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Satyakam Dev

Manipal Academy of Higher Education

Suman Chakraborty

suman.chakraborty@jaipur.manipal.edu

Manipal University Jaipur

Poornima Panduranga Kundapur

Manipal Academy of Higher Education

Sandeep S. Shenoy

Manipal Academy of Higher Education

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Satyakam Dev^{1, 2}

¹ Manipal School of Commerce and Economics,

² Manipal Institute of Technology,

Manipal Academy of Higher Education, Manipal, Karnataka, India – 576104

Email: satyakam.deo@manipal.edu

ORCID iD: 0000-0003-4525-7048

Contact: +91 9663611063

Suman Chakraborty (Corresponding Author)

Department of Economics,

TAPMI School of Business,

Faculty of Management, Commerce and Arts (FoMCA),

Manipal University Jaipur, Jaipur, Rajasthan, India – 303007

Email: suman.chakraborty@jaipur.manipal.edu

ORCID iD: 0000-0002-3999-7181

Contact: +91 8904916912

Poornima Panduranga Kundapur

Manipal Institute of Technology,

Manipal Academy of Higher Education, Manipal, Karnataka, India – 576104

Email: poornima.girish@manipal.edu

ORCID iD: 0000-0002-8271-524X

Sandeep S. Shenoy

Manipal Academy of Higher Education, Manipal, Karnataka, India – 576104

Email: sandeep.shenoy@manipal.edu

ORCID iD: 0000-0002-9848-9718

Abstract

Indian equity mutual fund managers may realize winning positions sooner than losing ones due to the disposition effect. This study asks whether this pattern is a cognitive bias in the manager or a by-product of meeting redemptions and whether it travels with the manager between firms or is imposed by the fund. The study uses the monthly portfolio holdings of 372 open-ended, direct-plan, growth equity mutual funds in India from 2013 to 2024. The disposition spread is measured as the proportion of paper gains realized, minus the proportion of paper losses realized. It is regressed on lagged fund outflows and market volatility in panel and logistic models with two-way clustering by funds and months. It is also tested around manager moves with a difference-in-differences design and split within each fund by the ESG rating of the held stock. The disposition spread is positive (mean +0.047; positive in 60% of fund-months), with fund outflow as a robust fund-level predictor. A prior-month redemption is associated with approximately a quarter higher odds of a positive spread, surviving four outflow measures, multiple-testing correction, the 2017–18 scheme recategorization split, and removal of the COVID-19 window. Market volatility has no significant effects. Managerial mobility cannot separate an intrinsic trait from the fund environment, and the spread shows no sizeable difference in a holding's ESG rating. Using a holdings panel and datable liquidity shocks, the study asks what the disposition spread responds to and favors a structural "straitjacket" account over a cognitive one.

Keywords: Disposition Effect; Mutual Funds; Forced Selling; Fund Flows; India; ESG; Sustainable Investing;

Paper type: Research paper

1 Introduction

The Indian mutual fund industry held approximately ₹73.73 lakh crore in assets under management (AUM) by March 2026, more than five times the Fig. a decade earlier [1]. Retail money arriving through monthly systematic investment plans (SIPs) has driven much of that growth. Over the same period, the Securities and Exchange Board of India (SEBI), the Indian market regulator, tightened the rules governing the funds. Both the increase in fund flows

and the evolving regulatory framework make the trading behavior of Indian fund managers worth studying.

As institutional money enters Indian equities, managers' biases may affect their decisions and, through them, market efficiency. The disposition effect is one such bias: the tendency to hold losing stocks for too long and sell winning stocks too soon [2], [3], [4]. Retail investors show it [3]. Whether institutional managers do is contested [5].

This paper attempts to take forward the discussion on the disposition effect among Indian mutual fund managers by asking four questions. First, do they show the disposition effect? Second, if they do, what produces it: a cognitive bias in the manager, or a mechanical by-product of having to meet redemptions, a "structural straitjacket"? Third, does a manager carry this bias while switching firms or while managing funds with different mandates within a firm? Fourth, do the disposition effect and its link to redemptions differ for different environmentally rated stocks held by a fund?

To address these questions, the following hypotheses were formulated:

- i. *Baseline Disposition Effect (H1)*: Indian equity fund managers realize winning positions more readily than losing ones, producing a positive disposition spread.
- ii. *Redemption Pressure (H2a)*: Redemptions force fund managers to sell liquid stocks to raise cash. This external pressure imposes a "structural straitjacket" on the manager and generates a positive disposition spread.
- iii. *Market Volatility (H2b)*: High market volatility raises the general pressure to sell and therefore widens the disposition spread.
- iv. *Nature vs. Nurture in Managerial Mobility (H3)*: If the disposition bias is a psychological trait ("nature"), it travels with the manager to a new asset management company (AMC). Instead, if the disposition bias is imposed by a mutual fund mandate ("nurture"), a manager switching to a different mandate within the same AMC adopts the new mandate's bias.

- v. *ESG-Contingent Disposition level (H4a)*: Within the same fund and month, the disposition spread differs between the fund's high-ESG and low-ESG holdings.
- vi. *ESG-Contingent Disposition interaction (H4b)*: The association between fund outflow and the disposition spread differs by the ESG status of the held stock.

These hypotheses test three competing accounts of a positive disposition spread, and each predicts something different. A preference account says that managers like to realize gains, so the spread should hold regardless of fund flows [4], [6]. A general-stress account says turbulence drives selling, so the spread should widen with volatility [7], [8]. A forced-selling account says redemptions push managers to raise cash by selling liquid winners, so the spread should widen with outflows [9], [10]. All three produce a positive average spread. The tests, therefore, ask which of the three accounts impacts the spread.

Splitting a fund's holdings by sustainability rating narrows the contest to two accounts, forced selling and preference [9], [11]. India's 2021 sustainability-disclosure requirement and its 2023 framework for ESG schemes give the question a supervisory audience [12], [13].

Using monthly holdings of 372 open-ended direct growth Indian equity funds from 2013 to 2024, the study measures the disposition spread by the standard holdings-based construction [3], [5]. The spread is then tested against fund redemptions, market volatility, and managerial mobility between firms and fund categories. India serves as the identification setting because two liquidity shocks within the sample period can be dated: the 2017–18 fund recategorization by the market regulator [14], and the COVID-19 redemption episode. Both require funds to trade for reasons outside the manager's control. Market volatility, measured by the India Volatility Index (India VIX), is a third source of selling pressure, but it is a market condition rather than a dated event.

This design yields four findings, one for each question raised above before the proposed hypotheses. The disposition spread is positive. It responds to redemptions and not to general volatility. Whether a manager's own tendency also contributes is a separate question, and the mobility tests are too small to settle it. The redemption result is robust to how outflow is measured, to two-way clustering, to multiple-testing correction, and to the 2017–18 fund

recategorization and the COVID-19 episode. The disposition spread shows no sizeable difference between a fund's sustainable and other holdings, though whether redemptions bite differently on those holdings is not settled at this sample size. The contribution of this work is to separate the structural and cognitive accounts of the disposition effect in an emerging market, using a holdings panel and datable shocks.

The paper is structured as follows: literature review, data and methodology, results, discussion, and conclusion.

2 Literature Review

2.1 Disposition Effect and Institutional Trading

The disposition effect follows from *Prospect Theory*, under which losses loom larger than equivalent gains [15]. [3] measured it with the proportion of gains realized (PGR), the share of winning positions sold in a period, and the proportion of losses realized (PLR), the corresponding share of losing positions. He found that investors sell winners too readily and hold losers too long, avoiding the pain of booking a loss. Later work reports the same pattern [2], [16].

[5] applied Odean's measure to mutual fund managers, which raises a measurement problem. [17] notes that literature suffers from unobserved actions. Because portfolio-holding disclosures occur only at period-end (e.g., quarter-end), researchers must assume that all trades occurred at the period's closing price. This creates a significant but well-known disturbance when calculating the cost basis using Odean's measure. Furthermore, fund managers place large orders as multiple smaller trades [18]. As a result of this trading strategy, the price driving a manager's decision differs from the period-end price. To mitigate this price disturbance, monthly holdings can be used instead of the quarterly data. However, this disturbance cannot be completely ruled out unless fund managers' transactional data are available in the public domain.

Moving forward, whether fund managers show the disposition effect is unsettled. [5] reports that greater financial knowledge helps managers avoid some cognitive traps. [19] review the

evidence and find a weaker effect among institutional investors than among retail traders. The cause of that residual effect is still disputed.

However, previous studies have found that what appears to be a cognitive bias may be something else. [10] shows that managers work under investor redemption pressure. With the objective of minimizing trading costs and maintain portfolio liquidity, fund managers often sell their profit-making liquid stocks and retain the loss-making ones. Generally, the losing stocks are harder to sell without causing a major price drop. The forced selling of profitable stocks artificially increases PGR which mimics the disposition effect pattern even though selling is driven by an external shock.

