IIMB Management Review (2021) 33, 71–87

available at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/iimb

Do retail mutual fund investments represent "dumb money"?

Sunderarajan Sourirajan*, Subhashree Natarajan

Finance, Accounts and Economics Division, Vellore Institute of Technology Business School (VITBS), Vellore, Tamil Nadu, India

Received 31 January 2018; revised form 20 February 2019; accepted 6 March 2021; Available online 23 March 2021

KEYWORDS
Dumb money;
Net fund flows;
Demonetisation;
Momentum;
Distribution channel;
Money weighted return;
Performance gap

Abstract This paper highlights the "dumb money" effect of Indian retail mutual fund investors who chase funds that subsequently underperform. Retail investors show twice the propensity to chase top past performers; their cash flows are strongly negatively correlated to contemporaneous market returns indicating a contrarian, rather than a "buy and hold" strategy. They make up to 1.3% less in terms of raw returns compared to institutional investors, and the gap is accentuated for funds with superior risk adjusted returns. Collectively, the results reveal that retail investors trade actively with poor timing and fund selection skills despite having access to professional fund management.

Introduction

Studies of investors globally reveal interesting trading behaviours that are a departure from expected rational strategies. There is evidence that investor trading practices are dictated by market price signals rather than any rational analysis. A study of 46 countries by Griffin, Nardari and Stulz (2007) found that in India, a one standard deviation increase in weekly returns was followed by a more than one standard deviation in turnover after 10 weeks. A study by Ferreira, Keswani, Miguel, and Ramos (2012) of 28 countries found that in emerging markets like India, investors accelerate cash flows into mutual funds with higher past performance. This phenomenon termed the flow-performance convexity, emphasises the non-linear relationship of cash flows to performance. According to Chevalier and Ellison (1997), the convexity of this relationship increases as fund managers seek to increase riskiness of their holdings to achieve higher returns and attract more funds. When this results in future out-performance, it is termed the "smart money" effect. Studies by Gruber (1996) and Zheng (1999) show how investors, in the absence of sophisticated market information, use price signals to achieve such "smart returns". These studies also infer that investors have the ability to select funds managed by skilled fund managers capable of producing higher returns. Conversely, performance chasing cash flows that lead to investment in underperforming funds and reduction in wealth is termed "dumb money" (Frazzini & Lamont, 2008).

A review of the literature chronologically listed in Table 1 explores this flow-performance relationship across countries and investor types for stocks and mutual funds and confirms the following:

- US (Del Guercio & Tkac, 2002; Sirri & Tufano, 1998; Warther, 1995); UK (Keswani & Stolin, 2008); and Korea (Oh & Parwada, 2007) based studies find investors chase

*Corresponding author: Mobile: + 91 991 665 9828.
E-mail address: sunderra@gmail.com (S. Sourirajan).

https://doi.org/10.1016/j.iimb.2021.03.004

Table 1 Chronological literature studies of the relationship between mutual fund and stock cash flows to market returns and to fund/stock performance. *Ind* represents individual or retail investors, *Inst* represents institutional investors.

Study	Country	Asset type	Investor type	Analysis level	Findings
(Warther, 1995)	US	Mutual Funds	Aggregate	Aggregate	Unexpected cash flows are positively correlated with current market returns, positive relation between flows and subsequent returns, negative relation between past returns and flows.
(Sirri & Tufano, 1998)	US	Mutual Funds	Aggregate	Aggregate	Top 20^{th} percentile funds attract more inflows than bottom 80^{th} as investors chase performance to avoid costly searches. Strong Flow-Performance convexity found.
(Grinblatt & Keloharju, 2001)	Finland	Stocks	Ind & Inst	Aggregate	Individual investors show greater reaction to past negative returns. Domestic individual and institutional investors are contrarian, foreign institutional investors are momentum driven.
(Del Guercio & Tkac, 2002)	US	Mutual Funds	Aggregate	Aggregate	Strong inflows to winning funds, weak outflows from losing funds. Auto-correlation effects found with fund flows i.e. investors repeat past actions.
(Oh & Parwada, 2007)	Korea	Mutual Funds	Aggregate	Aggregate	Positive relationship between flows and stock returns and returns are found to satisfy the "Granger causality" for flows.
(Friesen & Sapp, 2007)	US	Mutual Funds	Aggregate	Fund level	Poor timing of cash flow into funds reduces investor average returns by 1.56% annually and offsets the risk-adjusted alpha from well performing funds.
(Ferreira, Keswani, Miguel, & Ramos, 2012)	UK	Mutual Funds	Ind & Inst	Aggregate	All classes of investors display "smart money" effect. Fund inflows have a strong positive correlation with past performance while fund outflows display a weak negative correlation.
(Frazzini & Lamont, 2008)	US	Mutual Funds & Stocks	Aggregate	Aggregate	Fund flows are dumb money, individual investors are driven by sentiment stocks (high growth) and re-allocate capital across funds reducing wealth.
(Barber, Lee, Liu, & Odean, 2009)	Taiwan	Stocks	Ind & Inst	Aggregate	Individual investors lose 2.2% of GDP every day due to excessive trading, while institutions enjoy 1.5% annual performance boost despite active trading.
(Chhabra, De, Gondhi, & Pochiraju, 2012)	India	Stocks	Ind	Aggregate	Investors on aggregate, lose money due to mistiming of buys and sells, attracting high trading costs.
(Bose, 2012)	India	Mutual Funds	Domestic Inst, FII	Aggregate	Gross mutual fund flows of domestic investors have negative correlation to one-day lagged market returns while foreign institutional investor flows have a positive relation to returns.
(Feng, Zhou, & Chan, 2014)	China	Mutual Funds	Ind & Inst	Aggregate	Retail investors time the market poorly, moving funds in/out of under/out-performers exhibiting a "dumb money" effect. Institutional investors demonstrate a "smart money" effect.

performance of markets or funds. Their reaction to performance is asymmetrical with stronger positive flow correlation to winning stocks/funds and a weaker negative flow correlation to poorer performing stocks/funds;

- In contrast, Finnish retail and domestic institutional investors (Grinblatt & Keloharju, 2001) and Indian retail investors (Bose, 2012) are contrarian oriented with flows negatively correlated to contemporaneous and lagged market returns;
- Except in the UK (Keswani & Stolin, 2008), retail investors in the US (Frazzini & Lamont, 2008; Friesen & Sapp, 2007); Taiwan (Barber, Lee, Liu, & Odean, 2006); India (Chhabra, De, Gondhi, & Pochiraju, 2011) and China (Feng, Zhou, & Chan, 2014) lose money due to trading in stocks exhibiting a dumb money effect.
- In contrast, institutional investors show a smart money effect in the studies for the US (Gruber, 1996; Zheng, 1999); UK (Keswani & Stolin, 2008), Taiwan (Barber et al., 2006), India (De, Gondhi & Sarkar, 2012) and China (Feng et al., 2014);
- The result of these contrasting behaviours of retail and institutional investors means retail investors are losing out to their institutional brethren by excessive trading (De et al., 2012; Frazzini & Lamont, 2008).

Explanations for retail investor behaviours

This behaviour of retail investors can be explained by poor stock/fund selection ability and lack of market timing skills (Friesen & Sapp, 2007). They have a tendency to "buy high and sell low" (Hsieh, Yang, & Tai, 2010) resulting in sub-optimal performance. Investors make capital allocation mistakes during a market rise, putting too little into well-performing funds (Glode, Hollifield, Kacperczyk, & Kogan, 2009). According to Barber and Odean (2005), this lack of trading skills is attributable to not being financially savvy, having limited access to market information and exhibiting behavioural biases such as disposition effects, overconfidence and loss-aversion. When confronted with a multitude of choices as is the case with stocks and mutual funds, investors rely on shortcuts to make purchase decisions. This is often based on such naïve criteria as (a) past price performance, (b) what others are doing ("herding behaviour") and (c) buying stocks recently in the news (refer "Buying versus Selling" in Barber and Odean (2005)). According to Goetzmann and Peles (1997) "cognitive dissonance" or "the tendency to adjust beliefs to justify past actions" convinces investors to have an over-optimistic view of past performance ignoring any current loss-making streak. This causes an investor to hold on to losing funds for too long. They cognitively avoid the realisation that they may have been wrong in choosing a fund based solely on past performance.

The cited literature spanning over two decades demonstrates the difficulty in ascribing a singular theory or explanation to retail investor behaviours, but confirms that, predominantly: (a) retail investors asymmetrically chase performance, (b) their trading contrasts with institutional investors (c) and they lose money exhibiting a dumb money effect. The purpose of this paper is to determine if these conclusions can be applied to the Indian mutual fund retail investor.

