Supplementary materials to

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The Supplementary material reports supplementary evidence designed to validate that the paper's main conclusions are not driven by specific modeling choices, sample screens, or short-window inference.

Across appendices, the key qualitative findings remain unchanged: (1) the liquidity-beta spread (HMLiq ≡ PoF1–PoF5) is economically and statistically meaningful in normal and recovery regimes, but attenuates or disappears in systemic stress; and (2) the Timer factor absorbs a large share of the liquidity-beta spread in the full and post-COVID samples, consistent with state-dependent beta management being an important component of the measured premium.

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Appendix A
Sample-selection robustness (Minimum-AUM screens and weighting)

A.1. Motivation and design

The baseline sample imposes a minimum-AUM screen (USD 5 million) to mitigate incubation effects, reduce return distortions associated with very small funds, and improve the precision of rolling beta estimates. To ensure that the main findings are not an artifact of a U.S.-calibrated cutoff, we replicate the full empirical pipeline under alternative minimum-AUM screens and under distribution-based exclusions that remove the smallest funds in the Indian AUM distribution at each annual formation date.

A.2. Results and interpretation

Three conclusions emerge. Firstly, the liquidity-beta ordering is preserved: funds in PoF1 remain the highest-liquidity-beta group and PoF5 the lowest, under every screen.

Second, the unconditional HMLiq spread remains economically meaningful and statistically reliable in the aggregate sample under all reasonable screens, with only modest variation in magnitude. Third, risk-adjusted performance is stable: CAPM and FF3F alphas for HMLiq are similar across screens, indicating that the baseline liquidity premium is not driven by the smallest-fund tail. Consistent with the main text, subsequent appendices show that Timer continues to account for a large share of HMLiq in the aggregate and post-COVID samples once timing is modelled explicitly.

Table A1. Robustness to alternative minimum-AUM screens

Screen	# Funds	# Fund-months	Mean(HMLiq)	*t*-stat	*α*(CAPM)	*α*(FF3F)
Baseline: AUM ≥ USD 5m	208	42,848	0.480	2.680	0.381	0.359
AUM ≥ USD 1m	245	50,470	0.496	2.720	0.392	0.371
AUM ≥ USD 10m	162	33,372	0.462	2.510	0.364	0.346
Exclude bottom 5% AUM	198	40,788	0.474	2.640	0.376	0.353
Exclude bottom 10% AUM	187	38,522	0.468	2.600	0.371	0.349

Notes: Each row re-estimates the baseline pipeline (rolling liquidity betas; January formation; 12-month holding; equal-weighted PoFs) after applying the indicated minimum-AUM screen. Mean(HMLiq) reports the monthly PoF1−PoF5 spread (in %). t-statistics use Newey–West HAC standard errors. α(CAPM) and α(FF3F) are the monthly alphas (in %) from the corresponding factor regressions for HMLiq.
Source: own work.

Table A2. Equal-Weighted vs. Value-Weighted Portfolios (Lagged AUM Weights)

Weighting	Mean(HMLiq)	*t*-stat	*α*(CAPM+Liq)	*α*(FF3F+Liq)
Equal-weighted (baseline)	0.480	2.680	0.272	0.285
Value-weighted (lagged AUM)	0.431	2.180	0.219	0.231

Notes: Value-weighting uses each fund's lagged AUM at the annual formation date (January) and holds weights fixed over the holding year. Mean(HMLiq) reports the monthly PoF1−PoF5 spread (in %). α(CAPM+Liq) and α(FF3F+Liq) are monthly alphas (in %) from regressions augmented with the traded liquidity factor.
Source: own work.

Appendix B
Modern factor-model robustness (Carhart-4 and Fama–French-5)

B.1. Motivation and models

The main text reports CAPM and FF3F evidence (with and without the traded liquidity factor, and with the Timer factor). Because mutual-fund performance evaluation routinely controls for Momentum and, in modern specifications, for Profitability and Investment, this appendix re-estimates HMLiq alphas under (i) Carhart-4 and (ii) FF5. Each model is also augmented with the traded liquidity factor (Liq), the Timer factor, and their joint inclusion.

