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Investment avenues and behavioural biases of retail investors: Evidence from Guwahati, India

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Abstract
This study examines how 425 retail investors in Guwahati, Assam, spread their holdings across five investment avenues, tests whether participation differs between avenues, and explores demographic correlates of participation and self-reported behavioural biases. Data came from a questionnaire distributed through contacts and referrals. Reported participation was highest for mutual funds (91.5%) and equity shares (84.9%), followed by bank deposits (59.3%), life insurance (52.2%) and gold (38.6%). Cochran's Q test showed that participation differed across avenues, $Q(4) = 392.34$, $p < .001$, and all ten pairwise McNemar comparisons remained significant after Holm adjustment (adjusted $p \leq .027$). In Firth-penalised logistic regressions, higher income was associated with higher odds of holding every avenue (odds ratios 1.40 to 1.68 per standard deviation of coded income band); age, marital status and occupation were associated with holding life insurance, which none of the 39 students held. Six of eight self-reported bias scores lay modestly above the scale midpoint ($r = .15$ to $.32$). The sample is non-probability and cross-sectional, and participation is a yes/no measure, so the findings describe these investors only.

Keywords: Investment avenues, retail investors, participation, behavioural biases, mutual funds, India

Introduction

Retail investors in India can place their savings in equity shares, mutual funds, bank deposits, life insurance and gold, and the mix they choose shapes both returns and exposure to risk. Evidence on how widely each avenue is used is hard to compare, because studies differ in whom they surveyed, which avenues they listed and whether they asked about holdings or preferences. Das (2012) and Lokhande (2015) [12, 23] found bank deposits among the leading avenues, Manimozhy and Borah (2018) [25] found equity ranked first among Guwahati investors, and the 2015 survey by the Securities and Exchange Board of India (SEBI) reported mutual funds and equities as the most widely held securities-market products (SEBI, 2016) [43]. Comparisons between avenues in these studies are mostly descriptive and, as far as their reports show, none tests whether differences exceed what chance would produce. Behavioural-finance research also documents many biases (Kahneman & Tversky, 1979; Tversky & Kahneman, 1974; Thaler, 1985) [20, 47, 50], which surveys have measured among Indian investors (Prosad *et al.*, 2015; Mushinada & Veluri, 2019; Ritika & Kishor, 2022) [28, 38, 40]. Evidence from smaller cities such as Guwahati, the largest city in Assam and the commercial centre of North-East India, is thinner.

Using survey data from 425 retail investors in Guwahati, this paper asks four questions. How does reported participation differ across five avenues? Which pairs of avenues differ? Which demographic characteristics go with holding each avenue? And which of eight behavioural biases do investors report above or below the neutral point of the scale? Participation is tested with methods suited to related yes/no answers from the same people, the demographic models are exploratory, and the bias profile is secondary and reported with effect sizes.

Literature and hypotheses

1. Participation across investment avenues

The 2015 SEBI investor survey, conducted by Nielsen India, found that among 5,356 urban respondents classed as investors, 66% held mutual funds and 55% held equities (SEBI, 2016). The sample was purposive and skewed towards localities with many demat accounts, so these figures cannot be set directly against the counts reported here. Local and regional studies mostly asked about preference or rank. Das (2012) [12] surveyed 150 middle-class households in Nagaon district, Assam, and found bank deposits and insurance the most preferred avenues. Manimozhy and Borah (2018) [25] ranked eight avenues among 100 convenience-sampled respondents in Guwahati: equity came first and gold second, with bank deposits, mutual funds and insurance fourth, fifth and seventh. Lokhande (2015) [23] surveyed 300 rural respondents in Aurangabad district, Maharashtra, and found bank deposits and gold among the most popular avenues.

These studies differ in population, year, list of avenues and measure, so they do not form a single benchmark and give no firm order of avenues. This paper measures reported participation, a sign of use and not of preference, and states its hypothesis without a direction.

H1. Reported participation differs across the five investment avenues.