Novelty of research

This paper makes four novel and significant additions to existing research:

1) There is a paucity of Indian mutual fund research addressing the dumb money effect of retail investors, compared to advanced markets. Studies such as Arora (2016) and Narend and Thenmozhi (2016) focus on flows and the impact on stock market returns. In this paper, the dumb money effect and its explicit impact on investor performance is analysed;
2) Previous studies do not address retail investors independently despite their majority share of 48.5% in the industry assets under management (AUM). Most research in India is aggregated across investor types or is specific to foreign and domestic institutional investors (Naik & Padhi, 2015; Tayde & Rao, 2011). In this paper, investor types are segregated into retail, domestic and foreign institutional investors. The flow-performance relationship for each investor type is analysed independently and compared to provide insights into respective trading behaviours;
3) Previous studies used aggregate cash flows for analysis i.e., inflows (purchases) and outflows (redemptions) were aggregated across different funds. A fund-wise analysis is absent. Two issues arise: (a) individual fund level cash flows and performance can be positive or negative, and on aggregation, could have their effects suppressed or cancelled out; (b) investor fund selection and timing is based on individual funds, not on aggregated values. An accurate assessment of fund selection and timing is not possible once aggregation occurs. Aggregation therefore results in loss of useful information (Friesen & Sapp, 2007), and this paper avoids it by performing all analyses at individual fund level for each class of investor;
4) In India, over 90% of investor flows in and out of mutual funds are through brokers and agents[1], unlike in the US, where brokers contribute just 40%. Brokers and agents can significantly alter retail investor flow patterns. Studies such as Anagol, Marisetty, Sane and Venugopal's (2017) have looked at regulation driven changes in broker commissions and its effect on investor cash flows. This is the first study that explicitly analyses the effect of distribution channels on Indian retail investor mutual fund flows.

Summary of research findings

Mutual funds provide professional management, transparency in reporting and a higher degree of regulatory oversight. They are expected to provide a low cost, low risk entry for unsophisticated retail investors into equity markets. This presents investors an opportunity to make returns above current inflation, thereby creating wealth. The normative expectation of retail investors is that they adopt a passive investment posture and have a long-term investment horizon. In contrast, professional institutional investors with the benefit of greater access to information and resources are expected to be more aggressive and active investors.

[1] We use the term "brokers/agents" to refer collectively to both "Associate" and "Non-Associate" distributors; terms used in the sample data are explained in the Data section.

Table 2 The top 16 AMCs in the sample data who collectively contribute over 91% of the industry AUM for all fund types (equity and debt). Figures are in billion rupees.

AMC	AUM	%	AMC	AUM	%
ICICI	1,933.87	13.37	IDFC	542.64	3.75
HDFC	1,930.93	13.35	DSP BlackRock	424.12	2.93
Reliance	1,679.82	11.61	Axis	409.46	2.83
Birla Sun Life	1,493.78	10.33	Tata	353.31	2.44
SBI	1,204.35	8.33	L&T	284.04	1.96
UTI	1,121.69	7.75	Sundaram	245.36	1.70
Franklin Templeton	684.95	4.74	Invesco[a]	190.58	1.32
Kotak Mahindra	631.14	4.36	JPMorgan/Edelweiss[b]	55.84	0.39

Source: (AMFI, 2017)
[a]DHFL Pramerica is larger than Invesco but was not included due to data issues.
[b]JPMorgan was acquired by Edelweiss in November 2016 and ceased to exist, so data reported post November 2016 is for Edelweiss.

This study finds, to the contrary, that retail investors take a myopic view of mutual funds, treating them as short-term speculative investments manifested through cyclical flows. They practise poor fund selection and market timing and suffer anaemic returns. Their investment losses skew the market in favour of institutions that demonstrate smarter trading skills and gain thereof. As a result, mutual funds do not contribute to wealth creation. Despite efforts of the regulatory bodies and AMCs[2], the retail investor may well become disillusioned with poor returns over time. This could have a deleterious knock-on effect through “word-of-mouth”, deterring others from investing in this market. Increased investor awareness around the nature of mutual funds, benefits of having a long-term investment horizon, investor protection and the need to build investor trust in industry players such as regulators, brokers, fund managers and AMCs is imperative if this industry is to contribute to wealth creation for the retail investor.

The structure for the remainder of the paper is as follows: the next section covers the development of the research hypotheses, while the third section addresses the main determinants of fund flows. The fourth section covers the data and methodology used; followed by the sections on analysis, results and robustness tests for the findings; the final section presents the conclusions.

Development of research hypotheses

From March 2014, SEBI[3] mandated that AMCs provide average monthly AUM data at a level of detail hitherto unavailable. A visual inspection and initial analysis of this data provides the motivation to raise three research questions leading to the subsequent hypotheses central to this paper. We first discuss the initial analysis; then proceed to develop the hypotheses.

The Indian mutual fund industry AUM grew from 3.6 trillion rupees in 2007, to 14.46 trillion rupees[4] by June 2016 with assets being managed by 44 fund companies offering over 2,000 different schemes (AMFI, 2017). Table 2 shows how the top 16 AMCs contributed 91% of this AUM. Fig. 1 shows the growth in the average AUM of open-ended equity growth funds (the instrument of interest in this paper) for (a) retail investors and for (b) FIIs[5] and banks. There is a net growth in AUM for retail investors who were net buyers of funds. Institutional AUM growth, on the other hand, shows a speculative pattern with buying and selling of funds. Fig. 2 relooks at this AUM growth in terms of flows and compares fund flows for different classes of investors. Retail flows exhibit cyclical investment patterns with alternating inflows and outflows between the months of March and September. Similar cyclicality in mutual fund flows has been found in other studies (Del Guercio & Tkac, 2002). FIIs/banks do not show any discernible pattern in their investment flows. Retail flow is seen to have a negative relationship to the Nifty 500 market returns till September 2016. Fig. 3(a) looks at the normalised median flows[6] for the universe of funds in this study against performance measured by the six-month past performance categorised by deciles. For all retail investors, irrespective of the distribution channel they use, there is a non-linear flow to performance relationship with higher performance attracting more normalised flows. This is similar to the results of the study by Sirri and Tufano (1998). This curve is steeper for direct plan investors (who invest directly with the fund house bypassing any intermediary) compared to those with regular plans (who invest through intermediaries such as brokers/agents). Fig. 3(b) shows a greater percentage of flow activity for direct investors compared to regular plan investors. The former react more sharply to exogenous conditions such as the demonetisation event of November 2016.

Synthesising these visual findings, we evolve three research questions and attendant hypotheses. The first addresses the possibility that retail investors having to choose from such a large number of schemes from a few companies face “choice overload” resulting in sub-optimal selection of funds for investment. The related research question is “What criteria do retail investors use for entering/exiting markets and selecting funds?” Fig. 2 (a) indicates they are contrarian to the current market, and Fig. 3(a) implies they chase fund performance. Hence, we propose our first hypothesis: Retail investors are contrarian to market performance and chase fund performance.

[2] Asset Management Company or a Mutual fund house.
[3] Securities Exchange Board of India, the primary securities regulatory body in India.
[4] Equivalent to US$56 to $216 billion based on a rate of 1 US$=67.12 Indian rupees.
[5] Foreign institutional investors.
[6] Fund flows and normalised fund flows were calculated based on Eqs. (3) and (4) that appear in later sections.