Another factor that may affect a fund manager's trading and, in turn, may perpetuate the disposition effect, is market volatility. [20] observe that during market shocks, retail investors tend to hold on to the losing positions in the hope of recovery. On the other hand, fund managers focus on risk management. [21] and [22] find that managers raised cash during the COVID-19 pandemic which was more due to a breached value-at-risk threshold than panic. Volatility, therefore, operates through two channels that must be separated in a study. It can mechanically trigger a sale, and can shift a manager's judgment.

2.2 “Nature vs. Nurture” Debate in Institutional Architectures

If an institutional setup imposes a structural straitjacket, it is important to determine whether individual biases still matter. The “nature versus nurture” debate explores whether managers' behavioral traits are driven either by their own bias or the firm's structure. [23] examine how management structures, such as solo versus team-managed funds, affect performance, and find that strong governance reduces poor decisions.

Little research asks how moving to a new firm affects a manager's bias. When a manager joins a new AMC, it is unclear whether the old trading habits travel or the new firm's practice takes over. India offers a useful test because its AMCs differ sharply: public-sector undertaking (PSU) AMCs operate under bureaucratic rules, private AMCs are more aggressive, and bank-sponsored AMCs sit inside banks. How these structures shape a manager's reluctance to realize losses is unknown.

2.3 Sustainable Holdings and the Disposition Effect

Whether investors treat sustainable holdings differently is unsettled, and the two closest results disagree. [24] study customers of a retail bank and find a stronger disposition effect among those holding socially responsible stocks, though only among investors with a substantial share of the portfolio in such stocks. [25] compare socially responsible funds with conventional funds and find no difference. Neither compares the sustainable and conventional holdings sitting side by side in one portfolio.

Splitting one portfolio by sustainability rating separates two of the three accounts mentioned in the previous section. General stress cannot produce a difference, because volatility is common to every holding a fund owns in a month. Forced selling and preference predict opposite signs. In India, the rated universe is the large, liquid segment, so redemption pressure would fall there first, widening the spread, while a preference for sustainable holdings would narrow it [9], [11].

Which account dominates is an empirical question, and it may explain the disagreement mentioned above. Retail investors face no redemptions, so forced selling cannot operate on them. On the other hand, fund managers face both pressures at once, and the two may offset. The accounts are not independent either, since sustainable demand weakens under household income stress [26]. Preference is weakest in exactly the months when redemption pressure is strongest.

However, there are three measurement problems bound to such a test. First, sustainability rating agencies disagree on the same firm [27], so pooling agencies would sort firms by who rated them. The split here, therefore, uses one agency, CRISIL, which rates the largest number of Indian firms in the source data. Second, sustainability ratings track firm size and liquidity, so a size effect can appear to be an ESG effect, as size enters both as a control and as a matched robustness check. Third, a manager still chooses which stocks to sell when money leaves, and that choice is what this study measures [28].

2.4 Indian Context: A Unique Testing Ground

India is well-suited to explore the above-discussed aspects for structural reasons. Its capital markets have formalized as the economy has grown. Moreover, SEBI regulations on fund

categorization and holding disclosure make portfolios observable month by month. Steady SIP inflows sit alongside episodes in which the pressure to sell changes for reasons outside a manager's control. Those episodes are what make the competing accounts testable against each other.

Based on the above review of literature, four gaps emerge. First, holdings-based estimates rest on quarterly disclosure, so trades inside the quarter are unobserved. Second, the debate over managerial disposition bias has not separated a manager's preference from the pressure to meet redemptions. Third, whether the bias travels with a manager or is imposed by the firm and the mandate has not been tested. And lastly, no study splits the holdings within a single fund by their sustainability rating.

3 Methodology

3.1 Data Sources and Sample Construction

Monthly portfolio holdings of 372 open-ended direct growth equity schemes were obtained from the *ICRA Analytics*¹ database for January 2013 to October 2024. The sample holds 210 private, 133 bank-sponsored, and 29 PSU schemes. The database also carries total net assets, expense and turnover ratios, other fund features, and manager characteristics. The Carhart four-factor data set is obtained from the data library of the *Indian Institute of Management Ahmedabad* [29], [30]. The past 12-month Carhart-adjusted fund return series begins in January 2014. Because the disposition measure needs a prior month to establish a cost basis and to observe a change in share count, the measured panel begins in February 2013. Daily closing values of the India VIX are taken from the *National Stock Exchange of India* and averaged within each calendar month. Full names and access links for all four data sources are given in the Availability of Data and Materials statement.

For the ESG test, the CRISIL ratings of 854 firms for 2023-24 were downloaded from the *Capitaline AWS*² database. A held stock is high-ESG if its composite rating is at or above the

¹ Link: <https://www.icraanalytics.com/>

² Link: <https://awsone.capitaline.com/>

median of this rated universe and low-ESG otherwise, using one fixed cross-sectional cut, with the Environment sub-score as a secondary measure. Mandatory sustainability disclosure began for large listed firms in 2021, so rating coverage concentrates in the large-capitalization segment [12]. The rating is applied only to fund-months from *January 2023 to October 2024*. It is never carried back over the earlier sample.

3.2 Variable Construction: Quantifying the Disposition Effect

Disposition spread, the dependent variable, is constructed using the standard method for calculating the disposition effect [2], [3], [5]. The cost basis (or the reference price) for each equity position j held by Fund i at time t is calculated from the weighted average purchase price. If the current price of the held position is greater (less) than the reference price, then the stock is labeled as a paper gain (loss). PGR, PLR, and disposition spread are calculated as follows:

$$PGR_{i,t} = \frac{RG_{i,t}}{RG_{i,t} + PG_{i,t}}; PLR_{i,t} = \frac{RL_{i,t}}{RL_{i,t} + PL_{i,t}}; DISP_SPREAD_{i,t} = PGR_{i,t} - PLR_{i,t} \quad (1)$$

where RG is the number of stocks with realized gain during the month, and RL is the number of stocks with realized loss. PG is the number of stocks with paper (or unrealized) gain, and PL is the number of stocks with paper (or unrealized) loss. PGR is therefore the share of its winning stocks that a fund sold in the month, and PLR is the share of its losing stocks. DISP_SPREAD, the disposition spread, is the difference between the two rates. So, a positive value (tests H1) means the fund sold winners at a higher rate. As all four terms (RG , RL , PG , and PL) count stocks rather than money, the spread shows *how often a manager sells a winner, not how much that sale is worth*.

3.3 Econometric Specifications: Panel and Logistic Frameworks

A series of multivariate panel regressions tests H2a and H2b. The first model (Model 1) relates the disposition spread to fund characteristics and organizational structure:

$$DISP_SPREAD_{i,t} = \alpha + \beta_1 PTR_{i,t-1} + \beta_2 Outflow_{i,t-1} + \beta_3 AMC_i + \gamma X_{i,t-1} + \lambda F_t + \epsilon_{i,t} \quad (2)$$

where $PTR_{i,t-1}$ is the fund's lagged portfolio turnover, which tests whether the disposition spread varies with how often the fund trades. $Outflow_{i,t-1}$ is a binary indicator equal to 1 when the scheme recorded a negative net flow in the previous month and 0 otherwise. It is taken from the vendor's (*ICRA Analytics*) monthly flow. AMC_i indicates a PSU-managed, Private-managed, or Bank-managed fund. $X_{i,t-1}$ is a vector of lagged fund controls: the past 12-month Carhart-adjusted fund return, and the Herfindahl–Hirschman index (HHI), which measures portfolio concentration. F_t holds the four Carhart asset-pricing factors (MF, SMB, HML, WML). The two heavy-tailed continuous outflow measures introduced in the specification curve are winsorized at the 1st and 99th percentiles; that is, values beyond those percentiles are set to those percentiles.

Model 1b adds one variable to Model 1: the previous month's net flow in rupee crore. The outflow indicator records whether money left the fund; net flow records how much. Model 1b tests whether the outflow result survives once the amount is controlled.

The binary indicator records the fact of an outflow, not its size. Model 1 is, therefore, re-estimated with three further measures of the same event, leaving every control and the fixed effects unchanged and swapping only the outflow term. A set of estimates of one effect under alternative measurements of the same regressor is a specification curve. The first alternative is the size of the outflow in rupee crore, set to 0 in months of net inflow. The second divides that size by the fund's net assets, giving the share of the fund redeemed. The third is the fund's percentile rank on outflow size among all funds in the same month, which removes any month-specific scale. All four measures are lagged by one month, and the two size measures are winsorized at the 1st and 99th percentiles of the pooled panel. The size measure is 0 during inflow, which is 53% of the estimation sample, so it is not the signed net flow of Model 1b, and the two coefficients are not comparable.

