (2.56)	–0.090 (–1.98)	0.019 (3.33)	0.991
PoF3	–0.278 (–0.94)	0.794 (32.30)	0.102 (1.31)	–0.054 (–1.09)	0.007 (1.17)	0.990
PoF4	–0.153 (–0.41)	0.832 (32.46)	0.152 (1.53)	–0.070 (–1.20)	–0.003 (–0.52)	0.987
PoF5	–0.204 (–0.35)	0.669 (15.37)	0.034 (1.97)	–0.077 (–0.78)	–0.012 (–1.34)	0.964
Panel D: Jan 2020–Jun 2020						
PoF1	–0.312 (–0.95)	0.842 (11.23)	0.208 (2.01)	–0.044 (–0.55)	0.041 (1.78)	0.942
PoF2	–0.274 (–0.87)	0.864 (12.74)	0.191 (2.24)	–0.031 (–0.44)	0.027 (1.42)	0.936
PoF3	–0.198 (–0.64)	0.833 (10.48)	0.154 (1.75)	–0.026 (–0.39)	0.010 (0.55)	0.927
PoF4	–0.146 (–0.48)	0.790 (9.67)	0.120 (1.23)	–0.015 (–0.22)	–0.005 (–0.27)	0.912
PoF5	–0.121 (–0.43)	0.758 (8.92)	0.082 (0.97)	–0.009 (–0.14)	–0.014 (–0.69)	0.903
Panel E: Jul 2020–Dec 2024						
PoF1	0.284 (2.57)	0.889 (28.91)	0.165 (6.12)	–0.022 (–0.84)	0.036 (2.16)	0.963
PoF2	0.177 (1.97)	0.901 (31.42)	0.137 (5.47)	0.014 (0.65)	0.012 (1.01)	0.958
PoF3	0.062 (1.01)	0.872 (26.37)	0.128 (3.98)	–0.018 (–0.72)	0.009 (0.74)	0.952
PoF4	0.019 (0.34)	0.847 (24.26)	0.112 (3.55)	–0.020 (–0.83)	–0.007 (–0.59)	0.948
PoF5	–0.027 (–0.39)	0.803 (22.91)	0.098 (3.12)	0.021 (0.92)	–0.010 (–0.83)	0.941

Source: own work.

Two results are most salient. Firstly, timing loadings are concentrated in the high-liquidity-beta portfolios (PoF1 and, in some periods, PoF2), consistent with the idea that timing is most relevant where exposure is highest. Secondly, timing estimates are stronger and more precisely estimated in longer samples, while short crisis windows yield inherently noisy inference. To assess whether these timing estimates simply proxy for fund type, Appendix G in the Supplementary material relates γ (and β^{liq}) to lagged flows, size, turnover, fees, and age with fund and month fixed effects; flows remain an important predictor, but timing is not mechanically subsumed by standard characteristics.

Because contemporaneous interaction terms may capture both anticipatory behaviour and rapid reaction, Appendix C in the Supplementary material augments the timing regression with flow controls and outflow-state interactions to distinguish discretionary timing from mechanically-induced beta shifts driven by flows. Appendix E in the Supplementary material reports Timer diagnostics (correlations, VIFs, and orthogonalised Timer) to address multicollinearity and stress-proxy concerns.

3.5. Timing-adjusted performance: The timer decomposition

We now ask whether the residual HMLiq performance reflects state-dependent beta management rather than static exposure alone. Using the rolling-window estimates from (3), we estimate fund-level timing coefficients $\gamma_{m,i}$, sort funds into quintiles by $\gamma_{m,i}$, and form an investable Timer factor as the return on the highest-minus-lowest timing portfolio. We then re-estimate alphas for the liquidity-beta portfolios and for HMLiq after augmenting CAPM and FF3F with Timer. If timing captures an economically important component of HMLiq, the HMLiq alpha should attenuate materially once Timer is included. Results are reported in Table 6.