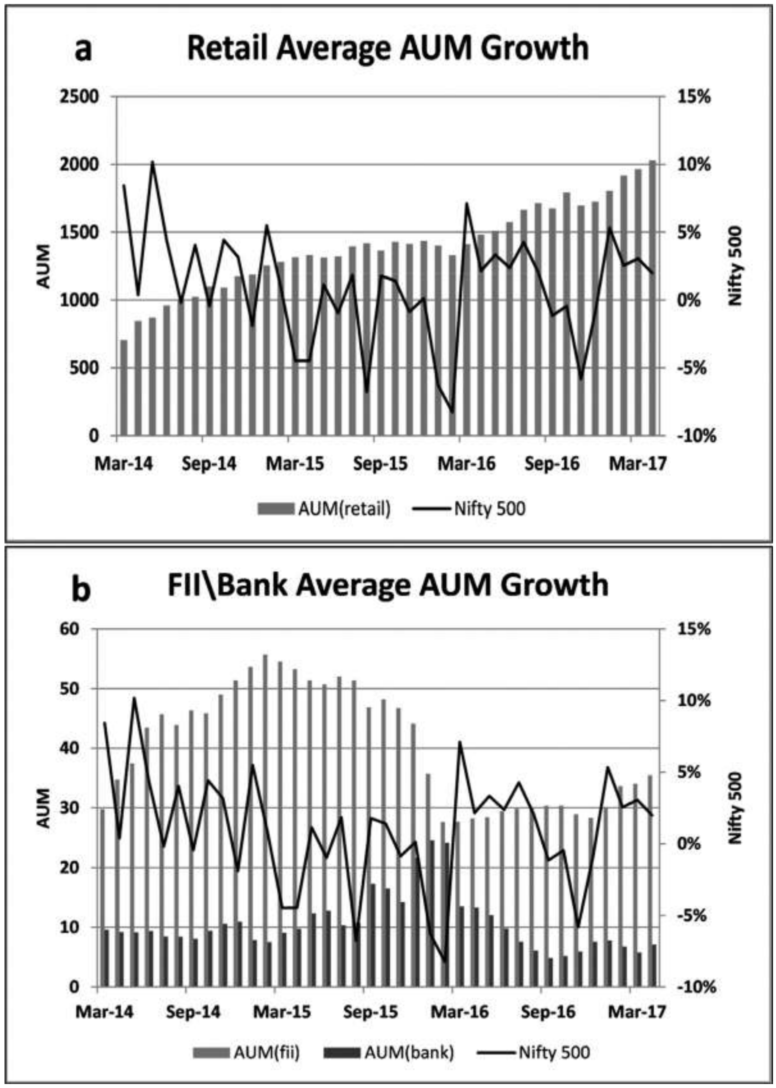

Fig. 1 (a) Growth in average AUM of open-ended equity growth funds for retail investors and for (b) FII and Bank investors across 16 AMCs for the period of the study. The Nifty 500 market monthly returns are shown for comparison. AUM figures are in billion rupees. *Source*: Author data.

The second question asks "Are the trading criteria of retail and institutional investors different?" As noted in studies, institutional investors represent the rational, successful investor class who make smart money and therefore represent a reference to compare retail investing behaviours. The second hypothesis emerging from this question is: Retail investor trading criteria is different from that of institutional investors.

The third question is related to performance of the retail investor and asks "Does the investment pattern (timing and fund selection) of retail investors lead to poor portfolio performance measured in raw returns?" The literature we reviewed earlier has shown that retail investors do lose money by trading actively. They exhibit poor fund selection, poor market timing and pay high transaction costs. Together, these represent costs that offset returns and hence their flows represent dumb money. Our visual inspection of Indian retail investors throws up many similarities to global studies; hence, we propose the hypothesis: Retail investors exhibit a dumb money effect.

Determinants of fund flows

We are interested in factors that determine how an investor selects a fund, times the entry/exit into/from the market. This is manifested through patterns in fund cash flows of purchases/investments and redemptions. We develop a model where the flows are the dependent variable affected by various factors, and controls as independent variables. We term the latter "determinants of fund flows" and list and discuss each below:[7]

[7] Fund age or the time since a fund was launched was also considered as a determinant similar to the cited studies. However, 89% of direct plan mutual funds in this study were launched on 1 January, 2013. As a result, the standard deviation in age for direct plans is one-fourth of regular plans. Inclusion of "Age" in the regression analysis of "(8)" provided no extra explanatory power (no changes to adjusted R^2) and Age itself was not found to be significant and hence dropped from the analysis.

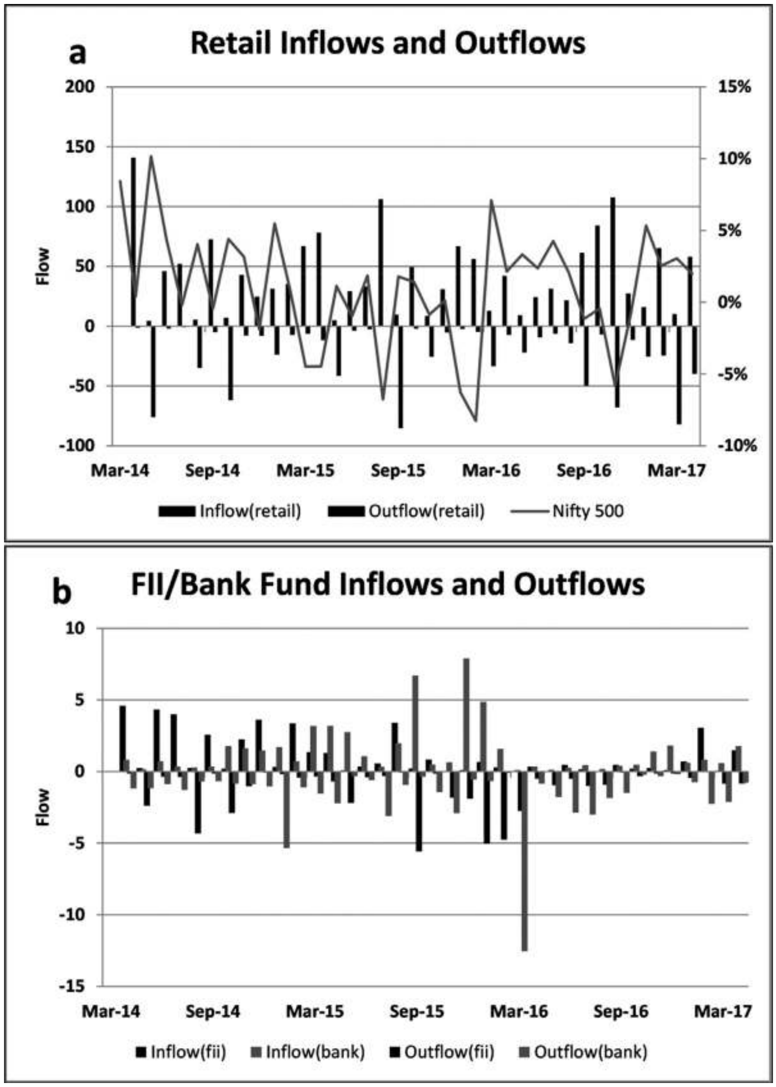

Fig. 2 (a) Retail monthly inflows and outflows against Nifty 500. (b) FII and Bank fund inflows and outflows. Flows are in billion rupees.

1) Market performance – As quoted in studies (Bose, 2012; Feng et al., 2014; Grinblatt & Keloharju, 2001; Oh & Parwada, 2007; Warther, 1995), investor flows have a strong relationship with stock market returns. These market returns are based on market indices such as Nifty 50 and Nifty 500.[8] We use the Nifty 500 in this paper due to the presence of mid cap and small cap funds within the portfolio of funds being studied.
2) Fund performance – There is literary evidence that investor flows follow past fund performance (Del Guercio & Tkac, 2002; Keswani & Stolin, 2008; Sirri & Tufano, 1998). There is also evidence (Grinblatt, Titman, & Wermers, 1995; Sapp & Tiwari, 2004) that investors adopt a momentum style of fund selection. To test both, we devise two measures of performance: (a) A comparison of the flows into two extreme portfolios, Top 20 and Bottom 20 (Bot 20) consisting of funds that are in the top two (9 and 10) and bottom two (1 and 2) deciles of six-month past returns of funds within their fund family.[9] Returns of a fund in time *t* are calculated from time *t-6* to *t-1* and then ranked in deciles within its fund family. The approach based on Sirri and Tufano (1998) handles asymmetry in flows by considering polar extremes of a fund's performance. (b) The second measure is a *Mutual Fund Momentum* factor to determine if investors adopt a momentum style of investing where they chase winners as opposed to losers over a one-year period. The momentum effect is measured as the weight adjusted difference in returns of winners over loser funds (Agarwalla, Jacob, & Varma, 2013). Past 11-month returns of a fund at time *t* (from end of *t-12* to *t-1*) are calculated and ranked by deciles within their fund family. The portfolio of the top 30% is

[8] The Nifty 50 and Nifty 500 are the Indian National Stock Exchange (NSE) stock market cap weighted indices of the top 50 and 500 Indian companies by market capitalization respectively.

[9] Each fund is classified into one of 10 fund families: Hybrid (arbitrage and mix of equity-debt funds), Multi-cap (diversified funds), Sector (e.g. FMCG, Infrastructure, Pharma, IT, Banking and Financial services), Large cap, Mid/Small cap (predominantly mid cap funds), Small cap, Index, International, Tax planning and Others (include thematic funds such as Entertainment, Rural, Lifestyle funds).