Model 2 adds two market-condition terms, $India_VIX_t$ and $COVID_Dummy_t$ to Model 1. $India_VIX_t$ is the India Volatility Index, averaged over the trading days in the month t and common to every fund. $COVID_Dummy_t$ equals 1 for the 10 months from March 2020 to December 2020 and 0 otherwise. Their interaction allows the association with volatility to differ within that window:

$$\text{DISP_SPREAD}_{i,t} = \alpha + \theta_1 \text{India_VIX}_t + \theta_2 \text{COVID_Dummy}_t + \theta_3 (\text{India_VIX}_t \times \text{COVID_Dummy}_t) + \gamma Z_{i,t} + \epsilon_{i,t} \quad (3)$$

Here, $Z_{i,t}$ denotes every regressor in the equation (2).

A logistic persistence model (Model 3) asks whether a positive disposition spread is a steady feature of a fund or a state that follows redemptions. It models the probability that a fund records a positive disposition spread, $(\Pr(\text{DISP_SPREAD}_{i,t} > 0))$ given the previous month's outflow ($\text{Outflow}_{i,t-1}$):

$$\ln\left(\frac{p_{i,t}}{1 - p_{i,t}}\right) = \alpha + \delta_1 \text{Outflow}_{i,t-1} + \delta_2 \text{AMC}_i + \delta_3 \text{HHI}_{i,t-1} + \epsilon_{i,t} \quad (4)$$

where $p_{i,t}$ is the probability that $\text{DISP_SPREAD}_{i,t} > 0$.

3.4 Generalized Difference-in-Differences (DiD) Framework

To separate a manager's behavioral bias ("nature") from the impact of company structure ("nurture"), a generalized difference-in-differences (DiD) framework is used. Inter-AMC mobility (managers moving from one AMC to another) and intra-AMC mobility (managers switching to a different fund within an AMC) are tracked. The inter-AMC specification is referred to as Model 4, and the intra-AMC specification as Model 5.

$$\text{DISP_SPREAD}_{m,i,t} = \theta_m + \lambda_t + \omega_1 \text{Post}_{m,t} + \omega_2 (\text{Post}_{m,t} \times \text{Target_Bias}_c) + X_{i,t} \beta + \epsilon_{m,i,t} \quad (5)$$

where θ_m and λ_t represent the manager and time fixed effects, respectively. $\text{Post}_{m,t}$ is a binary variable that takes 1 in the periods after the manager m takes over the new fund i . The interaction term $\text{Post}_{m,t} \times \text{Target_Bias}_c$ is the focus. Target_Bias_c is the mean disposition spread of the destination before the move, computed while leaving the mover out. The destination is the new AMC in Model 4 and the new fund category in Model 5. Being itself an estimate, Target_Bias_c is a generated regressor, and the standard errors are not adjusted for that.

Within an AMC, the firm's culture is held constant, so Model 5 isolates the pressure of the fund category itself. A causal reading requires an assumption that cannot be observed: that

without the move, the spread would have followed the same path as the comparison manager-months. The event study tests what can be tested, namely, whether the spread was already underway before the switch.

Three diagnostics accompany each model. An event study estimates the spread in 6-month bins around the move, against the 6 months before it as the base. Parallel trends require the pre-move bins to sit near zero. A placebo re-estimates the post-move term on 1,000 randomly assigned move dates for the same managers. It reports how often a random date produces an estimate as large as the true one. The minimum detectable effect, 2.8 times the standard error, gives the smallest effect the test could have detected at 80% power and 5% significance level. Reporting it allows a null to be read against that bound rather than against zero alone.

3.5 ESG-Contingent Disposition Test

Each fund's holdings in each month are split into a high-ESG and a low-ESG bucket. Then the disposition spread is recomputed within each bucket on the same average-cost, count-based construction as the equation (1). The classification engine runs over the full 2013–2024 history so that cost bases carry the complete holding record, but buckets are formed only for the rating window, January 2023 to October 2024. Earlier months enter through the cost basis alone and add no observation. A bucket enters only if it holds at least ten classifiable positions and one realized position that month, and a fund-month contributes only when both buckets clear that rule, because the fund-by-month fixed effect identifies the gap from the two buckets of the same fund in the same month.

For each bucket, PGR and PLR are computed over that bucket's positions, and their difference is taken as the bucket disposition spread:

$$PGR_{i,b,t} = \frac{RG_{i,b,t}}{RG_{i,b,t} + PG_{i,b,t}}; PLR_{i,b,t} = \frac{RL_{i,b,t}}{RL_{i,b,t} + PL_{i,b,t}}; DISP_SPREAD_{i,b,t} = PGR_{i,b,t} - PLR_{i,b,t} \quad (6)$$

where RG, RL, PG and PL are defined above in the subsection 3.2. Here they are considered for the positions in bucket b of fund i in month t . Three specifications on the fund-month by

ESG-bucket panel are estimated. The first (E1) regresses the bucket disposition spread on a high-ESG indicator with a fund-by-month fixed effect:

$$DISP_SPREAD_{i,b,t} = \delta_{i,t} + \beta_1 HighESG_b + \varepsilon_{i,b,t} \quad (7)$$

where $HighESG_b$ equals 1 for the high-ESG bucket and 0 for the low-ESG bucket, and $\delta_{i,t}$ is a fund-by-month fixed effect. Because this fixed effect absorbs everything common to a fund in a given month, β_1 is the average within-fund-month gap between the two buckets. The second (E2) adds the bucket's mean log market capitalization and its position count:

$$DISP_SPREAD_{i,b,t} = \delta_{i,t} + \beta_1 HighESG_b + \beta_2 \ln MCAP_{i,b,t} + \beta_3 NPOS_{i,b,t} + \varepsilon_{i,b,t} \quad (8)$$

The third (E3) adds the interaction of the high-ESG indicator with the prior-month fund-outflow indicator:

$$DISP_SPREAD_{i,b,t} = \delta_{i,t} + \beta_1 HighESG_b + \beta_2 \ln MCAP_{i,b,t} + \beta_3 NPOS_{i,b,t} + \beta_4 (HighESG_b \times Outflow_{i,t-1}) + \varepsilon_{i,b,t} \quad (9)$$

The outflow main effect is absorbed by the fund-by-month fixed effect, because outflow varies only at the fund-month level. Only the interaction term β_4 is identified. E1 and E3 are both two-sided tests because the two accounts discussed after hypothesis formulation predict opposite signs. Forced selling of liquid, highly rated stocks would widen the spread on high-ESG holdings. However, a preference for sustainable holdings would narrow it.

The level gap is re-estimated under seven alternative constructions, each changing one element of the split while the fixed effect and the clustering stay unchanged. They vary the rating source, the split rule, the window, and the dependent variable, and all are reported in Online Resource 1. Sample sizes differ because each rule leaves a different number of fund-months in which both buckets are usable. The minimum detectable effect, 2.8 times the standard error, is reported for the high-ESG term and the interaction.

3.6 Estimation and Inference

All panel models are estimated using ordinary least squares with fixed effects at the SEBI fund-category level. The standard errors reported throughout are two-way clustered, by

fund and by month. Heteroskedasticity-robust and fund-only clustered errors are computed alongside for comparison. The logistic model (Model 3) is estimated using maximum likelihood, with standard errors clustered at the fund level. AMC type is coded as Bank, Private, or PSU, with Bank as the omitted reference category, so the reported PSU and Private coefficients are differences relative to Bank-sponsored funds.

4 Results

This section reports the estimates and their diagnostics. Interpretation is presented in the Discussion.

4.1 Descriptive Statistics

Table 1 reports the disposition-effect measures across 39,070 fund-months. PGR averages 0.165 and PLR 0.118, giving a mean disposition spread of +0.047 (SE 0.00253, $p < .001$). The spread is positive in 60% of fund-months, negative in 28%, and zero in 12%, the last almost all being months with no realization of either kind. A positive spread means winners are realized more readily than losers, and these estimates test H1.

Table 1: Descriptive Statistics for the Disposition-Effect Measures

Measure	Mean	Median	SD	P25	P75
PGR	0.165	0.125	0.164	0.048	0.235
PLR	0.118	0.063	0.167	0.000	0.167
Disposition spread (PGR – PLR)	+0.047*** (0.00253)	+0.040	0.154	–0.017	+0.126

Note. PGR = proportion of gains realized; PLR = proportion of losses realized. Both are computed on a count basis, from an average-cost reference price. The spread has no value when a fund holds no position at a gain, or none at a loss, because one ratio then has no denominator; this removes 432 of the 39,502 fund-months, leaving 39,070 across 372 schemes, February 2013 to October 2024. The positive sign holds under all four reference-price rules and under 1/99% winsorizing. Weighting positions by rupee value rather than counting them leaves the spread positive but much smaller, at +0.0045. *** $p < .01$. ** $p < .05$. * $p < .10$.