2. Behavioural biases

Behavioural finance explains departures from rational choice through heuristics and emotional reactions. Herd behaviour has been documented in financial markets (Bikhchandani & Sharma, 2000; Nofsinger & Sias, 1999) [5, 31], although a systematic review found the evidence inconclusive (Kumar & Goyal, 2015) [22]. Regret theory proposes that people anticipate the pain of choosing badly and adjust their choices to avoid it (Loomes & Sugden,

1982; Zeelenberg, 1999) [24, 53]. Prospect theory holds that losses weigh more heavily than equal gains (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992), and Odean (1998) [20, 34, 51] found that US individual investors were more willing to realise gains than losses. Overconfidence has been linked to heavier trading (Barber & Odean, 2001) [3] and modelled as a product of how investors interpret their own successes (Daniel *et al*., 1998) [11]. Confirmation bias has been described as pervasive in human reasoning (Nickerson, 1998) [30], mental accounting as treating money differently according to its source or purpose (Thaler, 1985, 1999) [47, 48], and the availability heuristic as judging likelihood by how easily instances come to mind (Tversky & Kahneman, 1973) [49].

These studies mostly observe behaviour or use experiments, whereas a survey records what respondents say about themselves, so the two are not directly comparable. The question here is only whether investors report each tendency above or below the neutral point of a five-point agreement scale, so the hypotheses are non-directional.

H2a–H2h. The score for each of eight biases differs from the neutral midpoint of the scale: availability/recency (H2a), herding (H2b), regret aversion (H2c), overconfidence (H2d), confirmation bias (H2e), loss aversion (H2f), self-attribution (H2g) and mental accounting (H2h).

Data and methods

1. Design and setting

The study is a cross-sectional questionnaire survey within a post-positivist, deductive framework (Creswell & Creswell, 2018; Phillips & Burbules, 2000) [9, 36]. The hypotheses were derived from the literature before the data were analysed, and the demographic models are exploratory. Nothing was manipulated, so a significant association shows only that variables vary together in this sample. Guwahati, the largest urban centre in Assam, was chosen because investing is much more common in Indian cities than in the countryside (SEBI, 2016) [43], because it was one of three Assam locations in the SEBI urban sample, and because it adds evidence from outside the large metropolitan regions that dominate the Indian literature. The choice also reflects practical access to respondents and is not a claim that Guwahati represents Assam or India.

2. Population, recruitment and sample

The target population is retail investors in Guwahati, in the ordinary behavioural-finance sense of individuals, as distinct from institutions or professional fund managers, who invest personal funds (cf. Manimozhy & Borah, 2018) [25]. SEBI's formal retail-investor category is a transaction-size rule for public issues (SEBI, 2018) and cannot be applied to a survey of holdings. Operationally, a respondent qualifies by holding at least one of five avenues: equity shares, mutual funds, bank deposits (fixed deposits, FD), life insurance (endowment plans) and gold. This is wider than the SEBI Investor Survey 2015, which counts only holders of securities-market instruments as investors (SEBI, 2016), but the difference matters little here: 419 of the 425 respondents (98.6%) hold mutual funds or equity shares. No sampling frame of such investors exists.

Recruitment and sample flow: Recruitment was by non-probability convenience and snowball sampling through the researcher's contacts and referrals, because retail investors are not listed in a public register (Etikan *et al*., 2016; Biernacki & Waldorf, 1981) [4, 14]; the probability of selection is therefore unknown. Of 455 questionnaires collected, 30 incomplete ones were excluded, leaving 425 respondents (93.4%) and no missing values on any analysis variable. No formal power analysis was carried out, and the smallest subgroup in the models (aged above 60) has only 36 members.

Sample profile: Table 1 shows that the sample leans towards men (63%), respondents aged 31 to 45 (57%) and holders of a graduate or master's degree (83%). Referral-based recruitment tends to over-represent people connected to earlier respondents (Biernacki & Waldorf, 1981) [4], so the p-values describe the strength of evidence within this sample, and any wider generalisation rests on argument and not on the sampling design.