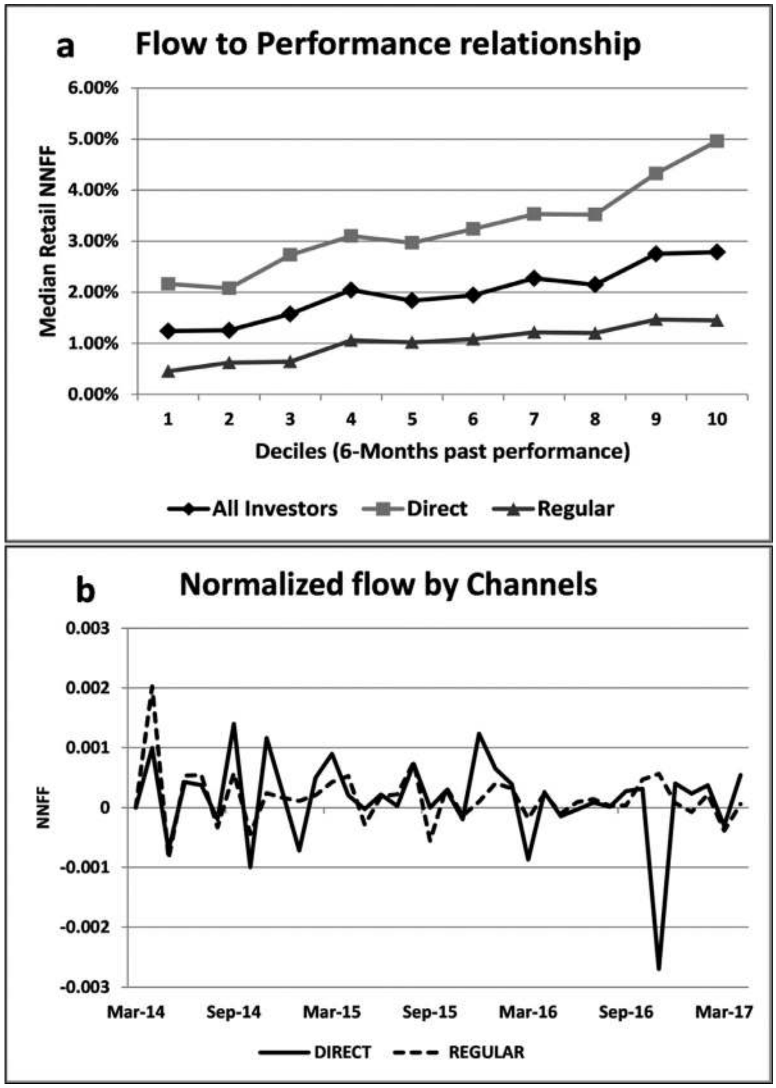

Fig. 3 Normalised net fund flows (NNFF) for retail investors. (a) Median NNFF into funds classified by their past six-month return performance decile. (b) NNFF by distribution channel – direct or regular. Investors can be direct (dealing directly with an AMC), regular using brokers/agents or all investors (direct and regular).

called "winners" and bottom 30% is termed "losers". Returns of each winner and loser portfolio are computed as the size (AUM) weighted average of the constituent fund returns and the difference is the momentum factor for the month *t*.

3) Fund Riskiness – Shu, Yeh, and Yamada (2002) and Griffin et al. (2007) use riskiness of funds as a factor influencing fund flows and measure this through the standard deviation in fund returns. Studies such as Feng et al's (2014) find that individual and institutional investors react to fund riskiness in opposite ways, with the individual investors reducing investments in risky assets. We use the historical standard deviation of fund monthly returns over the past year as the measure of riskiness as suggested by Sirri and Tufano (1998).
4) Fund size – Studies such as by Shu et al. (2002), Feng et al. (2014) and Narend and Thenmozhi (2016) consider fund size represented by the natural logarithm of the AUM as potentially "naive" criteria an investor may use in selecting a fund. Larger funds (and fund complexes) attract greater investments given their impression of safety and reliability.
5) Expense ratio – Management expense ratios are a percentage of the total net assets removed every year from a fund value to fund (a) investment fees (b) advisory fees (c) custodian agent fees, broker fees and (d) commissions and marketing. Studies such as by Anagol et al. (2017) and Shu et al. (2002), Sirri and Tufano (1998) and Narend and Thenmozhi (2016) use total fees/expense ratios and find investor flows are attracted by lower expense ratio funds which are expected to provide higher returns.
6) Distribution Channel – The sample data used includes information on investments made in "Direct plans" and "Regular plans". Direct plans are fund schemes where an investor buys/sells funds directly from the AMC bypassing the intermediate broker. Regular plans are purchased/sold by investors through brokers who are paid commissions by AMCs when (a) they grow the AUM for newly launched schemes (referred to as new money); (b) investors move cash between funds while switching schemes; (c) they keep

Table 3 Classification of funds in the data set by fund family.

	# of Obs	# of Funds		Expense ratios		Monthly returns		Volatility		Risk adjusted returns	
		Min	Max	Median	SD	Median	SD	Median	SD	Median	SD
Sector	2,312	46	66	2.18	0.56	1.21	5.29	0.0396	0.0172	−0.28	0.66
Hybrid	880	16	24	0.61	0.30	0.54	0.33	0.0387	0.0173	−0.04	0.18
Multi-Cap	4,090	78	122	2.05	0.57	1.35	4.78	0.0390	0.0176	−0.17	0.44
Mid-Small cap	2,120	48	58	2.01	0.49	2.24	6.13	0.0429	0.0190	0.05	0.50
Small Cap	826	18	22	2.16	0.54	3.00	7.29	0.0411	0.0187	0.35	0.62
International	526	10	16	2.115	0.64	0.62	3.26	0.0392	0.0181	−0.13	0.44
Large cap	2,242	50	64	2.05	0.57	1.19	4.42	0.0407	0.0189	−0.29	0.30
Index	988	24	30	0.5	0.31	1.49	5.56	0.0424	0.0184	−0.37	0.23
Other	1,480	34	44	2.34	0.67	1.37	5.99	0.0432	0.0181	−0.08	0.65
Tax	30	0	2	2	0.74	3.84	11.54	0.0450	0.0181	−0.05	0.32
Overall	15,494	330	438	2.02	0.72	1.22	5.23	-	-	-	-

Notes: Data set: Sector, Hybrid, Multi-cap, Mid-Small cap, Small cap, International, Large cap, Index, Other and Tax planning funds. # of Obs is sum of number of funds × months of observation for funds in each fund family for the study period. # of Funds varies by month due to new fund entry/old fund exits. Expense Ratio is obtained from Value Research. Monthly Returns are calculated from the daily NAV obtained from the AMFI site. Volatility is based on past 12-month standard deviation in monthly returns. Risk Adjusted Returns are the alphas or intercept values from the four-factor Carhart regression model. Overall monthly expense ratio and monthly returns are based on a size weighted average for the full portfolio of funds.

investors invested in a fund beyond a specific time and are paid trailer fees or trailing commission. A commission-motivated broker will affect fund flows (Anagol et al., 2017) by influencing fund selection and timing of investment decisions. This factor is included as a control variable on the flow behaviour, and to the authors' knowledge, this is the only India-based study where it has been considered.

Data

The data for this study comes from the monthly Average AUM (AAUM) reports provided by each AMC as mandated in 2014 by SEBI in a master circular entitled CIR/IMD/DF/18/2014, Section 5.6.[10] This requires AMCs to report AAUM by the following:

1) Fund names under a specific scheme category/scheme name such as debt oriented liquid or equity-growth;
2) Type of investor – retail, corporates (non-financial), banks/financial institutions (FIs), Foreign Institutional Investors/Foreign Portfolio Investors (FIIs/FPIs), High Net worth Individuals (HNIs);
3) Distributorship or sales channels including direct purchase plans (sales/purchase made directly from an AMC by the investor), associate distributors (sales agent associated with a mutual AMC or its promoters) or non-associated distributors (independent registered agents);
4) T15 or B15 city tier classification of investor location.

Data of the monthly average AUM is available from March 2014 to April 2017 (at the time of this study) resulting in 38 sets of monthly fund data. Based on information from AMFI,[11] as on April-June 2014, there were 46 AMCs with a total AUM of 993,23,24 million rupees which grew in April-June 2016 to 1,446,45,55 million rupees[12] managed by 44 AMCs. Of these, the top 16 AMCs across 2014-2016 contributed 91% of the total AUM. The AAUM data collected was restricted to these 16 AMCs only (Table 2) and this data was sans survivorship bias. The AMC data used fund names instead of the AMFI provided scheme and fund codes and had incorrect/misspelt fund names. This data was cleaned up by matching data in the AMFI site with a third-party vendor Value Research[13] supplied data. The fund scheme codes, mutual fund code and names provided by AMFI were used to uniquely identify each fund in the data set. The study considers only open-ended equity growth funds, and excludes dividend yield funds, ELSS and closed-ended equity funds, the latter two having limited cash inflows/outflows.[14] The number of funds change on a monthly basis as new funds enter and older ones exit or are merged. In March 2014, there were 330 plans from 165 funds, and by April 2017, there were 418 plans from 209 funds. Over this period, 252 new plans (126 funds) were added and 164 plans (82 funds) were redeemed/merged. The period of September 2016 to March 2017 saw heightened activity with 100 plans (50 funds) added and 112 plans (56 funds) exiting/being merged with other funds. Each fund in the data set includes a "regular" and a "direct" plan leading to 38 unbalanced panel data sets with a total of 15,494 fund × month-year observations for each type of investor, prior to removal of outliers.