Table 6. Liquidity timing skills–adjusted performance of liquidity–beta sorted portfolios

Model	Port1	Port2	Port3	Port4	Port5	Port1–Port5	Timer
Panel A: Nov 2007–Dec 2024							
CAPM	0.396 (1.44)	0.272 (1.00)	0.153 (0.62)	0.064 (0.25)	0.015 (0.05)	0.381 (2.21)	–
CAPM+Timer	0.366 (1.29)	0.325 (1.15)	0.223 (0.88)	0.147 (0.55)	0.230 (0.79)	0.136 (0.79)	0.618 (7.56)
FF3F	0.398 (1.49)	0.278 (1.03)	0.158 (0.64)	0.067 (0.26)	0.024 (0.08)	0.359 (2.32)	–
FF3F+Timer	0.392 (1.40)	0.346 (1.25)	0.232 (0.91)	0.152 (0.57)	0.229 (0.78)	0.162 (1.01)	0.540 (5.31)
Panel B: Jun 2009–Dec 2019							
CAPM	0.484 (3.94)	0.314 (3.09)	0.196 (2.97)	0.107 (1.58)	–0.014 (0.15)	0.498 (3.05)	–
CAPM+Timer	0.416 (3.38)	0.299 (3.14)	0.188 (2.77)	0.134 (1.94)	0.055 (0.60)	0.362 (2.28)	0.406 (3.86)

Model	Port1	Port2	Port3	Port4	Port5	Port1–Port5	Timer
FF3F	0.454 (4.02)	0.301 (3.36)	0.188 (2.83)	0.104 (1.53)	–0.012 (0.13)	0.466 (3.10)	–
FF3F+Timer	0.411 (3.59)	0.305 (3.58)	0.182 (2.67)	0.127 (1.83)	0.048 (0.53)	0.363 (2.45)	0.324 (3.25)
Panel C: Nov 2007–May 2009							
CAPM	–0.456 (–0.23)	–0.486 (–0.24)	–0.628 (–0.34)	–0.622 (–0.32)	–0.692 (–0.35)	0.236 (0.54)	–
CAPM+Timer	–1.332 (–0.47)	–1.272 (–0.45)	–1.171 (–0.45)	–1.216 (–0.44)	–1.182 (–0.30)	–0.520 (–0.75)	0.109 (0.06)
FF3F	0.712 (0.31)	0.751 (0.32)	0.555 (0.26)	0.605 (0.27)	0.571 (0.26)	0.141 (0.28)	–
FF3F+Timer	–0.990 (–0.35)	–0.889 (–0.31)	–0.800 (–0.31)	–0.832 (–0.29)	–0.386 (–0.14)	–0.606 (–0.88)	0.858 (1.84)
Panel D: Jan 2020–Jun 2020							
CAPM	–0.285 (–0.42)	–0.231 (–0.36)	–0.194 (–0.31)	–0.151 (–0.24)	–0.143 (–0.23)	–0.142 (–0.58)	–
CAPM+Timer	–0.398 (–0.61)	–0.342 (–0.55)	–0.291 (–0.49)	–0.232 (–0.38)	–0.211 (–0.34)	–0.176 (–0.72)	0.312 (2.14)
FF3F	–0.196 (–0.28)	–0.165 (–0.26)	–0.152 (–0.24)	–0.134 (–0.21)	–0.119 (–0.20)	–0.077 (–0.36)	–
FF3F+Timer	–0.317 (–0.47)	–0.278 (–0.44)	–0.239 (–0.40)	–0.195 (–0.32)	–0.171 (–0.28)	–0.168 (–0.66)	0.254 (1.87)
Panel E: Jul 2020–Dec 2024							
CAPM	0.412 (2.89)	0.297 (2.36)	0.204 (1.79)	0.128 (1.04)	0.024 (0.22)	0.388 (2.14)	–
CAPM+Timer	0.339 (2.41)	0.276 (2.21)	0.187 (1.64)	0.114 (0.97)	0.018 (0.15)	0.207 (1.29)	0.521 (4.62)
FF3F	0.395 (2.74)	0.283 (2.29)	0.197 (1.73)	0.121 (0.99)	0.021 (0.19)	0.374 (2.05)	–
FF3F+Timer	0.328 (2.31)	0.265 (2.14)	0.182 (1.59)	0.108 (0.92)	0.015 (0.14)	0.196 (1.22)	0.487 (4.21)

Source: own elaboration.

In the aggregate sample, adding Timer substantially reduces the HMLiq alpha, implying that a large fraction of the liquidity-beta spread is associated with systematic liquidity-state-dependent beta management. This attenuation is also evident in Jul 2020–Dec 2024. In Jun 2009–Dec 2019, a residual component remains after conditioning on Timer, suggesting that additional priced dimensions or fund selection effects contribute to the spread. In crisis windows, both HMLiq and its timing-adjusted counterpart are statistically weak, indicating limited scope for systematic timing to offset acute systemic stress. More broadly, Appendix G in the Supplementary material shows that Timer continues to absorb a large share of HMLiq even when the spread is recomputed within low- versus high-turnover and low- versus high-expense subsamples.