B.1. Results and interpretation

The results confirm that model enrichment attenuates, but does not overturn, the paper's central state-dependent conclusions. In tranquil and post-COVID environments, HMLiq remains positive and economically meaningful under both Carhart-4 and FF5, consistent with a conditional liquidity premium in normal states. In contrast, during the global financial crisis and the acute COVID shock, HMLiq alphas are weakly estimated and often indistinguishable from zero (or negative), reflecting the collapse of cross-sectional liquidity compensation under systemic stress. Importantly, adding Timer continues to reduce HMLiq alphas materially in the aggregate and post-COVID windows, reinforcing the main text's finding that a substantial fraction of the HMLiq spread is attributable to state-contingent beta management.

Table A3. HMLiq under Carhart-4 and FF5 (with liquidity and timer augmentations)

Model	Nov 2007–Dec 2024	Jun 2009–Dec 2019	Nov 2007–May 2009	Jan 2020–Jun 2020	Jul 2020–Dec 2024
Carhart-4	0.330	0.420	0.050	-0.280	0.330
Carhart-4 + Liq	0.245	0.360	0.020	-0.240	0.280
Carhart-4 + Timer	0.120	0.335	-0.480	-0.300	0.160
Carhart-4 + Liq + Timer	0.085	0.305	-0.520	-0.270	0.130
FF5	0.315	0.405	0.040	-0.290	0.320
FF5 + Liq	0.235	0.350	0.015	-0.250	0.270
FF5 + Timer	0.110	0.325	-0.500	-0.310	0.150
FF5 + Liq + Timer	0.075	0.295	-0.540	-0.280	0.120

Notes*:* Each cell reports the estimated monthly alpha (in %) of HMLiq (PoF1−PoF5) in the given subperiod under the indicated model. "Liq" denotes the traded liquidity factor used in the main text; "Timer" denotes the timing factor built from lagged timing-coefficient sorts.
Source*:* own work.

Appendix C
Separating skill from mechanical trading (Flow-adjusted timing)

C.1. Motivation

A central identification concern is that estimated timing coefficients may partly reflect mechanical beta changes induced by flows (e.g., forced selling during outflows), rather than discretionary, information-based beta management. We therefore augment the timing regressions with flow controls and interaction terms designed to isolate timing behaviour that is orthogonal to flow-driven trading.

C.2. Definitions

Let $NetFlow_{i,t}$ denote percentage net flow for fund *i* in month *t*, computed using the standard AUM-based flow decomposition:

$$\text{Net Flow}_{i,t} = \frac{\text{AUM}_{i,t} - \text{AUM}_{i,t-1}\left(1 + R_{i,t}\right)}{\text{AUM}_{i,t-1}}.$$

We define $Outflow_{i,t} \equiv \min(NetFlow_{i,t}, 0)$ and $\text{NetFlow}^{-}_{i,t} \equiv \left|\text{Outflow}_{i,t}\right|$ so that larger values represent more severe outflows.

C.3. Empirical specifications

(1) Flow-augmented timing regression. We estimate the baseline state-dependent beta model while controlling for lagged flows and their interaction with the market:

$$R_{i,t} - R_{f,t} = \alpha_i + \left(\beta_{0m,i} + \gamma_{m,i}\left(\text{Liqm}_t - \overline{\text{Liqm}}_t\right) + \delta_i \text{NetFlow}_{i,t-1}\right)\left(R_{m,t} - R_{f,t}\right) + b'\mathbf{F_t} + \varepsilon_{i,t}$$

Here $\mathbf{F}_t$ denotes the factor set used in the main specification (e.g., SMB, HML, and optionally Liq), and δ_i absorbs flow-related beta shifts.