4.2 Baseline Panel, Market-Condition and Persistence Models

Table 2 reports the panel and logistic estimates. In Table 2, Panel A, the dependent variable is the continuous disposition spread. Models 1 and 1b test H2a. Model 2 adds the India VIX, a COVID-19 indicator, and their interaction, and tests H2b. Table 2, Panel B replaces the spread with an indicator that equals 1 when the spread is positive and retests H2a.

Lagged fund outflow is the only fund-level variable that survives two-way clustering. A fund-month that follows an outflow month carries a spread higher by 0.0234 in Model 1 ($t = 8.35$, $p < .001$), about half the sample mean spread. Adding a net-flow control (Model 1b) leaves outflow positive at 0.0196 ($t = 6.88$, $p < .001$). Net flow itself enters negatively, at -0.00004 per rupee crore ($t = -3.40$, $p < .001$). Adding the India VIX, a COVID-19 dummy, and their interaction (Model 2) changes none of this; none of the three macro terms reaches significance (all $p > .10$). The India VIX takes one value per month, so Model 2 identifies it from 129 months rather than from the 32,449 fund-months that identify the outflow term. Under two-way clustering, none of the variables AMC dummy, the market factor, past fund alpha, portfolio turnover, the value factor, or the momentum factor is significant (Online Resource 1).

In Table 2, Panel B, a prior-month outflow is associated with odds of a positive spread about a quarter higher (odds ratio 1.27, $z = 6.91$, $p < .001$). Portfolio concentration is associated with lower odds (HHI, odds ratio 0.95, $z = -4.20$), and neither AMC dummy is significant.

Table 2: Panel and Logistic Estimates of the Disposition Spread

Panel A. Panel regressions (dependent variable: disposition spread)			
Variable	Model 1	Model 1b	Model 2
Constant	0.0289 (0.0195)	0.0323* (0.0194)	0.0255 (0.0219)
Portfolio turnover (t-1)	-0.00001 (0.00002)	-0.00001 (0.00002)	-0.00001 (0.00002)
AMC: PSU	0.0101 (0.0096)	0.0094 (0.0095)	0.0100 (0.0096)
AMC: Private	0.0078 (0.0048)	0.0073 (0.0047)	0.0077 (0.0048)
Herfindahl HHI (t-1)	0.00010 (0.0011)	0.00002 (0.0011)	0.00004 (0.0011)
Past fund alpha (t-1)	-0.1731 (0.1553)	-0.1495 (0.1550)	-0.1706 (0.1627)

Fund outflow (t-1)	0.0234*** (0.0028)	0.0196*** (0.0029)	0.0233*** (0.0028)
Net flow (t-1)	—	-0.00004*** (0.00001)	—
Market factor (MF)	-0.0004 (0.0004)	-0.0004 (0.0004)	-0.0004 (0.0004)
Size factor (SMB)	-0.0010** (0.0004)	-0.0010** (0.0004)	-0.0009** (0.0005)
Value factor (HML)	-0.0001 (0.0004)	-0.0001 (0.0004)	-0.0001 (0.0004)
Momentum factor (WML)	-0.0001 (0.0004)	-0.0001 (0.0004)	-0.00004 (0.0003)
India VIX	—	—	0.0002 (0.0006)
COVID-19 dummy	—	—	0.0060 (0.0155)
India VIX × COVID	—	—	-0.0001 (0.0007)
<i>N</i>	32,449	32,449	32,449
<i>R</i> ²	0.0117	0.0126	0.0119

Note. Estimator: OLS with fixed effects at the SEBI fund-category level. Two-way (fund and month) clustered standard errors are in parentheses. Panel A uses 32,449 of the 39,070 fund-months with a defined spread, covering 370 of the 372 funds over 129 months, February 2014 to October 2024. Two lagged controls bind: the past 12-month Carhart-adjusted return, unavailable in 4,781 fund-months because the vendor's rolling series begins in January 2014, and portfolio turnover, unavailable in 3,921 and never reported for two schemes, which therefore drop out. MF = market factor; SMB = size factor; HML = value factor; WML = momentum factor; HHI = Herfindahl-Hirschman index. *** $p < .01$. ** $p < .05$. * $p < .10$

Panel B. Logistic persistence (dependent variable: 1 if disposition spread > 0) (Model 3)

Variable	Coefficient (log-odds)	SE (fund- clustered)	z	Odds ratio
Constant	0.5555***	0.0639	+8.70	1.743
Fund outflow (t-1, binary)	0.2361***	0.0342	+6.91	1.266
Herfindahl HHI (t-1)	-0.0485***	0.0115	-4.21	0.953
AMC: PSU	0.0506	0.1158	+0.44	1.052
AMC: Private	-0.0478	0.0597	-0.80	0.953

Note. Estimator: binary logit, maximum likelihood, with standard errors clustered by fund. N = 38,325; 372 fund clusters; McFadden pseudo- R^2 = .0058; mean of the dependent variable = .607. The model loses 745 fund-months for want of a lagged outflow value, 369 of them a fund's first observed month. Adding category dummies leaves the outflow odds ratio at 1.26. *** $p < .01$. ** $p < .05$. * $p < .10$.

4.3 Outflow Specification Curve

Fig. 1 reports Model 1 re-estimated under the four outflow measures defined in the Methodology, and Online Resource 1: Table S8 gives the estimates behind it. The coefficient stays positive and significant at the 1% level under two-way clustering in all four (t between 4.3 and 8.7), with a per-standard-deviation effect of .006 to .013. The ratio to fund assets is the weakest, at about half the others and with a fit a third lower (R^2 = .008 against .012). Scaling by fund size attenuates the association without removing it. This retests H2a.

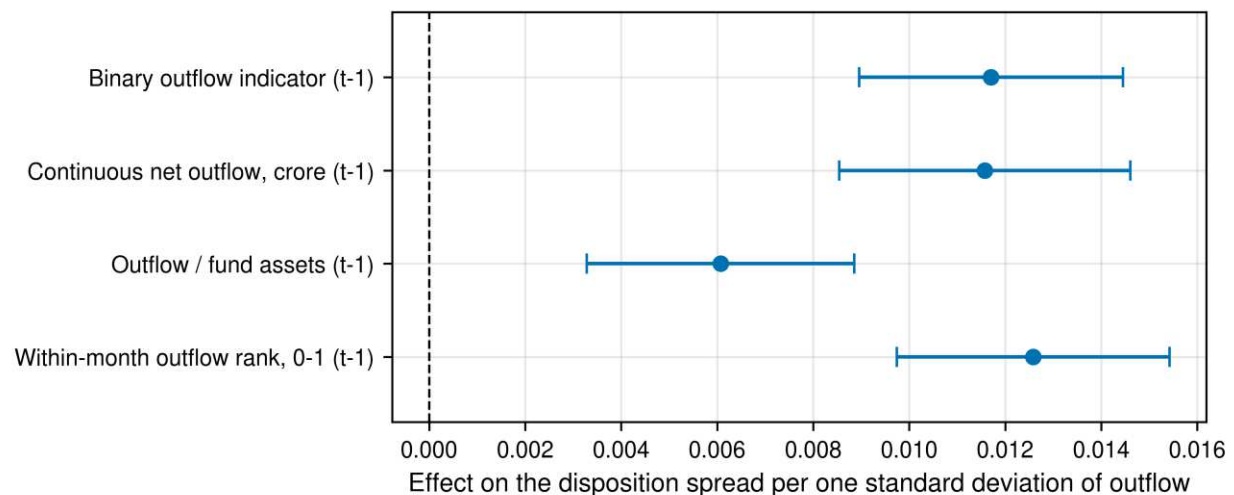


Fig. 1 Outflow specification curve

Note. Model 1 re-estimated under four measures of prior-month fund outflow, with 95% confidence intervals from two-way (fund and month) clustered standard errors. Points are the effect on the disposition spread per 1 SD of outflow.

4.4 Managerial Mobility

H3 asks whether the disposition effect is a trait of the manager or a product of the firm and the mandate. It is tested on a manager-month panel, the spread averaged over the funds each manager runs. Model 4 covers changes of firm and Model 5 changes of fund category within a firm. Each is estimated with the post-move indicator alone (Specification A) and with its interaction with the destination's bias (Specification B).