Timer is constructed from lagged timing signals and rebalanced on the annual formation calendar, which mitigates look-ahead concerns. Appendices B-F in the Supplementary Material report robustness checks (modern benchmarks, flow-adjusted timing, Timer diagnostics, post-pandemic heterogeneity, and crisis-window inference). Across the full sample, liquidity exposure is associated with economically meaningful return differentials in normal and recovery regimes but not in acute stress states.

Traded liquidity risk explains a nontrivial share of the liquidity-beta spread, and a separate timing channel—captured by state-dependent betas and the investable Timer factor—accounts for an additional substantial component, particularly outside systemic stress. These conclusions are reinforced by robustness and identification checks in the appendices: alternative AUM screens and weighting (Appendix A in the Supplementary material), modern factor benchmarks (Appendix B), flow-adjusted timing (Appendix C), post-COVID subperiods (Appendix D), Timer diagnostics (Appendix E), and rolling-window and daily COVID inference (Appendix F).

4. Discussion

Our results point to a conditional liquidity-risk premium in delegated portfolios. In the long sample, the liquidity-beta spread is economically meaningful (HMLiq averages about 0.48% per month), and it is most reliably estimated outside acute stress episodes (0.47% per month in the 2009–2019 tranquil regime and 0.31% per month post-COVID). In contrast, the spread becomes statistically weak during the Global Financial Crisis and the 2020 COVID shock. This state dependence is consistent with liquidity-risk pricing frameworks in which expected returns are increasing in exposure to aggregate liquidity shocks (Acharya & Pedersen, 2005; Pástor & Stambaugh, 2003) and with emerging-market evidence that local market liquidity is a first-order driver of expected returns (Bekaert et al., 2007). The novelty here is that we document these patterns in a large Indian mutual fund cross section, where the intermediary channel is potentially stronger because open-end funds transform underlying asset liquidity into daily redeemability.

At the same time, the crisis evidence highlights an important nuance: a standard risk-premium interpretation would predict higher compensation in bad states, yet realised cross-sectional premia compress when liquidity risk becomes systemic. A standard "risk premium" interpretation might lead one to expect higher compensation for liquidity exposure when marginal utility is high. Instead, we find that realised cross-sectional premia compress precisely when aggregate liquidity risk is most salient. A plausible reconciliation is that systemic episodes are dominated by market-wide funding and market-liquidity spirals (Brunnermeier & Pedersen, 2009), which raise return commonality and reduce dispersion across fund portfolios. In these states, cross-sectional differences in liquidity exposure may be swamped by (1) correlated liquidity shocks, (2) binding trading constraints, and (3) "flight to quality" dynamics, all of which make it difficult for high-exposure funds to earn (as opposed to require) a premium within a short crisis window.

A second contribution is to separate static liquidity exposure from dynamic beta management. Prior work documents that mutual-fund liquidity risk can show up as performance differentials that are not fully absorbed by standard traded factors (Dong et al., 2019; Foran & O'Sullivan, 2014). Our findings echo that logic: adding a traded stock-level liquidity factor attenuates HMLiq in normal/recovery regimes but does not fully eliminate it. The additional explanatory power comes from a timing mechanism. Building on liquidity timing tests in Cao et al. (2013), we show that state- dependent liquidity betas and an investable Timer factor—constructed from lagged timing-coefficient sorts—absorb a substantial incremental share of the liquidity-beta spread, particularly outside systemic stress.

This timing result is novel in two ways. Firstly, it provides a portfolio-level decomposition that clarifies why fund-level liquidity-beta spreads can persist even when traded liquidity factors only partially explain them: part of the spread behaves like *managed* exposure rather than a fixed characteristic. Secondly, the Timer factor offers a practical benchmark for performance attribution in emerging markets, where (1) liquidity is highly time-varying and (2) the mapping between stock-level liquidity factors and delegated-portfolio returns is less direct. Consistent with this interpretation, timing effects are concentrated in the high-liquidity-beta portfolios, suggesting that liquidity-sensitive mandates provide both the incentive and the opportunity to vary exposure across liquidity states.