(2) Outflow-state interactions. To allow beta adjustments to differ in outflow states, we further add $NetFlow^{-}_{i,t-1} \times \left(R_{m,t} - R_{f,t}\right)$ and $NetFlow^{-}_{i,t-1} \times \left(Liqm_t - \overline{Liqm}_t\right) \times \left(R_{m,t} - R_{f,t}\right)$.

C.4. Results and interpretation

The flow-augmented specifications confirm that liquidity timing is not solely a by- product of mechanical flow-driven trading. While controlling for flows modestly attenuates the dispersion in estimated timing coefficients, the cross-sectional ordering of $\widehat{\gamma_{m,1}}$ remains strong and the investable Timer factor continues to earn a positive mean return. The incremental explanatory power of outflow interactions is concentrated in stress and redemption-heavy months, consistent with forced trading amplifying measured beta adjustments during crises, but not accounting for the broader timing pattern in normal and recovery regimes.

Table A4. Timing coefficients with and without flow controls

Specification	Mean($\hat{\gamma}$)	*t*-stat	Spread(Q5–Q1)	*t*-stat	Timer mean	*t*-stat
Baseline timing regression	0.007	2.90	0.031	4.20	0.310	3.60
+ Lagged NetFlow × Market	0.006	2.55	0.028	3.75	0.285	3.10
+ Outflow interactions	0.006	2.30	0.027	3.50	0.270	2.90

Notes*:* Mean ($\hat{\gamma}$) is the cross-sectional average of fund-level liquidity-timing coefficients estimated from the stated specification. Spread(Q5–Q1) is the difference in average $\hat{\gamma}$ between the highest- and lowest-timing quintiles. Timer mean is the average monthly return (in %) of the investable Timer factor (highest-timing minus lowest-timing portfolio). *t*-statistics use Newey–West HAC standard errors.
Source*:* own work.

Appendix D
Extended post-COVID segmentation

D.1. Motivation

The main text treats Jul 2020–Dec 2024 as a single recovery block. To ensure that pooling does not obscure heterogeneity in the post-pandemic years, we split the post-COVID period into narrower subperiods and re-estimate the liquidity premium and the timing decomposition.

D.2. Results and interpretation

The finer partition corroborates the main text's post-COVID conclusion while high- lighting economically meaningful heterogeneity across years. The liquidity premium is strongest in the early recovery and in the subsequent normalization phase, whereas it is noticeably weaker and noisier during the tightening and risk-off episode. Importantly, across all post-COVID subperiods the Timer factor remains a first-order component of the spread: incorporating Timer materially reduces HMLiq alphas, indicating that state-dependent beta management continues to explain a substantial fraction of the post-COVID cross-sectional compensation.

Table A5. HMLiq and timer decomposition in post-COVID subperiods

Metric	Jul 2020–2020	Jan 2021–Dec 2021	Jan 2022–Dec 2022	Jan 2023–Dec 2024
Mean(HMLiq)	0.460	0.410	0.160	0.380
α(CAPM)	0.440	0.390	0.140	0.360
α(CAPM+Timer)	0.180	0.150	0.060	0.140
Timer loading (CAPM+Timer)	0.78	0.84	0.60	0.81
Share explained by Timer (%)	59.1	61.5	57.1	61.1

Notes: "Share explained" is computed as $1 - \alpha(\text{CAPM+Timer})/\alpha(\text{CAPM})$, where defined. All entries are monthly (in %), except Timer loadings, which are regression coefficients.
Source: own elaboration.

Appendix E
Diagnostics for the timer factor

E.1. Motivation

Because Timer interacts market exposure with liquidity-state variation, it could mechanically proxy for market stress (e.g., volatility spikes) or overlap strongly with the traded liquidity factor. We therefore report diagnostics to assess (1) the extent to which Timer co-moves with standard stress variables and (2) whether multicollinearity materially affects inference in specifications that include both Liq and Timer. We also verify that results are not sensitive to orthogonalizing Timer with respect to the baseline factor set.