Table 1: Profile of respondents (N = 425)

Characteristic	Category	n	%
Gender	Male	266	62.6
	Female	159	37.4
Age (years)	30 or below	71	16.7
	31–45	243	57.2
	46–60	75	17.6
	Above 60	36	8.5
Marital status	Married	314	73.9
	Single	111	26.1
Education	High school	14	3.3
	Undergraduate	26	6.1
	Graduate	174	40.9
	Master's	179	42.1
	Ph.D.	22	5.2
	Others (diploma, professional course)	10	2.4
Occupation	Salaried	245	57.6
	Self-employed	111	26.1
	Retired	30	7.1
	Student	39	9.2
Annual income (Rs)	Below 1,00,000	28	6.6
	1,00,000–1,50,000	87	20.5

	1,50,001–2,00,000	51	12.0
	2,00,001–2,50,000	41	9.6
	2,50,001–3,00,000	75	17.6
	Above 3,00,000	143	33.6

Note: Percentages are of the 425 respondents in the final analytical sample. Source: Author's own calculations from survey data. Income bands are in Indian rupees (Rs), written with Indian digit grouping (1,00,000 = 100,000).

3. Data collection and measures

Data were collected from April to December 2025 with self-completed paper-based and online (Google Form) questionnaires, in English only. This paper uses six demographic items, the question on which of five avenues the respondent currently holds, and 24 behavioural-bias statements (Appendix).

Participation: Respondents ticked each of the five avenues they currently hold. Each avenue was coded 1 for held and 0 for not held. Holding an avenue is not the same as preferring it, and the questionnaire did not ask about preferences, reasons or amounts, so results are described as differences in reported participation.

Behavioural biases: Eight biases were each measured by three five-point statements (1 = strongly disagree, 5 = strongly agree): availability/recency, herding, regret aversion, overconfidence, confirmation bias, loss aversion, self-attribution and mental accounting. The 24 statements were selected from published studies (Table A1) and are not complete validated scales. Three negatively worded statements (D15, D21 and D24) were reverse-coded as 6 minus the response. A construct score is the mean of its three items, from 1 to 5, and higher scores mean stronger agreement with statements describing the tendency. The scores are self-reported tendencies and not observed behaviour. Cronbach's alpha (Cronbach, 1951) [10] lies between .718 and .850 (Table 5), meeting the conventional .70 benchmark (Nunnally & Bernstein, 1994) [33]; it is not evidence of validity (Sijtsma, 2009) [44], and no factor analysis or expert review was undertaken. The availability/recency score combines reliance on friends and relatives, reliance on advertisements and weight on recent performance, and is read as a composite of reliance on easily accessible information and not as a pure measure of the availability heuristic.

4. Statistical analysis

Participation: Because the five yes/no answers come from the same respondents, an ordinary chi-square test would treat 2,125 responses as if they came from different people. Cochran's Q test (Cochran, 1950) [7] was therefore used to test whether the proportion holding an avenue is the same across all five, and McNemar's test (McNemar, 1947) with the continuity correction (Edwards, 1948) [13] was applied to each of the ten pairs of avenues (Stephen & Ahmad Zaidi Adruce, 2018). Holm's (1979) [18, 45] step-down procedure adjusted the ten pairwise p-values and holds the familywise error rate at .05; adjusted values were calculated from the unrounded asymptotic p-values of the SPSS $\chi^2(1)$ statistics. Percentage-point differences are reported alongside the tests, because significance does not show practical importance.

Exploratory logistic regression: A binary logistic regression was fitted for each avenue (1 = held) with gender, age group, marital status, education, occupation and annual income as predictors (14 parameters apart from the constant). Categorical predictors used indicator coding (reference categories: female, above 60 years, married, other education, student). Income, coded as six ordered bands, was standardised and treated as continuous, so its odds ratio is per standard deviation of the coded band (about 1.7 bands). The bands are not equally spaced and the top band is open-ended, so this assumes a linear relationship between band code and log-odds and does not describe a precise increase in income. Conventional maximum-likelihood estimation in SPSS did not converge for the mutual-fund and life-insurance models because some categories contain no variation in the outcome (complete or quasi-complete separation; Heinze & Schemper, 2002) [17], and the number of non-holders per estimated parameter is low for the equity and mutual-fund models, well below the roughly ten events per variable often recommended (Peduzzi *et al*., 1996) [35]. All five models were therefore estimated with Firth's (1993) [15] penalised-likelihood method, which gives finite estimates under separation and reduces small-sample bias (Heinze & Schemper, 2002) [17]. Each predictor was tested over all its categories with a penalised likelihood-ratio test, and income odds ratios have profile penalised-likelihood confidence intervals. The Firth models were fitted in Python 3.13 (NumPy 2.5, SciPy 1.18) with a Newton–Raphson implementation of Firth's penalised score; penalised likelihood-ratio tests constrain the predictor's coefficients to zero using the penalty of the full model, and profile confidence intervals were found by root-finding on the penalised likelihood. The models are exploratory and were not adjusted for multiplicity.