Table 3 reports both models with the mover counts and the minimum detectable effect, so each null can be read against a bound. Inter-firm moves involve 38 managers over 1,370 manager-months. The post-move indicator is 0.002 ($p = .89$) and the interaction with the destination's bias is 1.41 ($p = .40$), against a minimum detectable effect of 0.047 on the post-move term, about the size of the mean spread, so this test is underpowered. Its event study shows no pre-move trend (Fig. 2), and a placebo on 1,000 randomized move dates places the estimate inside the random distribution (Fig. 3, share .78). Intra-firm moves involve 165 managers over 5,226 manager-months, with a minimum detectable effect of 0.025. The interaction is 1.07 ($p = .016$) and the post-move term -0.057 ($p = .011$), together implying convergence on the destination category's mean spread; no placebo draw exceeds the Specification A estimate. The intra-firm event study does not support parallel trends (Fig. 2): the spread sits 0.033 above its pre-move base two years out and falls steadily to that base by the move, and the post-move bins continue the same decline. In both tests the lagged outflow control stays positive within-manager ($p < .001$).

Table 3: Managerial-Mobility DiD Estimates of the Manager-Month Disposition Spread

Variable	Inter-AMC, Spec A	Inter-AMC, Spec B	Intra-AMC, Spec A	Intra-AMC, Spec B
Post-move (= 1 after)	0.0022 (0.0166)	-0.0592 (0.0737)	-0.0153* (0.0088)	-0.0572** (0.0224)
Post × Target bias	—	1.4135 (1.6837)	—	1.0709** (0.4443)
Past alpha (t-1)	-0.6945 (0.9714)	-0.6692 (0.9525)	-0.2383 (0.5322)	-0.2415 (0.5057)
Herfindahl HHI (t-1)	0.0074 (0.0052)	0.0065 (0.0051)	-0.0021 (0.0024)	-0.0028 (0.0023)

Portfolio turnover (t-1)	0.0001 (0.0002)	0.0001 (0.0002)	-0.0000037 (0.0000485)	-0.0000036 (0.0000491)
Fund outflow (t-1)	0.0403*** (0.0105)	0.0407*** (0.0106)	0.0317*** (0.0060)	0.0315*** (0.0059)

Note. Manager and month fixed effects; two-way (manager and month) clustered standard errors are in parentheses. Specification A includes the post-move indicator only; Specification B adds its interaction with target bias, the destination's leave-the-mover-out pre-move mean spread, which is a generated regressor. Inter-AMC: 38 movers, 1,370 manager-months, within- R^2 .021, minimum detectable effect 0.047. Intra-AMC: 165 movers, 5,226 manager-months, within- R^2 .009, minimum detectable effect 0.025. The placebo and event-study diagnostics are reported in the text and in Figures 2 and 3. *** $p < .01$. ** $p < .05$. * $p < .10$.

Fig. 2 plots the event study around a move, inter-firm, and intra-firm. Fig. 3 plots the placebo distribution against the true estimate.

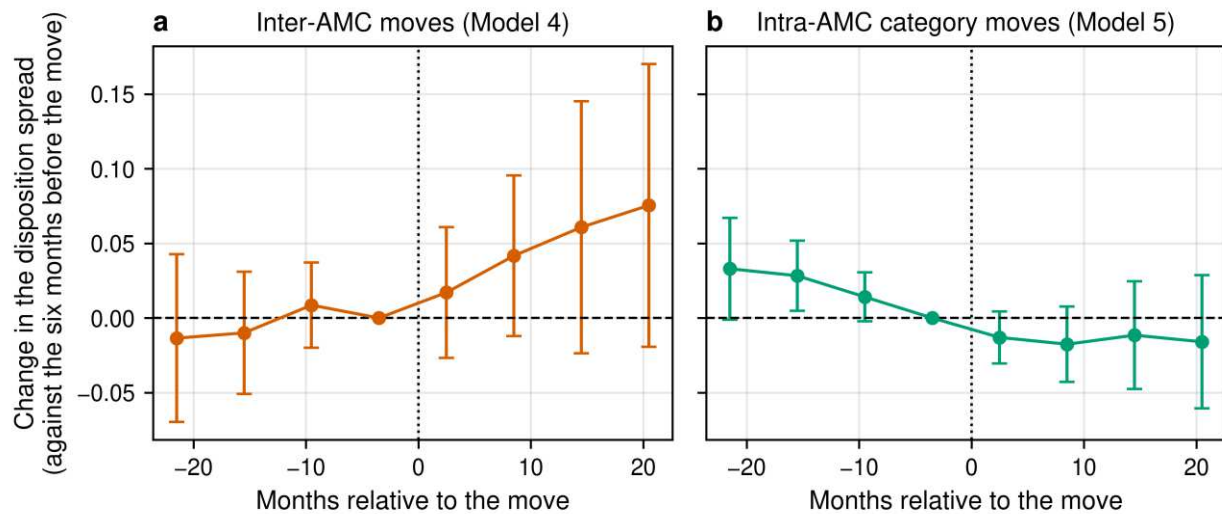


Fig. 2 Manager-mobility event study

Note. Change in the manager-month disposition spread in six-month bins around a move, against the six months before it, with manager and month fixed effects and two-way clustered

95% confidence intervals. an inter-AMC moves, Model 5. The dotted vertical line marks the move.

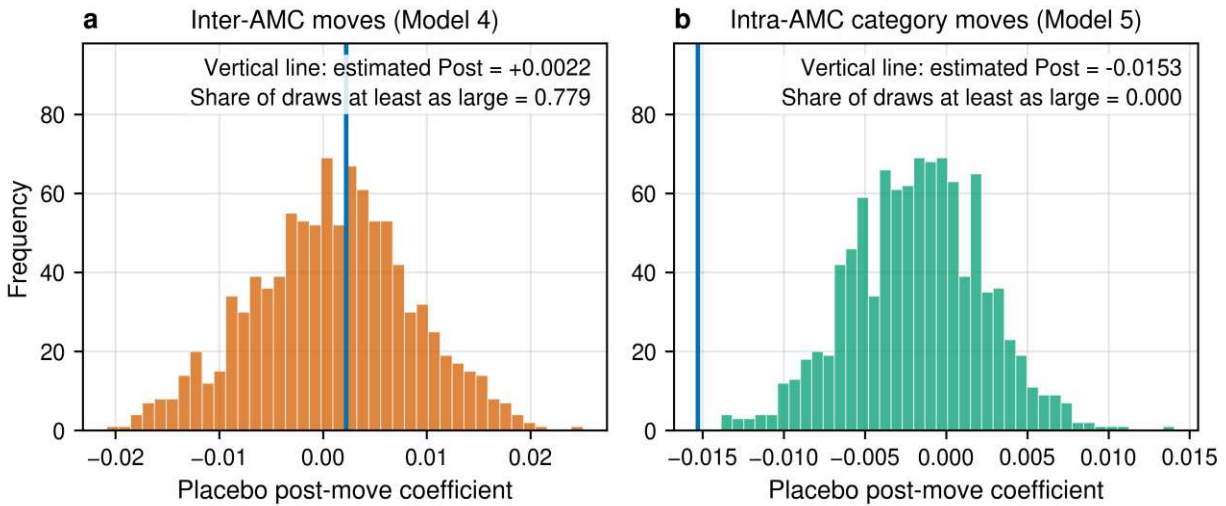


Fig. 3 Placebo distributions from randomized move dates

Note. Distribution of the post-move coefficient over 1,000 random move dates for the same managers, with the estimated coefficient marked. a inter-AMC, Model 4. b intra-AMC, Model 5

4.5 Disposition Spread by ESG Status

The rating window, January 2023 to October 2024, contains 8,184 fund-months, in which CRISIL-rated stocks account for 92.7% of fund equity value on average, with a median of 47 rated positions per fund-month. Splitting those holdings gives 15,880 bucket-months, of which 9,826 clear the ten-position rule and 9,372 have a defined spread. Only 2,342 fund-months, drawn from 223 of the 372 schemes, hold a usable bucket on both sides, and these identify the estimate; of the 4,688 unpaired bucket-months, 4,498 are high-ESG buckets whose low-ESG counterpart is too thin. Table 4 reports the three specifications; E1 tests H4a and E3 tests H4b.

The within-fund-month gap between high- and low-ESG holdings is -0.010 (standard error 0.012, $t = -0.82$), against an average spread of $+0.047$ in the full sample. It is not distinguishable from zero ($p = .409$), and its minimum detectable effect is 0.033, about 70% of the $+0.047$ full-sample mean spread. The estimate uses 4,684 bucket-months across 2,342

fund-month cells, 223 funds, and 22 months, and it equals the mean within-cell high-minus-low difference exactly.