Table 3 lists key statistics of the funds by their parent fund family and establishes a face validity check of the data:

- Expense ratios of passive funds such as index and hybrid (arbitrage) funds are lower with median values of 0.5 to 0.61, whereas funds requiring active management such as small cap, sectoral and others are higher at 2.16 to 2.34.

[10] http://www.sebi.gov.in/cms/sebi_data/attachdocs/1412152811369.pdf

[11] http://portal.amfiindia.com/NavHistoryReport_Frm.aspx

[12] $148 billion to $216 billion.

[13] https://www.valueresearchonline.com/funds/

[14] Equity linked Savings and closed-ended schemes have a three-year lock-in period.

- Monthly returns from mid cap and small cap funds show higher median monthly returns of 2.24% to 3.0% reflecting the higher risk they bear. The volatility median values at 0.0429 and 0.0411 also bear out this higher risk to return view.
- Risk adjusted excess returns or alphas are based on the four-factor Carhart model (Carhart, 1997). The four-factor Carhart model is an asset pricing regression model that uses four risk factors as independent variables to predict asset returns as the dependent variable. The four factors are (i) excess market return to risk free return or Jensen's factor; (ii) differential returns of small market cap to large market cap stocks; (iii) differential returns of high value stocks to low value stocks where value is measured by book value to market value. The last two factors are the Fama-French additions; (iv) differential returns of winner stocks to loser stocks called the momentum factor which is the Carhart addition. The intercept of this regression model represents the alpha or the excess risk adjusted return. Data on the four factors for this model was provided by Agarwalla et al. (2013). Since this model requires 36 months of continuous data, only funds that existed this long and beyond were considered.[15] Based on this model, the median risk adjusted returns vary from −0.29% (large cap funds) to 0.35% (small cap), reflecting the excess return created by active fund management over and above a passive index strategy. Index funds following a passive management style are expected to have near zero alpha values but show large negative values that can be attributed to tracking errors (where the index fund portfolio does not track the market index exactly).

Methodology

Definition of fund flows

NAVs[16] were obtained from the AMFI site and monthly returns were computed using the geometric mean "(2)" from the daily NAV returns of "(1)" according to

$$R_{i,t} = \log\left(\frac{NAV_{i,t}}{NAV_{i,t-1}}\right) \tag{1}$$

$$R_{i,m} = \prod_{t=1}^{n}(1 + R_{i,t}) \tag{2}$$

$NAV_{i,t}$ represents the NAV values for fund i at time t, $R_{i,t}$ is the daily return for the fund i for time t, log is the natural logarithm and $R_{i,m}$ is the monthly return for fund i. For each fund i, the *Net fund flows* (*NFF*) for the month m was computed following the approach of Feng et al. (2014), Sirri & Tufano (1998) and Warther (1995):

$$NFF_{i,m} = AUM_{i,m} - (1 + R_{i,m}) \times AUM_{i,m-1} \tag{3}$$

$AUM_{i,m}$ is the AUM for fund i and month m. This assumes fund flows occur at the end of the month m.[17] To remove the effects of fund sizes and smooth data, over time the net fund flows NFF are *normalised* using the fund size to get the *normalised net fund flow (NNFF)*:

$$NNFF_m = \frac{(AUM_m - AUM_{m-1}) - R_m \times AUM_{m-1}}{AUM_{m-1}} \tag{4}$$

The normalised net fund flow values were "winsorised" by restricting them to within +/- 100% for investor flows. As a result, the number of observations dropped from 15,494 to 15,017, 14,753 and 15,062 for retail, FII and bank investor flows, respectively.

Definition of performance gap

Returns earned by an investor during a period are measured in two ways: one accounting for cash flows over time and another that only accounts for time. The first uses the internal rate of return (IRR) method to include cash flows (inflows and outflows) and gives the money weighted return (MWR). This is computed as the rate MWR_i for fund i that satisfies the equation:

$$-I_{i,0} + \sum_{t=1}^{T}\frac{CF_{i,t}}{(1 + MWR_i)^t} + \frac{E_{i,T}}{(1 + MWR_i)^T} = 0 \tag{5}$$

where I is the initial investment at time 0, CF is the net cash flow for time t and E is the final value of the portfolio for fund i at the end of the period T. The MWR accounts for changes due to frequency and amount of flows in and out of funds every period. The second method of calculating returns ignores all cash inflows and outflows and computes the geometric mean of a series of returns and is called time weighted return (TWR). This is given as:

$$TWR_i = \left(\prod_{t=1}^{T}(1 + R_{i,t})\right)^{1/T} - 1 \tag{6}$$

where R is the monthly return at time t based on Eq. (2). This method is identical to a strategy where investors buy and then hold the portfolio for the duration. Based on Friesen and Sapp (2007), the difference between the MW and TW return is computed and termed the "performance gap". This is the gap created by active trading by an investor. It is used to assess the relative performance of funds by different investor types. For a fund i the performance gap is given by:

$$Performance\ Gap_i = MWR_i - TWR_i \tag{7}$$

This analysis at fund level will reveal how an investor fares when actively trading as opposed to adopting a buy and hold strategy for the same period. The returns and the gap based on the normalised net fund flow is calculated for each fund in a fund family. A negative gap would mean

[15] The Jensen single factor and Fama-French three-factor analysis was also done and the resulting alphas were found to be insignificantly different from the four-factor Carhart model which was adopted.

[16] Net asset value or price per unit of the fund.

[17] A test assuming net flows occur at the beginning of the month did not alter the final results significantly.

[18] To understand how a performance gap is created by untimely flows, imagine an investor increases flows into a fund just before the fund returns start to fall or redeems funds just before fund returns start rising. In both cases, the investor makes less or suffers a performance gap compared to taking no action ("hold strategy").

Table 4 Regression results of how retail normalised net fund flows (*NNFF*) are impacted by different factors.

	1	2	3	4	5
Constant	0.060*** *(0.004)*	0.113** *(0.044)*	0.105** *(0.040)*	0.178*** *(0.041)*	0.178*** *(0.041)*
Nifty	−1.132 *(0.725)*	−1.140 *(0.739)*	−1.145 *(0.740)*	−6.484*** *(1.311)*	−6.484*** *(1.311)*
Nifty-1	0.763 *(0.725)*	0.765 *(0.739)*	0.772 *(0.740)*	0.592 *(0.751)*	0.592 *(0.751)*
Log(AUM-1)	5.45×10^{-7}	-1.95×10^{-5}***	-1.05×10^{-5}*	-4.16×10^{-6}	-4.16×10^{-6}
	(8.58×10^{-7})	(5.76×10^{-6})	(5.91×10^{-6})	(5.87×10^{-6})	(5.87×10^{-6})
Exp Ratio	−0.016*** *(0.002)*	−0.109** *(0.038)*	−0.099* *(0.040)*	−0.094** *(0.032)*	−0.094** *(0.032)*
Risk	−0.078 *(0.078)*	−0.327*** *(0.117)*	−0.323** *(0.114)*	−1.034*** *(0.118)*	−1.034*** *(0.118)*
MFMOM	-	0.060*** *(0.011)*	0.086*** *(0.013)*	0.111+ *(0.060)*	0.111+ *(0.060)*
Top 20	-	-	0.011*** *(0.003)*	0.012*** *(0.003)*	0.012*** *(0.003)*
Bot 20	-	-	−0.007** *(0.003)*	−0.009** *(0.003)*	−0.009** *(0.003)*
DEMON	-	-	−0.026*** *(0.003)*	-	-
DP	-	-	-	-	0.123+ *(0.054)*
Fund FE	No	Yes	Yes	Yes	Yes
Month × Year FE	No	No	No	Yes	Yes
Adjusted R^2	2.63%	9.38%	10.16%	16.24%	16.24%