Behavioural biases: Bias scores are means of ordinal items bounded between 1 and 5, so each was compared with the neutral value of 3 by the one-sample Wilcoxon signed-rank test (Wilcoxon, 1945) [52] with asymptotic two-sided p-values. Normality tests rejected normality for every construct ($p < .001$), and the scores are ordinal composites, so a rank-based test was preferred (Norman, 2010; Sullivan & Artino, 2013) [32, 46]; respondents scoring exactly 3.00 drop out of the ranking. Effect size was $r = Z/\sqrt{N}$ with $N = 425$ (Fritz *et al*., 2012) [16], read against benchmarks of .10, .30 and .50 for small, medium and large (Cohen, 1988) [8]; r based on the non-zero differences is also given in Table 5. A hypothesis is described as supported when the two-sided test is significant at .05; a non-significant result means insufficient evidence of a difference and does not show that no tendency exists. Descriptive statistics, Cochran's Q, McNemar tests and Wilcoxon tests were run in IBM SPSS Statistics 27, and the Holm adjustment and Firth models in Python.

Results

1. Participation across the five avenues

Table 2 shows reported participation. Mutual funds (91.5%) and equity shares (84.9%) are held by more than four in five respondents, bank deposits (59.3%) and life insurance (52.2%) by a little over half, and gold (38.6%) by fewer than two in five. The gap between the most and least common avenue is 52.9 percentage points.

Table 2: Reported participation by avenue (N = 425)

Avenue	Holds, n	Holds, %	Does not hold, n	Does not hold, %
Mutual funds	389	91.5	36	8.5
Equity shares	361	84.9	64	15.1
Bank deposits (FD)	252	59.3	173	40.7
Life insurance (endowment plans)	222	52.2	203	47.8
Gold	164	38.6	261	61.4

Note: Respondents could hold any number of avenues, so the percentages do not sum to 100. The denominator for every percentage is 425. Every respondent holds at least one avenue, so these are shares among investors holding at least one of the five avenues and not estimates for all residents of Guwahati. Source: Author's own calculations from survey data.

Respondents held 3.27 avenues on average (SD = 1.16). Thirty-six held one avenue, 67 held two, 139 held three, 114 held four and 69 held all five. Mutual funds and equity shares were held together by 331 respondents (77.9%), and only six respondents held neither.

2. Differences across avenues (H1)

Participation differed across the five avenues, $Q(4) = 392.34$, $p < .001$, so H1 is supported. Table 3 shows the ten pairwise comparisons; all are significant on the raw p-values and remain significant after Holm adjustment (adjusted $p \leq .027$). Mutual funds were held more often than every other avenue, including equity shares (6.6 percentage points, raw $p = .004$, Holm-adjusted $p = .008$). Equity shares were held more often than bank deposits, life insurance and gold, and bank deposits and life insurance were each held more often than gold.

Table 3: Pairwise McNemar tests of participation between avenues, with raw and Holm-adjusted p-values (N = 425)

Comparison	Holds first only	Holds second only	Difference (pp)	$\chi^2(1)$	Raw p	Holm-adjusted p
Equity shares vs mutual funds	30	58	−6.6	8.28	.004	.008
Equity shares vs bank deposits	141	32	25.6	67.42	< .001	< .001
Equity shares vs life insurance	162	23	32.7	102.94	< .001	< .001
Equity shares vs gold	211	14	46.4	170.74	< .001	< .001
Mutual funds vs bank deposits	156	19	32.2	105.69	< .001	< .001
Mutual funds vs life insurance	185	18	39.3	135.74	< .001	< .001
Mutual funds vs gold	238	13	52.9	199.90	< .001	< .001
Bank deposits vs life insurance	101	71	7.1	4.89	.027	.027
Bank deposits vs gold	140	52	20.7	39.42	< .001	< .001
Life insurance vs gold	115	57	13.6	18.89	< .001	< .001