Adding the bucket's size and count controls (E2) moves the estimate to +0.002 and raises the standard error from 0.012 to 0.032, so E2 is the less precise of the two level estimates, with a minimum detectable effect of 0.089. Both controls sit close to the bucket indicator by construction, since the rated universe is the larger-capitalization segment. Adding the interaction with prior-month outflow (E3) gives +0.018 (SE 0.023, $t = 0.80$, $p = .422$) and a minimum detectable effect of 0.064. The high-ESG level term in E3 is -0.003 (SE 0.031), the gap in months without a prior outflow.

The level gap was re-estimated under seven alternative constructions, reported in Online Resource 1. Two address the most direct objections to the split: the Environment sub-score in place of the composite rating gives -0.002 , and a split on the median rating within each market-capitalization tercile, which holds size fixed, gives -0.004 . Across all seven, the gap stays small and insignificant, and the largest absolute t is 1.20. Sample sizes differ because each rule leaves a different number of fund-months with both buckets usable, and three rows exceed the primary panel because they classify stocks the primary split leaves out. The value basis is the only construction with a positive estimate, at +0.0046.

Table 4: ESG-contingent estimates of the within-fund-month disposition spread

Variable	E1	E2	E3
High-ESG bucket	-0.0097 (0.0118)	+0.0020 (0.0318)	-0.0032 (0.0307)
Bucket mean ln(market cap)	—	-0.0064 (0.0265)	-0.0086 (0.0267)
Bucket position count	—	-0.0003 (0.0008)	-0.0003 (0.0008)
High-ESG $\times$ outflow ($t-1$)	—	—	+0.0184 (0.0229)
N (bucket-months)	4,684	4,684	4,678
Fund-month cells	2,342	2,342	2,339
Within- R^2	.001	.002	.003
Minimum detectable effect	0.033	0.089	0.064

Note. Dependent variable: the disposition spread (PGR minus PLR) per fund-month by ESG bucket, average-cost count basis. Fixed effect: fund by month cell; two-way (fund and month) clustered standard errors in parentheses. A fund-month enters only when both of its buckets clear the inclusion rule. The minimum detectable effect applies to the high-ESG term in E1 and E2 and to the interaction in E3. No estimate is significant at the 10% level.

Fig. 4 plots mean spreads by bucket, with and without a prior-month outflow, over the 9,362 bucket-months carrying both. These means carry no fixed effect and are not the estimates in Table 4.

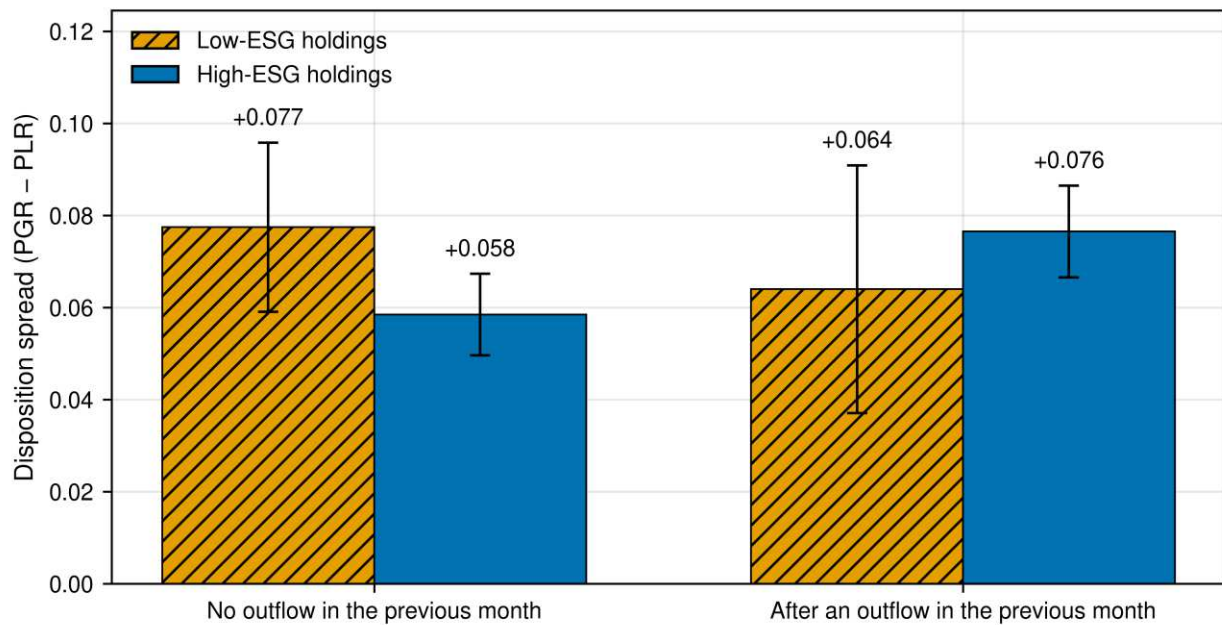


Fig. 4 Disposition spread on high- versus low-ESG holdings, in months with and without a prior-month fund outflow

Note. Bars are mean within-bucket spreads over 9,362 bucket-months, with 95% confidence intervals clustered on fund. Hatched bars are low-ESG holdings. These means carry no fixed effect and are not the estimates in Table 4.

4.6 Robustness

Online Resource 1 reports robustness checks, and the redemption result holds across all of them. Fund outflow is the only baseline coefficient surviving both a Romano–Wolf step-down and a Benjamini–Hochberg correction at the 5% level; the size factor survives the step-down

at .003 but clears Benjamini–Hochberg only at 10% (Online Resource 1: Table S1). The largest variance inflation factor is 1.502 (Online Resource 1: Table S2). The monthly mean spread is stationary while the India VIX is persistent, which is why its coefficient is read with care (Online Resource 1: Table S3). Split at the 2017–18 SEBI recategorization, lagged outflow is +0.0154 before and +0.0273 after, positive and significant in both eras, though estimated on separate samples and not tested against each other (Online Resource 1: Table S4). Removing the COVID-19 window leaves outflow at +0.0215, $p < .001$ (Online Resource 1: Table S5). Volatility is insignificant wherever it is estimated. Across the three panel models the two-way clustered standard error is the largest of the three constructions for all 34 slope coefficients, so the reported inference is the most conservative available (Online Resource 1: Table S6). Seven further ESG constructions leave the level gap small and insignificant (Online Resource 1: Table S7).

5 Discussion

This section analyzes the estimates against the three accounts set out in the Introduction.

5.1 Summary of the Hypothesis Tests

Table 5 presents the findings on each hypothesis, the estimate behind it, and where that estimate is reported.

Table 5: Verdict on Each Hypothesis

Hypothesis	Statement	Verdict	Reported in	Basis
H1	Positive disposition spread	Supported	(Table 1)	Mean +0.047 ($t = 18.6$, $p < .001$); positive in 60% of 39,070 fund-months
H2a	Redemption pressure widens the spread	Supported	(Tables 2; Fig. 1; Online Resource 1)	+0.023 ($t = 8.35$); positive under all four outflow measures, the logit, the multiple-testing correction, the SEBI split and the ex-COVID window
H2b	Market volatility	Not supported	(Table 2, Model 2;	India VIX +0.0002 per index point ($t = 0.35$); insignificant wherever volatility is estimated

	widens the spread		Online Resource 1)	
H3 nature	The bias travels with the manager between firms	Not testable at this power	(Table 3)	38 movers; minimum detectable effect 0.047, about the size of the mean spread
H3 nurture	The firm and mandate reshape the bias	Suggestive, not causal	(Table 3; Fig. 2)	Convergence toward the destination mean, but the spread was already falling for two years before the move and keeps falling after it
H4a	Level gap by ESG status	Precise null	(Table 4)	-0.010; minimum detectable effect 0.033
H4b	Outflow interaction by ESG status	Imprecise; sign consistent with forced selling	(Table 4)	+0.018; minimum detectable effect 0.064
<i>Note.</i> Verdicts follow from the estimates reported in the Results. Panel estimates use two-way (fund and month) clustered standard errors; the mobility estimates are clustered by manager and month. A null is read against its minimum detectable effect rather than against zero alone.				

5.2 Disposition Effect Is Present and Positive

Indian equity fund managers realize winners more readily than losers. The disposition spread averages +0.047 and is positive in 60% of fund-months. Its size here is of the same order as the +0.05 [3] reports for those accounts and the +0.03 [31] reports for United States mutual funds. Chen et al. [32] report a stronger effect for Chinese investors than for the United States benchmark. The comparison is one of direction and order of magnitude, not of rank, because both ratios fall as portfolios grow and each study aggregates them differently [3], [5]. A positive spread does not identify its cause.

5.3 Redemptions, Not Manager Preference, Best Explain the Spread

The three accounts predict different things. Preference implies the spread holds whatever the flows are; general stress implies it widens with volatility; forced selling implies it widens when money leaves the fund. Table 5 gives the verdict on each.