Notes: NNFFs are impacted by factors such as current and lagged markets return (Nifty, Nifty_1), fund size (Log of 1-month lagged AUM), Expense Ratio, Risk, Mutual fund Momentum (MFMOM), Top 20 and Bot 20 percentile fund portfolios. Risk is the standard deviation in monthly returns, momentum factor is the differential return between 30^{th} percentile top and bottom performers based on past 11 month returns, Top 20 and Bot 20 are indicators of fund portfolios in the top 20 and bottom 20 percentile by past six-monthly returns. DEMON and DP are indicator variables to control for effects of demonetisation and distribution channels. Fixed effects are controlled by the Fund Fixed Effects (Fund FE) and time effects by Month × Year (M*Y) interaction variable. All coefficients are unstandardised values; standard errors are in brackets.
Significance levels: *** 0.001.
**0.01.
*0.05.
+0.1, ' ' 1.

trading by investors has resulted in a loss and is a sign of the dumb money effect.[18]

Analysis

Regression of fund flows, performance

To test our first two hypotheses, a regression analysis on the unbalanced panel data is done with various determinants of flow, discussed earlier. We explicitly control for time-invariant fund characteristic differences (using fund fixed effects), time effects and effects of special events. The following estimation equation is used (Anagol et al., 2017):

$$\begin{aligned} NNFF_{i,t} = \; & \beta_0 + \beta_1 MP_{t,t-1} + \beta_2 AUM_{i,t-1} + \beta_3 FP_{i,t} \\ & + \; \beta_4 Risk_{i,t} + CN + \; \gamma_i + \tau_t \; + \; \in_{i,t} \end{aligned} \tag{8}$$

The dependent variable, in this case, is the normalised net fund flows from Eq. (4) $NNFF_{i,t}$ for the fund i for the month t. The $MP_{t,t-1}$ represents market performance both contemporaneous and one-month lagged given by the Nifty 500 monthly returns. Size of fund effect on investor flows is represented by Log of AUM for fund i at one-month lag. The fund performance *FP* is represented by two measures discussed earlier: (a) flows into Top 20/Bot 20 funds as an indicator variable whose value is 1 or 0 and (b) a variable *MFMOM* incorporating the mutual fund momentum measure to capture the momentum style investing, if practised. $Risk_{i,t}$ captures the riskiness of the fund expressed in terms of the standard deviation of the past one-year monthly returns. The term *CN* stands for controls that are either (a) fund specific, such as distribution channels (a direct investment channel used by the investor is assigned an indicator variable *DP* with a value of 1, and is 0 if it is indirect - a regular plan); or (b) common across funds, for e.g., events like demonetisation of the Indian currency in November 2016.[19] This effect is captured by an indicator variable *DEMON* which takes a value of 1 for data observations after November 2016, and 0 prior to this period. The $\gamma_i$factor is a fund level fixed effect which controls for time-invariant fixed factors such as fund type, expense ratios and management style specific to each fund. The factor τ_t is used to control the aggregate time-series effects where, if all values were to rise, over time, it could lead to spurious correlations between otherwise unrelated items. The control is represented as an interaction term of Month × Year representing each observation month of the study.

Table 4 presents the results of the analysis using the regression (8) to test the first hypothesis. This looks at the relationship between retail normalised fund flows and market performance, size of the fund, expense ratio, fund risk and fund performance (including momentum effects). Controls are included for effects of distribution channel and demonetisation events, and for fund fixed effects, time fixed effects in a sequential fashion from columns 1 to 5. The second hypothesis is tested by repeating this regression

[19] On 8 November, 2016, 500 and 1,000 rupee notes were made illegal tender in India.

Table 5 Descriptive statistics of retail normalised net fund flows into Top 20 and Bot 20, high and low risk and into high expense and low expense ratio funds.

Figures are in % of retail normalised net fund flows (NNFF)						
Term	Min	25%	Median	75%	Max	SD
Top 20	−0.998	−0.008	0.028	0.072	0.998	0.139
Bot 20	−0.986	−0.016	0.012	0.045	0.961	0.111
High risk	−0.996	−0.012	0.020	0.056	0.973	0.116
Low risk	−0.998	−0.011	0.018	0.053	0.998	0.118
High expense ratio	−0.996	−0.015	0.015	0.048	0.929	0.107
Low expense ratio	−0.998	−0.007	0.024	0.062	0.998	0.127

Notes: Top 20/Bot 20 performance is based on past six-month return deciles. High and low risks are measured as past year standard deviation of returns above and below the median value. Expense ratios are classified as high/low based on being above or below the median value. The median values in the latter two cases are by fund family.

for FII and bank investors. A comparison of these results with retail findings reveals similarities and differences and is presented in Table 6.

Performance gap analysis: Dumb money effect

To test the third hypothesis "Do retail investors exhibit a dumb money effect?", we employ Eq. (7) to determine the return performance gap for investors. If the performance gap is significantly negative, it implies investors lose money by trading funds rather than staying invested. This speaks of poor fund selection and market timing. To further highlight this fund selection/timing ability or lack of it, we calculate the performance gap for three groupings of funds having different risk adjusted returns or alpha characteristics: (a) a poor performance group consisting of large cap and sectoral funds with an alpha of −0.29% to −0.28% (b) a medium performance group consisting of hybrid (arbitrage) funds at −0.04% alpha and (c) a high performance group comprising mid and small cap funds with alphas of 0.05% and 0.35%. The MWR, TWR and performance gap is calculated for all funds that fall into these three groups and an ANOVA F-test is employed to ascertain that the performance gap values are statistically significant.

Results

Flows versus performance - retail investors

Table 4 shows that investor behaviour of reversing flows based on current market return is consistent across all cases, becoming significantly negative once time effects are controlled (columns 4 and 5), while lagged market returns are insignificant in all cases. Investors use current market returns as an indicator for timing entry/exit of funds and turn contrarian when the market rises as they increase (decrease) outflows (inflows). Investors do not chase past market returns. Fund size is not a factor influencing investor flows as it is insignificant (with one exception) in the seven cases and the effect size is very small. Fund flows are significantly (at 1%) negatively correlated with expense ratios implying investors increase flows into low expense ratio funds, as other studies have confirmed. Fund risk is also a very significant factor in columns 2 to 5 and is consistently negatively correlated to fund flows. This bears out other studies showing retail investors prefer lower risk funds for investment. The mutual fund momentum factor is positively very significant in columns 2 and 3 but becomes less significant once time effects are controlled. This indicates the effect may be due to aggregate behaviours of the data across time than due to a momentum style of investing. This behaviour is unlike that observed in the US where retail investors invest in long term winners as opposed to losers (Grinblatt et al., 1995). The most significant finding from columns 3 to 5 is that net flows into the Top 20 performance fund portfolios is significantly positive (at 0.1%), and is significantly negative (1% to .1%) into Bot 20 portfolios. Retail investors move more money into fund portfolios that have shown high past six-month performance and less into funds with poor past six-month performance. The regression coefficients are consistent across all cases and lends significance to Fig. 3(a) and establishes the flow-performance convexity phenomenon described by Ferreira et al. (2012) and Sirri and Tufano (1998) for Indian retail investors.

Column 3 studies the effect of the demonetisation event (*DEMON*) on net retail flows and shows a significant negative relation implying a decrease in normalised fund flows of 2.6% after the event. In column 5, the effect of controlling for distribution channels using *DP* shows that it is not significant. The regression coefficient is positive, indicating that direct channel investors have greater flows into the Top 20/Bot 20 funds compared to investors going through brokers/agents. This is confirmed by Fig. 3(a) and (b) where direct plan investors show higher percentage flows compared to regular plan investors. Direct plan investors have a steeper convex flow curve from lower to higher performance. In regular plans, intermediation by brokers/agents appears to reduce the frequency of fund flows, potentially improving the chances of creating wealth.

Table 5 provides descriptive statistics of size effects of performance, volatility and expense ratio on the median flows. Performance and expense ratios have a greater effect on flows than fund risk. While median flows into Top 20 is more than twice that into Bot 20 portfolios, the flows into low expense ratio funds is 1.6 times that into high expense ratio funds. The median fund flows show no discernible difference between high and low risk funds.

Table 6 Regression results showing how the normalised net fund flows (NNFF) are impacted for each type of investor.