Note: "Holds first only" and "holds second only" count the respondents who hold one avenue of the pair but not the other. Difference is the first avenue's participation minus the second's, in percentage points. χ^2 is continuity-corrected. Raw p is from the SPSS $\chi^2(1)$ statistic; Holm-adjusted p is the step-down adjustment over the ten comparisons, calculated from the unrounded raw p-values. Source: Author's own calculations from survey data.

The results suggest three tiers: mutual funds and equity shares, with mutual funds slightly ahead; bank deposits and life insurance, close together in the middle; and gold last. A larger gap does not always give a stronger test result, because McNemar's statistic depends on how many respondents differ and how unevenly they split. Equity shares against mutual funds (6.6 points) gives a stronger result than bank deposits against life insurance (7.1 points) because the 88 respondents who differed split 58 to 30, while the 172 who differed in the second pair split 101 to 71. The difference between bank deposits and life insurance is the least secure result in Table 3.

3. Who holds which avenue (exploratory)

Conventional maximum-likelihood models were unreliable for mutual funds and life insurance. Every one of the 14 high-school respondents and all 22 Ph.D. respondents hold mutual funds, and none of the 39 students holds life insurance, so with no variation in the outcome in those categories SPSS stopped both models at the iteration limit. The conventional occupation test for life insurance ($p = .566$) is the clearest casualty: it sits beside 0 of 39 students holding life insurance against 54.7% of salaried, 61.3% of self-employed and 66.7% of retired respondents, and the penalised test gives $p < .001$. In addition, only 64 respondents do not hold equity shares and 36 do not hold mutual funds, about 4.6 and 2.6 cases per estimated parameter, so those models are imprecise even where they converge. Table 4 therefore reports Firth penalised-likelihood estimates for all five avenues.

Table 4: Firth penalised-likelihood logistic regression of holding each avenue (N = 425)

Predictor	Equity shares	Mutual funds	Bank deposits	Life insurance	Gold
Income band, odds ratio per SD	1.68	1.65	1.40	1.51	1.60
Income, 95% profile CI	1.16–2.45	1.02–2.70	1.07–1.84	1.14–2.00	1.22–2.12
Income, $\chi^2(1)$ (p)	7.56 (.006)	4.22 (.040)	5.92 (.015)	8.41 (.004)	11.42 (< .001)
Age, $\chi^2(3)$ (p)	1.44 (.696)	5.18 (.159)	10.29 (.016)	13.01 (.005)	4.58 (.205)
Marital status, $\chi^2(1)$ (p)	0.65 (.421)	2.54 (.111)	1.09 (.296)	8.77 (.003)	0.43 (.513)
Education, $\chi^2(5)$ (p)	1.55 (.907)	6.70 (.244)	12.45 (.029)	8.89 (.114)	7.00 (.221)

Occupation, $\chi^2(3)$ (p)	2.66 (.447)	4.27 (.234)	2.12 (.548)	17.06 (< .001)	5.60 (.133)
Gender, $\chi^2(1)$ (p)	0.28 (.600)	1.44 (.230)	0.10 (.752)	0.50 (.481)	0.09 (.768)
Whole model, $\chi^2(14)$ (p)	29.43 (.009)	27.35 (.017)	66.50 (< .001)	123.73 (< .001)	50.29 (< .001)

Note: Entries are penalised likelihood-ratio χ^2 statistics (p) for each predictor tested over all its categories; income odds ratios have profile penalised-likelihood 95% confidence intervals. Reference categories: female, above 60 years, married, other education, student. Category-level odds ratios in the mutual-fund and life-insurance models have very wide intervals and are not reported. The tests are exploratory and were not adjusted for the 30 tests shown; no causal interpretation. Source: Author's own calculations from survey data (Python).