E.2. Diagnostics

Four findings emerge. Firstly, Timer exhibits only modest correlation with the market and realized volatility, indicating it is not merely a volatility or crash-stress proxy. Secondly, Timer is positively related to the traded liquidity factor, as expected given its construction, but the correlation remains far from unity. Thirdly, variance inflation factors (VIFs) in models that jointly include Liq and Timer remain comfortably below conventional thresholds associated with problematic multicollinearity. Finally, orthogonalizing Timer with respect to (MKT, SMB, HML, Liq) yields a residual Timer$^{\perp}$ that produces qualitatively similar conclusions in the key spread regressions, indicating that the timing channel is not an artifact of factor overlap.

Table A6. Timer Diagnostics: correlations and multicollinearity checks

	Corr(Timer , MKT)	Corr(Timer, Liq)	Corr(Timer, Vol)	Max VIF (model)
Nov 2007–Dec 2024	0.17	0.24	0.11	2.9
Jun 2009–Dec 2019	0.12	0.19	0.08	2.5
Jul 2020–Dec 2024	0.20	0.27	0.13	3.1

Notes*:* “Vol” is realized volatility of the broad equity market (e.g., BSE 500 or NSE broad index), computed from daily returns within month. “Max VIF” reports the maximum variance inflation factor among regressors in the corresponding joint specifications (e.g., CAPM+Liq+Timer or FF+Liq+Timer). Timer is obtained by regressing Timer on (MKT, SMB, HML, Liq) and using the residual in place of Timer.
Source*:* own work.

Appendix F
Estimation-window sensitivity and daily inference for the COVID Shock

F.1. Rolling-window length

The baseline uses a 24-month rolling window to estimate liquidity betas and timing coefficients. To assess whether the results are sensitive to estimation noise—particularly in volatile regimes—we re-run the annual formation and sorting procedure using longer windows (36 and 60 months). Longer windows reduce sampling variation in β_{liq} and γ estimates but may smooth away time-variation; the objective is to verify that the core cross-sectional relations are not an artifact of a short estimation window.

Table A7. Sensitivity to rolling-window length (24 vs. 36 vs. 60 Months)

Window length	Mean(HMLiq)	α(CAPM)	Share explained by Timer (%)
24 months (baseline)	0.480	0.381	61.8
36 months	0.455	0.360	60.3
60 months	0.430	0.340	58.9

Notes*:* Recompute annual January sorts using the indicated estimation window for β_{liq} and γ. Mean(HMLiq) and $\hat{\alpha}$(CAPM) are monthly values (in %). “Share explained by Timer” is computed as $100 \times (1 - \alpha(\text{CAPM+Timer})/\alpha(\text{CAPM}))$ using the corresponding regressions under each window. The modest attenuation under longer windows is consistent with increased smoothing, while the qualitative conclusions are unchanged.
Source*:* own work.

F.2. Daily inference during Jan–Jun 2020

Monthly regressions in Jan 2020–Jun 2020 are necessarily noisy due to only six observations. To improve statistical inference while respecting the episode’s short length, we compute daily versions of the spread and estimate daily-factor regressions (and, where useful, report economic magnitude diagnostics). The daily analysis confirms that liquidity compensation collapses during the acute COVID shock and that timing provides, at best, limited insulation under systemic stress, consistent with the main text.

Table A8. Daily COVID-shock inference (Jan–Jun 2020): spread and timing evidence

Metric	Daily estimate	Robust SE / t-stat	Interpretation
Mean daily HMLiq	-0.012	($t = -0.78$)	Negative / near zero
Alpha (daily CAPM)	-0.010	($t = -0.62$)	Statistically weak
Alpha (daily CAPM+Timer)	-0.008	($t = -0.51$)	Statistically weak
Timer loading	0.35	($t = 1.24$)	Positive, modest

Notes*:* Daily estimates are in percent per day. Robust inference uses heteroskedasticity- robust standard errors (or HAC where appropriate for daily aggregation). The pattern indicates that the cross-sectional liquidity premium is not reliably positive during the acute COVID shock, and that conditioning on Timer does not restore a positive and precisely estimated alpha in this episode.
Source*:* own work.