	Retail		FII		Bank	
	1	2	1	2	1	2
Constant	0.105** *(0.040)*	0.178*** *(0.041)*	0.001 (*0.002*)	−0.005 (*0.007*)	0.203^{+} (*0.112*)	0.197^{+} (*0.112*)
Nifty	−1.145 *(0.740)*	−6.484*** (*1.311*)	−0.027^{+} (*0.013*)	0.289 (*0.363*)	−0.925 (*0.830*)	−1.843^{+} (*1.098*)
Nifty-1	0.772 *(0.740)*	0.592 (*0.751*)	−0.023^{+} (*0.012*)	−0.037 (*0.024*)	0.767 (*0.830*)	0.796 (*0.844*)
Log(AUM-1)	*v.low*$^{+}$ *(v.low)*	−*v.low (v.low)*	−*v.low (v.low)*	−*v.low (v.low)*	*low (v.low)*	*low (v.low)*
Expense Ratio	−0.099* *(0.040)*	−0.094** (*0.032*)	-1.3×10^{-5} *(0.001)*	0.0002 (*0.002*)	−0.203^{+} (*0.109*)	−0.204^{+} (*0.108*)
Risk	−0.323** (*0.114*)	−1.034*** (*0.118*)	−0.039 (*0.050*)	−0.043 (*0.053*)	−0.172 (*0.124*)	−0.033 (*0.131*)
MF MOM	0.086*** *(0.013)*	0.111^{+} (*0.060*)	0.015^{+} (*0.007*)	0.013 (*0.009*)	0.032*** (*0.010*)	0.059** (*0.023*)
Top 20	0.011*** *(0.003)*	0.012*** (*0.003*)	−0.002 (*0.002*)	−0.002 (*0.001*)	−0.005 (*0.004*)	−0.005 (*0.004*)
Bot 20	−0.007** (*0.003*)	−0.009** (*0.003*)	−0.004** (*0.001*)	−0.004** (*0.001*)	0.0060^{+} (*0.003*)	0.006^{+} (*0.003*)
DEMON	−0.026*** (*0.003*)	-	−0.0002 (*0.002*)	-	−0.006^{+} (*0.004*)	-
DP	-	0.123^{+} (*0.054*)	-	0.002 (*0.003*)	-	0.226^{+} (*0.137*)
#of Obs	15,017	15,017	15,062	15,062	14,753	14,753
#non-zero Obs	15,011	5,011	1,655	1,655	5,193	5,193
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Month × Year (FE)	No	Yes	No	Yes	No	Yes
Adjusted R^2	10.16%	16.24%	3.86%	4.25%	4.65%	5.07%

Notes: Retail (repeated from Table 4), FII and banks based on the columns 3 and 5 described in Table 4. Entries with *low* and *v.low* indicate absolute numbers 1×10^{-4} to 1×10^{-5} and less than 1×10^{-5} respectively. All coefficients are unstandardised values; standard errors are in brackets.

Significance levels: *** 0.001.

**0.01.

*0.05.

$^{+}$0.1, ‘ ’ 1.

Table 7 Performance gap measured as difference between the money weighted return (*MWR*) and time weighted return (*TWR*) by five fund families grouped in ascending order of their alpha returns (risk adjusted excess returns) for retail investors.

	Min	25%	Median	75%	Max	SD
Poor performance group						
Large cap funds with alpha = −0.29%						
MWR	−4.14%	0.38%	0.81%	2.03%	8.59%	1.27%
TWR	−3.89%	0.53%	1.03%	2.18%	11.11%	1.48%
Performance Gap (*F-29.62****)	−0.25%	−0.15%	−0.22%	−0.14%	−2.52%	−0.20%
Sectoral funds with alpha = −0.28%						
MWR	−4.01%	0.48%	1.09%	2.35%	12.05%	1.60%
TWR	−4.27%	0.70%	1.26%	2.52%	11.87%	1.80%
Performance Gap (*F-18.7****)	0.25%	−0.21%	−0.16%	−0.17%	0.18%	−0.21%
Medium performance group						
Hybrid funds with alpha = −0.04%						
MWR	0.10%	0.49%	0.54%	0.58%	0.77%	0.07%
TWR	0.24%	0.54%	0.57%	0.60%	0.69%	0.06%
Performance Gap *(F-76.91***)*	−0.14%	−0.05%	−0.03%	−0.02%	0.08%	0.01%
High performance group						
Mid-small cap funds with alpha = 0.05%						
MWR	−2.09%	0.79%	1.43%	3.17%	11.18%	1.71%
TWR	−1.65%	1.20%	1.85%	3.52%	14.69%	1.85%
Performance Gap *(F-66.3***)*	−0.44%	−0.42%	−0.42%	−0.34%	−3.50%	−0.14%
Small cap funds with alpha = 0.35%						
MWR	−1.38%	0.96%	1.65%	3.18%	10.45%	1.90%
TWR	−0.74%	1.78%	2.44%	4.23%	11.18%	2.03%
Performance Gap (*F-71****)	−0.64%	−0.83%	−0.79%	−1.05%	−0.73%	−0.14%

Notes: The ANOVA F-statistic value in brackets determines if the performance gap measure is statistically significant at a 5% level (actual F-statistic value in brackets).
Significance levels: *** 0.001.
** 0.01.
*0.05+ 0.1, ‘ ’ 1.

In summary, retail investors “chase fund performance rather than past market returns and turn contrarian to current market returns”, and our first hypothesis cannot be rejected. Comparing this behaviour of the Indian retail investor with that of his US counterpart based on studies cited in Table 1, we see that chase fund performance and US investor fund flows are positively correlated to current market returns, unlike the Indian retail investor.

Retail versus financial institutional investors

The next analysis compares retail investors to banks/FIs and FIIs. The latter represent professional investors and are expected to possess superior market knowledge and skills. FII and bank/domestic financial institutional investor flows are analysed in a similar fashion to retail investors employing regression Eq. (8). The specifications of columns 3 and 5 having relatively higher adjusted R^2 scores from Table 4 were selected and the results are presented in Table 6. Factors relevant to retail investors such as current market returns, fund risk, expense ratios and Top 20 performance funds are insignificant for FIIs. Only Bot 20 fund portfolios demonstrate significant reduction in inflows/increased outflows. Studies in Indian equity markets show that FIIs are strong momentum traders (Bose, 2012; Tayde & Rao, 2011); however, this is not evident for mutual funds. Banks also share no common significant factors with retail but show a significant positive momentum effect (at 1%). They follow a momentum style investing even after controlling for time effects. For banks and FIIs, distributor channels and demonetisation do not have a significant impact on fund flows.

In conclusion, trading criteria and behaviours of financial institutions are significantly different to retail investors and hence the hypothesis “trading criteria of retail investors is different from financial institutions” cannot be rejected. We will see further differences between these classes of investors in terms of performance in the next section. It is to be noted that Banks and FIIs have three to 10 times *lower* non-zero fund flows, than retail investors, and the results have to be viewed in this context.

Performance gap analysis - all investors

Table 7 demonstrates that retail investors have a median performance gap that is significantly negative for all types of funds. This implies they have done poorly by actively trading than by adopting a buy and hold strategy. The gaps range from −0.03% to −0.79% with larger gaps occurring for higher alpha funds such as mid cap and small cap. The F-statistic is significant in all cases and the results match findings in the US studies by Friesen and Sapp (2007). As Barber et al. (2006) have shown, excessive trading by retail investors leads to negative/poorer returns. Table 8 compares this performance gap to that of FIIs and banks. Institutional investors clearly do better in their fund selection and timing of buys and sells and

Table 8 Performance gap measured as the difference between the money weighted return (*MWR*) and time weighted return (*TWR*) return of the five fund families grouped in ascending order of their alpha returns (risk adjusted excess returns) for retail, FII and banking investors.

	Retail	FII	Bank
Poor performance group			
Large cap funds with alpha = −0.29%			
MWR	0.81%	1.56%	0.96%
TWR	1.03%	0.88%	0.98%
Performance gap *(F-statistic)*	−0.22% *(29.62)****	0.68% *(29.96)****	−0.02% (1.17)
Sectoral funds with alpha = −0.29%			
MWR	1.09%	2.07%	2.38%
TWR	1.26%	0.88%	1.23%
Performance gap *(F-statistic)*	−0.16% *(18.7)****	1.19% *(45.92)****	1.15% *(44.16)****
Medium performance group			
Hybrid funds with alpha = −0.05%			
MWR	0.54%	0.47%	0.60%
TWR	0.57%	0.27%	0.54%
Performance gap *(F-statistic)*	−0.03% *(76.91)****	0.20% *(7.68)*	0.06% *(45.38)****
High performance group			
Mid-small cap funds with alpha = 0.05%			
MWR	1.43%	2.28%	1.93%
TWR	1.85%	1.45%	1.55%
Performance gap *(F-statistic)*	−0.42% *(66.3)****	0.83% *(27.22)****	0.37% *(33.18)****
Small cap funds with alpha = 0.35%			
MWR	1.65%	0.91%	1.30%
TWR	2.44%	0.93%	0.85%
Performance gap *(F-statistic)*	−0.79% *(71)****	−0.03% *(6.63)****	0.45% *(0.699)*

Notes: The returns are all median values for each fund group. The ANOVA F-statistic values in brackets determine if the performance gap is statistically significant at a 5% level.

achieve *positive* performance gaps of 0.06% to 1.19% returns across most groups of funds above the simple buy and hold strategy. This translates to superior returns of 1.31% to 1.35% in the low performance group (sectoral funds), to 0.8% to 1.2% in the high-performance group (mid-small cap) for institutional over retail investors.