The data matches the third account. In the month after net withdrawals, a fund's disposition spread is 0.023 higher than after a month of net inflows, about half the average spread (Table 2, Panel A), and the odds that the spread is positive are about a quarter higher (Table 2, Panel B). The result holds under four measures of outflow (Fig. 1), after correcting for the number of tests run, on both sides of the 2017–18 SEBI recategorization, and with the COVID-19 months removed (Online Resource 1). Outflow is the only fund-level variable that stays positive and significant through all of these checks. No other variable is positive and significant across all of these.

However, volatility behaves differently. A one-point rise in the India VIX is associated with a 0.0002 change in the spread, which is not significant ($t = 0.35$), and volatility is insignificant in every model that includes it (Table 2, Panel A; Online Resource 1). Preference cannot explain why the spread moves with withdrawals at all. General stress predicts a link to volatility that the data does not show. Forced selling fits both facts. This is the structural straitjacket, and the evidence favors it over the cognitive-bias reading.

The two readings call for different responses. If the spread reflected a manager's bias, the lever would be training or incentives. Since it moves with redemptions, the lever is how the fund handles liquidity: its redemption terms, its cash buffer, and how easily its holdings can be sold. Responsibility sits with the AMC and the product design more than with the individual manager.

5.4 Nature Versus Nurture: What the Data Can and Cannot Say

The two mobility tests differ in size. The between-firm test is based on 38 managers switching AMCs. This movement has created a disposition effect of 0.047 which is about the size of the average spread. The test could have caught a change large enough to double the spread or erase it (Table 3). Its estimate is 0.002, and 78 of every 100 randomized move

dates produce an estimate at least as large (Fig. 3). The null means the test is too small, not that there is nothing to find.

The within-firm test is larger: 165 managers who changed mandate inside the same firm, with a smallest detectable effect of 0.025. After such a move, a manager's spread tracks the destination category's average almost one for one (1.07, $p = .016$). No randomized draw of 1,000 reproduces the post-move estimate (Table 3; Fig. 3). On its own, this looks like the mandate shaping how a manager trades.

The event study weakens that reading. The spread had already been falling for two years before the move and continued to fall afterward (Fig. 2). This is as far as the data go. The two tests also ask different questions of different managers, so a result in one and a null in the other does not show that the firm matters more than the person. What can be said is narrower: within a firm, after a manager takes on a new mandate, they begin to sell winners closer to that mandate's norm. However, whether a personal bias travels between firms remains untested.

5.5 India as the Identification Setting

Two external shocks, the 2017–18 scheme mandate recategorization and the COVID-19 redemptions. Neither makes the estimate causal. The outflow coefficient is positive and significant on both sides of the recategorization, at +0.0154 before and +0.0273 after. Also, it stays positive at +0.0215 when the COVID-19 months are dropped (Online Resource 1). What they show is that the link between withdrawals and the disposition spread is unaffected by any single regulatory change or external crisis.

5.6 No Sizeable Difference Between Sustainable and Other Holdings

Forced selling and preference predict opposite signs here, so the sign is the test. Within the same fund in the same month, the gap between high-ESG and low-ESG holdings is -0.010 , against a smallest detectable gap of 0.033 (Table 4; Fig. 4). A preference effect of 0.033 or more is therefore ruled out: managers do not hold their sustainable winners noticeably longer. The interaction with prior-month outflow is +0.018, which points in the forced-selling direction, but the smallest interaction the test could have detected is 0.064, larger than the average spread itself. That question is not settled either way. So the level of the

spread does not differ appreciably by a stock's sustainability rating. Whether outflows widen the spread more on high-rated holdings than on low-rated ones cannot be settled at this sample size.

The level result agrees with the fund-level null of [25] rather than with the retail findings of [24]. The settings differ in a way that explains this: retail investors face no redemptions, so forced selling cannot apply to them, whereas a manager faces both pressures at once.

One alternative reading has to be ruled out. The rated universe in India is also the large, liquid segment, so a size effect could be mistaken for a sustainability effect. Splitting on the median rating within each market-capitalization tercile holds size fixed, leaving the gap at -0.004 (Online Resource 1). Adding size and count controls directly moves the estimate to $+0.002$ but raises the standard error from 0.012 to 0.032. It is for this reason that the tercile split is the better check (Table 4).

The implication is cautious. The interaction is $+0.018$, the sign forced selling predicts. But the smallest effect this test could have detected is 0.064, more than three times as large. The evidence therefore neither shows that redemptions push managers out of sustainable holdings nor rules it out.

5.7 Limitations

Four limitations bound this study. (a) Month-end holdings cannot see a stock bought and sold within the same month. (b) The sample is restricted to direct plans, whose investors buy directly and may redeem differently. (c) The mobility tests rest on a few movers, especially the 38 who changed firms. (d) The ESG rating covers mainly large firms and is a single 2023–24 vintage held fixed.

6 Conclusion

This paper attempted to answer four questions about the disposition effect among Indian equity mutual fund managers, using monthly holdings data for 372 schemes over 12 years.

First, the managers do show the effect. The disposition spread averages $+0.047$ and is positive in three of five fund-months, an order of magnitude in line with the figures reported

for retail accounts and for United States mutual funds. Second, redemptions rather than manager preference best explain it. The previous month's outflow is associated with a spread that is 0.023 higher, about half the average spread. It is with odds of a positive spread that are about a quarter higher. Market volatility is not: a one-point rise in the India VIX is associated with a change of 0.0002, which is not significant. That asymmetry is what separates the structural reading from the cognitive one, which holds under four measures of outflow, two-way clustering, the logistic model, two multiple-testing corrections, both sides of the 2017–18 SEBI recategorization, and removal of the COVID-19 window.

Third, the mobility evidence cannot separate a portable personal trait from the fund environment. The between-firm test rests on 38 movers and is underpowered. The within-firm convergence followed a spread that had been falling for two years before the move. So, it is suggestive rather than causal. Fourth, the spread on a fund's sustainable holdings sits 0.010 below the spread on the rest, against a test that could have detected 0.033. This indicates that managers do not hold sustainable winners noticeably longer. Whether redemptions affect those holdings more is not settled, since the test could only have detected a difference of 0.064.

For asset management companies, the lever these results identify is the fund's redemption design and the liquidity of its holdings, not the individual manager. For investors, separate disclosure of turnover following redemptions would help distinguish forced selling from chosen trading. The contribution is to test the forced-selling account against its alternatives in an emerging market with datable liquidity events, rather than to add another country's point estimate. Two limits point to the next step: transaction-level records would close the within-month gap, and a longer panel with more movers would settle whether a personal tendency travels between employers.

Declarations

Authors' Contribution

SD: Conceptualization, Methodology, Software, Formal Analysis, Data Curation, Visualization, Writing – Original Draft. SC: Conceptualization, Methodology, Validation,

Writing – Review & Editing, Supervision. PPK: Investigation, Writing – Original Draft, Writing – Review & Editing. SSS: Writing – Review & Editing, Supervision. All authors reviewed and approved the final manuscript.

Competing Interests

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

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Use of Generative AI

Generative AI tools (Claude and Gemini) assisted with analysis programming scripts, language and presentation, and literature search.

Availability of Data and Materials

This study analyses four datasets. Two are commercial products supplied under licence and two are publicly available online. The monthly portfolio holdings, fund characteristics and net flows for the 372 schemes were licensed from the ICRA Analytics mutual fund database (ICRA Analytics Limited, Navi Mumbai, India), <https://www.icraanalytics.com/>. The CRISIL ESG ratings were obtained from the Capitaline database (Capital Market Publishers India Pvt Ltd, Mumbai, India), <https://www.capitaline.com/>. The authors cannot redistribute either dataset. Both are available from the vendors named above on the same commercial terms on which the authors obtained them. The Carhart four-factor returns are publicly available from the Fama French and Momentum Factors Data Library for the Indian Market, maintained at the Indian Institute of Management Ahmedabad, at <https://faculty.iima.ac.in/iffm/Indian-Fama-French-Momentum/> [29], [30]. The daily India VIX closing series is published by the National Stock Exchange of India and is available at <https://www.nseindia.com/reports->

indices-historical-vix. The analysis code and the aggregate outputs underlying every table and figure in this article are available from the corresponding author on reasonable request.

Ethics, Consent to Participate, and Consent to Publish

Not applicable.

Clinical Trial Number

Not applicable.