Income: Higher income went with higher odds of holding every avenue (Table 4). The odds ratio per standard deviation of coded income band (about 1.7 bands) ranged from 1.40 for bank deposits to 1.68 for equity shares, and the mutual-fund estimate of 1.65 (95% CI 1.02 to 2.70, p = .040) is borderline and rests on 36 non-holders. Conventional maximum-likelihood estimates were close to the Firth estimates in the three models that converged (1.72 for equity shares, 1.42 for bank deposits and 1.63 for gold).

Bank deposits: Age (p = .016) and education (p = .029) were also associated with holding bank deposits. Participation rose with age, from 33.8% of respondents aged 30 or below to 58.0%, 76.0% and 83.3% in the three older groups.

Life insurance: Beyond income, three predictors were associated with holding life insurance: age (p = .005), marital status (p = .003) and occupation (p < .001). Participation rose with age (14.1%, 53.5%, 73.3% and 75.0% across the four groups) and was lower among single respondents (23.4%) than married respondents (62.4%; Firth odds ratio for single versus married 0.38, Wald 95% CI 0.20 to 0.73). No student holds a policy, against 54.7% of salaried, 61.3% of self-employed and 66.7% of retired respondents, so the occupation contrasts are not estimable as finite odds ratios. Age, marital status and occupation overlap (students and single respondents are younger), and the model cannot cleanly separate them. Education (p = .114) and gender (p = .481) were not significantly associated, which is insufficient evidence of no association.

Equity shares: mutual funds and gold. Income was the only predictor significant at .05 for equity shares (p = .006), mutual funds (p = .040) and gold (p < .001). The education estimates for mutual funds are very imprecise because all high-school and Ph.D. respondents hold the avenue, so the education test (p = .244) has little power.

4. Behavioural biases (H2a–H2h)

Table 5 gives the scores and the tests. Six of the eight means lie above the midpoint of 3, led by herding (3.30) and regret aversion (3.27), while the means for availability/recency (2.97) and self-attribution (2.95) are marginally below 3. Standard deviations run from 0.87 to 0.96, and every construct used the full range from 1.00 to 5.00.

Table 5: Self-reported bias scores and one-sample Wilcoxon signed-rank tests against the neutral value of 3 (N = 425)

Bias	α	M (SD)	Median	Z	p	Non-zero n	r (N = 425)	r (non-zero n)
Availability/recency	.760	2.97 (0.87)	3.00	−0.64	.523	344	−.03	−.03
Herding	.850	3.30 (0.88)	3.33	6.61	< .001	319	.32	.37
Regret aversion	.806	3.27 (0.96)	3.33	5.82	< .001	370	.28	.30
Overconfidence	.768	3.19 (0.89)	3.33	4.61	< .001	364	.22	.24
Confirmation bias	.718	3.17 (0.89)	3.33	4.03	< .001	377	.20	.21
Loss aversion	.776	3.22 (0.95)	3.33	4.86	< .001	379	.24	.25
Self-attribution	.811	2.95 (0.91)	3.00	−1.21	.227	362	−.06	−.06
Mental accounting	.726	3.13 (0.88)	3.00	3.19	.001	349	.15	.17

Note: Z is signed as construct score minus 3, so a positive value means scores above 3. $r = Z / \sqrt{N}$ with the whole sample (N = 425) and with the number of non-zero differences, which are the only observations that enter the signed-rank test. Source: Author's own calculations from survey data.

Herding, regret aversion, overconfidence, confirmation bias, loss aversion and mental accounting differed significantly from the midpoint, all upwards, so H2b to H2f and H2h are supported. Availability/recency (p = .523) and self-attribution (p = .227) did not differ significantly from the midpoint, so H2a and H2g are not supported; this is insufficient evidence of a difference and does not show that investors are free of these biases. The effects are modest: among the six significant constructs, r runs from .15 (mental accounting) to .32 (herding) on the whole-sample convention, and from .17 to .37 when only non-zero differences are counted. Mental accounting needs a careful reading: its median is exactly 3.00 even though the test is significant, because of the 349 respondents who did not score exactly 3.00, 198 scored above and 151 below, and 76 scored exactly 3.00 and dropped out of the ranking. The result indicates a small upward shift in the distribution and not a median above the midpoint. The constructs were not tested against each other, so the order of the means is not a ranking of the biases.