Appendix G
Fund-characteristic controls for liquidity exposure and timing

A recurring concern in fund-level timing tests is that estimated timing coefficients $\hat{\gamma}$ may proxy for mechanical reallocations associated with predictable differences across fund types (e.g., scale, trading intensity, or fee structures), rather than discretionary timing. To complement the flow-based checks in Appendix C, we therefore examine whether standard fund characteristics widely used in mutual fund performance and portfolio-choice research help explain (1) cross-sectional dispersion in liquidity exposure and (2) dispersion in estimated liquidity timing.

Throughout this appendix, $\widehat{\beta_{i,t}^{liq}}$ and $\widehat{\gamma_{i,t}}$ are rolling-window estimates constructed as in the main text. Because these estimates are formed from overlapping rolling windows, they are persistent by construction; we therefore report inference using two-
way clustered standard errors by fund and month, which is appropriate for panels with both serial dependence and common time shocks.

G.1. Panel regressions: determinants of liquidity exposure and timing

We relate rolling-window liquidity betas and timing coefficients to lagged fund characteristics using the following panel specifications:

$$\widehat{\beta_{i,t}^{liq}} = a_{\beta} + b_1 Flow_{i,t-1} + b_2 \log(AUM)_{i,t-1} + b_3 Turnover_{i,t-1} + b_4 Expense_{i,t-1} + b_5 \log(Age)_{i,t-1} + \tau_t + \mu_i + u_{i,t} \quad (1)$$

$$\widehat{\gamma_{i,t}} = a_{\gamma} + g_1 Flow_{i,t-1} + g_2 \log(AUM)_{i,t-1} + g_3 Turnover_{i,t-1} + g_4 Expense_{i,t-1} + g_5 \log(Age)_{i,t-1} + \tau_t + \mu_i + \varepsilon_{i,t} \quad (2)$$

where τ_t denotes month fixed effects and μ_i denotes fund fixed effects. Net flow is measured in the standard way (net new money scaled by lagged AUM). AUM is in INR. Age is months since inception. Turnover and expense ratios are taken from fund disclosures when available and carried forward between reporting dates. Standard errors are two-way clustered by fund and month.

Sample and coverage*.* Because turnover and expense ratios are disclosed intermittently and are not available for all funds throughout the sample, the regressions are estimated on the subset of fund-months with sufficient coverage for these characteristics (with carry-forward between reporting dates). This restriction reduces the number of fund- month observations relative to the baseline sample used in the main tests.

Table A9. Fund characteristics and liquidity exposure/timing (Panel regressions)

	$\hat{\beta}^{liq}_{i,t}$	$\hat{\gamma}_{i,t}$
$\text{Flow}_{i,t-1}$	0.012**	0.041***
	(2.42)	(4.67)
$\log(\text{AUM})_{i,t-1}$	0.021**	−0.006
	(2.11)	(−0.74)
$\text{Turnover}_{i,t-1}$	0.008*	0.019**
	(1.78)	(2.46)
$\text{Expense}_{i,t-1}$	0.004	0.013*
	(0.61)	(1.69)
$\log(\text{Age})_{i,t-1}$	−0.018**	−0.010
	(−2.06)	(−1.12)
Month FE	Yes	Yes
Fund FE	Yes	Yes
N (fund-months)	23,840	23,840
Adj. R^2	0.17	0.12

Notes: Dependent variables are rolling-window estimates of liquidity exposure ($\hat{\beta}^{liq}$) and liquidity timing ($\hat{\gamma}$), constructed as in the main text. $\text{Flow}_{i,t-1}$ is net flow scaled by lagged AUM; AUM is measured in INR; Age is months since fund inception. Turnover and Expense are taken from fund disclosures when available and carried forward between reporting dates. Month fixed effects absorb common time variation in estimated exposure and timing, while fund fixed effects absorb time-invariant fund heterogeneity (e.g., baseline mandate or investor clientele). Standard errors are two-way clustered by fund and month.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Source: own elaboration.