The fact that timing does not provide reliable protection in crisis windows is informative. It aligns with the mutual-fund fragility literature, which emphasises strategic complementarities in investor redemptions and the externalities created by forced selling in illiquid markets. In particular, payoff complementarities can make outflows highly sensitive to bad performance (Chen et al., 2010), and flow-driven trading can generate fire-sale price pressure (Coval & Stafford, 2007). When market-wide illiquidity is high, these forces are amplified in more illiquid funds (Goldstein et al., 2017) and can become especially salient during systemic events such as COVID-19 (Falato et al., 2021). In our setting, such mechanisms can help explain why (1) HMLiq collapses during systemic stress and (2) the incremental contribution of timing is statistically fragile: during a liquidity shock, the marginal ability to rebalance is curtailed exactly when rebalancing is most valuable. Appendix G also indicates that turnover and fee intensity correlate with measured timing, consistent with trading frictions shaping implementation, but these characteristics do not overturn the conclusion that timing is fragile in systemic stress states.

Importantly, this interpretation also disciplines what we can claim about "skill." Although Timer is built from predictable variation in estimated betas, similar in spirit to conditional risk-premium forecasting exercises (Ali & Naz, 2025b), part of the apparent timing could still reflect mechanical effects of flows, endogenous risk-taking, or composition changes in the investable universe. The flow-adjusted timing specifications in Appendix C in the Supplementary material are designed to separate discretionary timing from mechanically-induced beta shifts. We therefore interpret Timer as evidence of a timing channel rather than a clean measure of managerial skill.

For investors and researchers, the results suggest that evaluating Indian equity mutual funds with static-factor alphas can be misleading: liquidity-related performance is state-dependent, and a meaningful component is tied to dynamic exposure management. For regulators and risk monitors, the evidence is consistent with a world in which open-end funds can be procyclical: in normal states, liquidity exposure is rewarded, while in stress states, flows and market-wide illiquidity dominate and cross-sectional premia compress.

Some limitations point to natural extensions. Firstly, liquidity is measured through innovations in aggregate market liquidity; future work could combine this with holdings-based liquidity (portfolio "illiquidity" and concentration) to better separate exposure from endogenous trading. Secondly, crisis windows are short and statistically noisy, so inference about stress-state premia should remain cautious. Thirdly, because emerging markets can undergo structural and regulatory changes over long samples, further work could study whether the liquidity exposure–timing mapping shifts across subperiods and fund categories (e.g., large-cap versus mid/small-cap mandates).

Overall, the key takeaway is that liquidity in delegated portfolios is not only a priced exposure in normal times but also a managed exposure; however, the benefits of such management are sharply limited when liquidity risk becomes systemic.

Conclusions

This paper examines how liquidity exposure and liquidity timing jointly shape the cross section of Indian equity mutual fund returns over 2007–2024, covering the Global Financial Crisis, the COVID-19 shock, and the post-pandemic recovery. The main result is that the fund-level liquidity premium is regime contingent: funds with higher exposure to innovations in aggregate market liquidity earn higher average returns in tranquil and recovery regimes, whereas the high-minus-low liquidity-beta spread (HMLiq) contracts sharply and becomes statistically weak during systemic stress.

A second key finding is that the liquidity-beta spread reflects not only static exposure but also dynamic beta management. A liquidity-augmented factor model explains a meaningful portion of HMLiq, and an independently constructed, tradable Timer factor—built from lagged timing-coefficient sorts—absorbs an additional share of the spread in the aggregate sample and especially in the post-COVID period. Timing effects are most pronounced among high-liquidity-beta portfolios, consistent with the view that liquidity-sensitive mandates are the primary locus of state-contingent exposure adjustment. However, timing does not provide reliable protection in acute stress states: when liquidity risk becomes system-wide, both the spread and timing-adjusted performance are statistically fragile.

These findings have practical implications. For investors, liquidity exposure should be treated as a regime-dependent source of expected return rather than a crisis hedge: it is rewarded in normal and recovery environments but offers limited insulation when liquidity deteriorates abruptly. For asset managers, the evidence supports the value of monitoring liquidity states and adjusting exposure in a disciplined manner, while also highlighting the limits of such strategies under market-wide stress. For policymakers, the results reinforce the importance of tools that reduce redemption externalities and curb fire-sale dynamics, since fund-level actions alone are unlikely to offset aggregate liquidity shocks.

Several extensions could further strengthen identification and external validity. Future work can incorporate richer benchmark models (e.g., Momentum, Profitability, and Investment) and holdings-based measures of portfolio liquidity to better distinguish residual performance from omitted risks. Higher-frequency estimation and explicit modelling of flows and trading costs would help separate anticipatory timing from rapid reaction. Finally, linking timing capacity to microstructure conditions (depth, resilience, and price impact) can clarify when liquidity management is effective and when structural fragility dominates outcomes.

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