References

- [1] Association of Mutual Funds in India, “AMFI monthly report, March 2026,” 2026. [Online]. Available: <https://portal.amfiindia.com/spages/ammar2026repo.pdf>
- [2] C. Cueva, I. Iturbe-Ormaetxe, G. Ponti, and J. Tomás, “An experimental analysis of the disposition effect: Who and when?,” *J. Behav. Exp. Econ.*, vol. 81, pp. 207–215, Aug. 2019, doi: 10.1016/j.socec.2019.06.011.
- [3] T. Odean, “Are Investors Reluctant to Realize Their Losses?,” *J. Finance*, vol. 53, no. 5, pp. 1775–1798, 1998, doi: 10.1111/0022-1082.00072.
- [4] H. Shefrin and M. Statman, “The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence,” *J. Finance*, vol. 40, no. 3, pp. 777–790, 1985, doi: 10.1111/j.1540-6261.1985.tb05002.x.
- [5] G. Cici, “The Prevalence of the Disposition Effect in Mutual Funds’ Trades,” *J. Financ. Quant. Anal.*, vol. 47, no. 4, pp. 795–820, Aug. 2012, doi: 10.1017/s0022109012000348.
- [6] M. Grinblatt and B. Han, “Prospect theory, mental accounting, and momentum,” *J. Financ. Econ.*, vol. 78, no. 2, pp. 311–339, Nov. 2005, doi: 10.1016/j.jfineco.2004.10.006.
- [7] I. Ben-David, F. Franzoni, and R. Moussawi, “Hedge Fund Stock Trading in the Financial Crisis of 2007–2009,” *Rev. Financ. Stud.*, vol. 25, no. 1, pp. 1–54, Jan. 2012, doi: 10.1093/rfs/hhr114.
- [8] L. Pástor and B. Vorsatz, “Mutual Fund Performance and Flows during the COVID-19 Crisis,” *Rev. Asset Pricing Stud.*, Jul. 2020, doi: 10.1093/rapstu/raaa015.
- [9] J. Coval and E. Stafford, “Asset fire sales (and purchases) in equity markets,” *J. Financ. Econ.*, vol. 86, no. 2, pp. 479–512, Nov. 2007, doi: 10.1016/j.jfineco.2006.09.007.
- [10] M. Wardlaw, “Measuring Mutual Fund Flow Pressure as Shock to Stock Returns,” *J. Finance*, vol. 75, no. 6, pp. 3221–3243, 2020, doi: 10.1111/jofi.12962.
- [11] A. Riedl and P. Smeets, “Why Do Investors Hold Socially Responsible Mutual Funds?,” *J. Finance*, vol. 72, no. 6, pp. 2505–2550, 2017, doi: 10.1111/jofi.12547.
- [12] Securities and Exchange Board of India, “Business Responsibility and Sustainability Reporting by Listed Entities,” Securities and Exchange Board of India, Mumbai, India, Circular SEBI/HO/CFD/CMD-2/P/CIR/2021/562, May 2021. Accessed: Aug. 22, 2026. [Online]. Available: https://www.sebi.gov.in/legal/circulars/may-2021/business-responsibility-and-sustainability-reporting-by-listed-entities_50096.html
- [13] Securities and Exchange Board of India, “New Category of Mutual Fund Schemes for Environmental, Social and Governance (ESG) Investing and Related Disclosures by Mutual

- Funds,” Securities and Exchange Board of India, Mumbai, India, Circular SEBI/HO/IMD/IMD-I-PoD1/P/CIR/2023/125, Jul. 2023. Accessed: Aug. 22, 2026. [Online]. Available: https://www.sebi.gov.in/legal/circulars/jul-2023/new-category-of-mutual-fund-schemes-for-environmental-social-and-governance-esg-investing-and-related-disclosures-by-mutual-funds_74186.html
- [14] Securities and Exchange Board of India, “Categorization and rationalization of mutual fund schemes,” SEBI/HO/IMD/DF3/CIR/P/2017/114, Oct. 2017. [Online]. Available: https://www.sebi.gov.in/legal/circulars/oct-2017/categorization-and-rationalization-of-mutual-fund-schemes_36199.html
 - [15] D. Kahneman and A. Tversky, “Prospect Theory: An Analysis of Decision under Risk,” *Econometrica*, vol. 47, no. 2, pp. 263–291, 1979, doi: 10.2307/1914185.
 - [16] N. Da Costa, A. Paraboni, and M. Goulart, “Disposition effect and reference points: An experimental study,” *PLOS ONE*, vol. 18, Apr. 2023, doi: 10.1371/journal.pone.0284171.
 - [17] R. De Winne, “Measuring the disposition effect,” *J. Behav. Exp. Finance*, vol. 29, p. 100468, Mar. 2021, doi: 10.1016/j.jbef.2021.100468.
 - [18] A. Barzykin, P. Bergault, and O. Gu’eant, “Algorithmic market making in dealer markets with hedging and market impact,” *Math. Finance*, vol. 33, pp. 41–79, Jun. 2021, doi: 10.1111/mafi.12367.
 - [19] L. Andreu, C. Ortiz, and J. Sarto, “Disposition effect in fund managers. Fund and stock-specific factors and the upshot for investors,” *J. Econ. Behav. Organ.*, vol. 176, pp. 253–268, Aug. 2020, doi: 10.1016/j.jebo.2020.04.002.
 - [20] B. Tekçe, N. Yılmaz, and R. Bildik, “What factors affect behavioral biases? Evidence from Turkish individual stock investors,” *Res. Int. Bus. Finance*, vol. 37, pp. 515–526, May 2016, doi: 10.1016/j.ribaf.2015.11.017.
 - [21] B. N. Ashraf, “Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets,” *J. Behav. Exp. Finance*, vol. 27, pp. 100371–100371, Jun. 2020, doi: 10.1016/j.jbef.2020.100371.
 - [22] S. Papadamou, A. Fassas, D. Kenourgios, and D. Dimitriou, “Effects of the first wave of COVID-19 pandemic on implied stock market volatility: International evidence using a google trend measure,” *J. Econ. Asymmetries*, vol. 28, Jun. 2023, doi: 10.1016/j.jeca.2023.e00317.
 - [23] J. C. Adams, T. Nishikawa, and R. P. Rao, “Mutual fund performance, management teams, and boards,” *J. Bank. Finance*, vol. 92, pp. 358–368, Jul. 2018, doi: 10.1016/j.jbankfin.2016.09.006.
 - [24] B. van Dooren and R. Galema, “Socially responsible investors and the disposition effect,” *J. Behav. Exp. Finance*, vol. 17, pp. 42–52, Mar. 2018, doi: 10.1016/j.jbef.2017.12.006.
 - [25] B. Boumda, D. Duxbury, C. Ortiz, and L. Vicente, “Do Socially Responsible Investment Funds Sell Losses and Ride Gains? The Disposition Effect in SRI Funds,” *Sustainability*, vol. 13, no. 15, p. 8142, Jan. 2021, doi: 10.3390/su13158142.
 - [26] R. Döttling and S. Kim, “Sustainability Preferences Under Stress: Evidence from COVID-19,” *J. Financ. Quant. Anal.*, vol. 59, no. 2, pp. 435–473, Mar. 2024, doi: 10.1017/S0022109022001296.
 - [27] F. Berg, J. F. Kölbel, and R. Rigobon, “Aggregate Confusion: The Divergence of ESG Ratings*,” *Rev. Finance*, vol. 26, no. 6, pp. 1315–1344, Nov. 2022, doi: 10.1093/rof/rfac033.
 - [28] E. A. Berger, “Selection Bias in Mutual Fund Fire Sales,” *J. Financ. Quant. Anal.*, vol. 58, no. 3, pp. 1039–1077, May 2023, doi: 10.1017/S0022109022001223.

- [29] S. K. Agarwalla, J. Jacob, and J. R. Varma, “Fama French and Momentum Factors: Data Library for Indian Market,” Sep. 05, 2013. Accessed: Aug. 23, 2022. [Online]. Available: <https://faculty.iima.ac.in/iffm/Indian-Fama-French-Momentum/>
- [30] S. K. Agarwalla, J. Jacob, and J. R. Varma, “Four factor model in Indian equities market,” Indian Institute of Management, Ahmedabad, Working Paper W.P. No. 2013-09-05, 2013. [Online]. Available: <https://faculty.iima.ac.in/iffm/Indian-Fama-French-Momentum/four-factors-India-90s-onwards-IIM-WP-Version.pdf>
- [31] A. Frazzini, “The Disposition Effect and Underreaction to News,” *J. Finance*, vol. 61, no. 4, pp. 2017–2046, 2006, doi: 10.1111/j.1540-6261.2006.00896.x.
- [32] G. Chen, K. A. Kim, J. R. Nofsinger, and O. M. Rui, “Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors,” *J. Behav. Decis. Mak.*, vol. 20, no. 4, pp. 425–451, 2007, doi: 10.1002/bdm.561.

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