Results and interpretation. Flow is a strong predictor of the estimated timing coefficient $\hat{\gamma}$ even after controlling for fund fixed effects, consistent with the identification concern that a non-trivial component of measured timing reflects flow-induced reallocations. Turnover and (more weakly) expense ratios are also associated with $\hat{\gamma}$, suggesting that trading intensity and fee structures are correlated with estimated timing. Importantly, conditioning on these characteristics does not eliminate dispersion in either $\hat{\beta}^{liq}$ or $\hat{\gamma}$, and the overall fit remains modest (Adj. R^2 of 0.17 and 0.12). Taken together, these results are consistent with the main-text conclusion that liquidity exposure and the timing channel are not mechanically subsumed by standard fund-type covariates, while still acknowledging that flows (and correlated characteristics such as turnover) contribute to measured timing.

G.2. Conditional double-sorts (turnover and fees)

As an alternative, non-parametric check, we implement conditional (double) sorts designed to test whether the liquidity premium and the timing channel are confined to "high-churn" or "high-fee" funds. Each month, we first split funds into low- and high-turnover groups using the cross-sectional median of turnover measured at $t-1$.

Within each turnover subsample, we form liquidity-beta quintiles using $\widehat{\beta^{liq}}$ (estimated from information available up to $t-1$) and compute the high-minus-low liquidity- beta spread, HMLiq, as in the main text. We then quantify the extent to which the Timer factor absorbs this spread within the turnover-conditioned subsample using the same decomposition as in Table A7. We repeat the same procedure conditioning on expense ratios. If the timing channel were purely mechanical—arising only among high-turnover or high-expense funds—then the HMLiq spread and Timer absorption would be expected to concentrate in those subsamples; if the timing mechanism is broader, the pattern should persist across both low and high subsamples.

Table A10. Conditional Double-Sorts: Liquidity-Beta Spreads Conditioning on Turnover and Expense

Conditional subsample	Mean(HMLiq)	α(CAPM)	Share explained by Timer (%)
Low turnover	0.27	0.24	56
High turnover	0.33	0.30	62
Low expense	0.28	0.25	58
High expense	0.32	0.29	61

Notes*:* The table reports liquidity-beta spreads computed *within* turnover- or expense-conditioned subsamples. Each month, funds are first split into low/high turnover (or low/high expense) using lagged medians. Within each subsample, funds are sorted into $\hat{\beta}^{liq}$ quintiles and HMLiq is computed as Q5–Q1. Mean(HMLiq) and α(CAPM) are reported in % per month. "Share explained by Timer" is computed using the same Timer-based decomposition as in Table A7. The intent is to verify that the liquidity premium and the timing channel are not mechanically confined to turnover- or fee-
intensive funds.
Source*:* own elaboration.

Results and interpretation. Conditioning on turnover and expense does not eliminate the liquidity-beta spread nor the timing channel. Mean(HMLiq) and α(CAPM) remain economically meaningful in both low- and high-turnover subsamples, and the fraction of the spread absorbed by the Timer factor remains large (56–62%). A similar pattern holds when conditioning on expense ratios (58%–61%). This evidence is inconsistent with a purely mechanical interpretation in which the Timer channel arises only among high-churn or high-fee funds; instead, the timing-related component of the liquidity spread appears to operate more broadly across fund types, which is consistent with the main-text findings.

Implementation note. To ensure the conditional sorts are forward-looking, turnover/expense breakpoints use values measured at $t-1$, and liquidity-beta quintiles use $\widehat{\beta^{liq}}$ estimated from information available up to $t-1$ (consistent with the main sorting procedure).