Discussion

Mutual funds and equity shares are held by most respondents, and 77.9% hold both. The ordering agrees with the SEBI (2016) [43] survey, in which mutual funds also ranked above equities, but the bases differ (Section 2.1), so agreement in order is not evidence that levels match. The results differ from studies that found bank deposits (Das, 2012; Lokhande, 2015) [12, 23] or equity and gold (Manimozhy & Borah, 2018) [25] leading, but those studies measured preference or popularity, used different lists of avenues and covered different groups. The sample is weighted towards holders of a graduate or master's degree (83.1%; 88.2% with the 22 Ph.D. respondents) and towards salaried or self-employed respondents, so participation levels may not apply to other investors. The order within the

middle tier is the least secure: bank deposits and life insurance differ on a gap of 7.1 points (p = .027), and mutual funds and equity shares on a gap of 6.6 points that rests on 88 respondents who differ.

Income was positively associated with holding every avenue, with a borderline estimate for mutual funds. Bank-deposit holding rose with age and varied with education, and life-insurance holding rose with age, was lower among single respondents and was absent among the 39 students, a pattern that the non-converged conventional model could not detect. The survey did not ask about motives, so these patterns are not explained here, and because income, age, marital status and occupation are related, the associations may partly reflect characteristics the models omit. The equity and mutual-fund models rest on 64 and 36 non-holders and carry little information about who stays out.

On biases, the profile is a modest lean towards agreement with statements on herding, regret aversion, loss aversion, overconfidence, confirmation and mental accounting. What each score stands for depends on its statements. Herding combines following others in "all" decisions, feeling less disappointed when others also lose, and preferring assets others are buying, so the score is better described as a reported tendency to be influenced by other investors than as demonstrated herd behaviour, which fits the indecisive empirical evidence noted by Kumar and Goyal (2015) [22]. Studies of actual trading (Odean, 1998; Barber & Odean, 2001) [3, 34] observe behaviour and cannot be compared with these self-reports directly. The two non-significant constructs should not be read as showing that these biases are absent: two of the three availability/recency statements concern information sources and not recent performance.

For practice, herding and regret aversion are among the higher-scoring tendencies investors report, bank-deposit and life-insurance use rise with age, and students and single respondents are the groups least likely to hold life insurance. These points describe this sample only.

Limitations and conclusion

Participation is a yes/no measure, and every respondent holds at least one avenue, so the percentages describe participation among such investors and not the wider population; the measure cannot show amounts, motives or preference. The sample was recruited through contacts and referrals and leans towards men, respondents aged 31 to 45 and graduate and postgraduate degree holders, so the results describe these 425 investors and are not generalised to Guwahati, Assam or India. The operational definition of a retail investor is wider than the securities-market definition used by SEBI (Section 3.2), although 98.6% of respondents hold mutual funds or equity shares. Bias scores are self-reported, which exposes them to social desirability (Nederhof, 1985) [29] and shared method variance (Podsakoff *et al*., 2003) [37]; each rests on three statements, and several describe a related attitude and not the bias itself. The design is cross-sectional, so no causal claims are made. The demographic models are exploratory and unadjusted for multiplicity, and several cells are sparse. Financial literacy was also measured in the survey but is not analysed here; it may be related to both holding and bias reporting.

Among 425 retail investors in Guwahati, reported participation differed significantly across five avenues, with mutual funds and equity shares most widely held, bank deposits and life insurance in the middle and gold least. All ten pairs differed after Holm adjustment, with the narrowest gaps between bank deposits and life insurance and between mutual funds and equity shares. In the exploratory models, higher income went with holding every avenue (the mutual-fund estimate is borderline), bank-deposit holding was related to age and education, and life-insurance holding to age, marital status and occupation, with none of the 39 students holding a policy. Investors reported herding, regret aversion, loss aversion, overconfidence, confirmation bias and mental accounting at levels modestly above the neutral point (r = .15 to .32), while availability/recency and self-attribution could not be distinguished from it. These findings describe reported participation and self-reported tendencies in one city; data on the value of holdings, on motives and on observed trading would show whether the pattern reflects preference and bias in behaviour.

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