By actively trading, retail investors exhibit a negative performance gap when compared to adopting a passive strategy. They also have a negative performance gap compared to institutional investors. So, we cannot reject the hypothesis that "retail investors show a dumb money effect".

Robustness tests

To determine if the results of this paper are stable and robust, we repeatedly run the model based on Eq. (8) under different conditions, incorporating the specification of column 4 in Table 4. We compare the size and sign (direction) of the model coefficients for stability and consistency with this base specification. The results of these tests are given in Table 9. The first column in the table presents the original base result reproduced from column 4 in Table 4,[20] while columns 2 to 7 represent the different test run results.

[20] Note in Table 9 we have only displayed Nifty 500, Top 20 and Bot 20 as factors to compare under different conditions; however, results for all other factors are available from the author on request.

Sub-sample period stability: The second to the fourth column contains results of the regression model rerun using a yearly sub-sample of the original three year data (Frazzini & Lamont, 2008). Each column uses one year's data for the sub-periods of March 2014 to February 2015, March 2015 to February 2016, and March 2017 to February 2017, respectively. The sub-period was chosen to coincide with the Indian financial year start and end, widely recognised as a time when most retail investors exhibit high frequency of cash flows. The time fixed effects interaction term is removed for these runs as year on year effects are not relevant.

In all cases, the fund flows have a consistent negative relationship with the Nifty i.e. inflows reduce (outflows increase) as market returns increase. Flows into Top 20 portfolios show significant to very significant positive relationship, while with the exception of the second period (which is insignificant), flows into Bot 20 show a significant negative relationship. This indicates that the base reference results are stable and robust over sub-periods.

Sub-sample test based on flow direction: The fifth and sixth columns contain results of testing the model with inflows (positive normalised net flows) and outflows (negative normalised net flows), each as a dependent variable instead of a single net flow. Investors potentially behave differently towards fund performance during purchase than when redeeming funds (Friesen & Sapp, 2007).

For inflows (column 5), the relationship of flows to Nifty, Top 20 and Bot 20 funds remain unchanged from the base

Table 9 Results of robustness tests performed on the regression model of Table 4 using the column 4 specification.

	Base	Period sub-sample			Inflows	Outflows	Alpha
	1	2	3	4	5	6	7
Nifty	−6.484*** (1.311)	−3.39* (1.625)	−0.292 (0.317)	−0.073 (0.291)	−2.508^{+} (1.426)	0.784 (2.218)	−6.476*** (1.316)
Top 20	0.012*** (0.003)	0.027*** (0.007)	0.009* (0.004)	0.010*** (0.003)	0.019*** (0.013)	−0.011* (0.004)	0.006^{+} (0.003)
Bot 20	−0.009** (0.003)	−0.023** (0.008)	0.001 (0.003)	−0.006** (0.003)	−0.007** (0.002)	0.004 (0.004)	−0.011** (0.004)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month × Year (FE)	Yes	No	No	No	Yes	Yes	Yes
Adjusted R^2	16.24	16.92	18.08	11.29	21.16	24.1	16.04
#of Obs	15,017	4,088	5,416	5,513	10,098	4,919	15,017

Notes: For the sake of brevity, we show only three factors from the original specification, i.e. Nifty or current market return, Top 20, Bot 20 portfolio flow as independent variables with normalised net fund flow as the dependent variable. Column 1 presents the original base result repeated from Table 4, column 4. The next three columns (2 to 4) are results of the same regression run as three yearly period sub-samples starting from March 2014 to February 2017. The fifth and sixth column runs the original model with dependent variable as normalised inflows and outflows separated respectively, instead of a single net flow. The seventh column uses risk adjusted returns (Carhart alpha) as an alternate performance measure to determine the Top 20 and Bot 20 portfolios. All coefficients are unstandardised and standard errors are in brackets.

Significance levels: *** 0.001.

** 0.01.

* 0.05.

$^{+}$ 0.1, ' ' 1.

reference. While effect size for Nifty is lower, the effect size for Top and Bot 20 effects are significant and quite similar in magnitude to the base values.

For outflows (column 6), the signs of the flow into Top 20 are reversed (negative) showing that investors reduce outflows from high performance portfolios. This implies investors continue to repose faith in high performing funds, and is consistent with our base reference. Our findings are robust and stable to the direction of cash flows.

Using an alternate measure of fund performance*:* The original regression model used six-monthly raw returns to allocate funds into the Top 20 and Bot 20 portfolios. We rerun the model using an alternate performance measure i. e. the risk adjusted return or alpha value (Carhart alpha) of funds as employed by Friesen and Sapp (2007), Sapp and Tiwari (2004) and Feng et al. (2014). The alpha value represents the excess returns from a fund after controlling for various market risk factors, and is attributable to active fund management.

Column 7 shows that Nifty and Bot 20 factors are consistent in terms of effect size, sign and significance with the base reference. The Top 20 factor, while lower in effect, has the same relation with fund flows as the base reference but is reduced in significance. Overall, we can conclude that our results are robust to using alternate measures of performance.

In conclusion, we see that this paper's findings are robust over time, for different types of flows and different measures of fund performance. As already demonstrated in earlier sections, the findings are also robust for effects of fund size, fund risk, expense ratios and special events like demonetisation and the impact of using different distribution channels.[21]

Conclusions

The study confirms that retail investors chase fund performance and react to current market returns by turning contrarian. Retail investors trade actively moving in and out of funds rather than staying invested over longer periods. Their trading activity results in a loss of 0.22% to 0.79% in returns compared to a simple buy and hold strategy, demonstrating the dumb money effect. In contrast, institutional investors use different criteria such as a focus on poor performing funds and momentum style of investing, and despite trading actively, make up to 1.3% superior returns over retail investors. Retail investors react to macro-event shocks such as demonetisation while institutions seem impervious to it. Distribution channels have a marginal effect on retail investors with greater flow fluctuations for direct investors compared to those going through brokers/agents. It would appear intermediaries have a moderating effect on retail investors.

The not-so-flattering picture that emerges of the retail mutual fund investor is one of individuals relying on unsophisticated broad market and fund performance signals and reacting to market-wide events, losing money to skilled institutional investors and having a short-term view of mutual fund investments. While the scope of this paper was

[21] Methodology related robustness tests for multi-collinearity, Breusch-Pagan test for heteroscedasticity of standard errors and Hausman test (Hausman, 1978) for appropriateness of the fixed effects regression model were all done and are available on request.

not to explore why retail investors behave this way, we have provided some explanations earlier such as: a disposition effect of differentially disposing of winners too soon while holding on to losers longer; "cognitive dissonance" explaining why investors rely on past good performance while ignoring current loss making performance; overconfidence in trading abilities causing them to enter and exit markets aggressively despite lacking any special professional investment skills or training that institutional investors possess.

Apart from behavioural biases, this study raises two other possible reasons for investor behaviours: one related to how investors regard mutual funds (a question of awareness and trust), and the second regarding the effect of brokers/agents on investors. The basis for the first reason is the cyclical behaviour of fund flows for retail investors noted in this study. This cannot be explained by mere liquidity requirements or tax-loss booking needs. The retail investor seems to either have a lack of trust towards mutual funds and/or treats them as short-term money making, speculative instruments akin to stocks, and aims to book profits rather than stay invested for longer periods. The influence of brokers/agents could also be a cause for the cyclical flows. By separating direct and regular plan investors, the study has assessed this impact, which, while not significant, does deserve greater attention in future research. In an attempt to spur growth in January 2013, AMCs introduced direct plans targeted at retail investors to benefit from dealing directly with an AMC who levied lower fees and provided higher returns. The annual growth in open-ended equity AUM of such direct plans during the course of this study has been 32% (authors' data) showing that investors have whole heartedly embraced direct plans. Yet, as this study shows, such direct plan investors are also most prone to the hazards of poor fund selection, poor market timing and excessive trading. Direct plans may, in fact, have led to destruction in retail investor wealth, not an outcome intended when they were introduced. Investors going through brokers/agents, in contrast, seem less reactive to exogenous signals and while all retail investors demonstrate a dumb money effect, brokers/agents seem to have a restraining influence on cash flow movement. This would suggest that the industry and investor would be better served if there was less emphasis on creating and selling new fund schemes/plans and more on educating/training brokers/agents to be true advisors to investors.

The impact of biases, trust in the industry players, and impact of distribution channels can be topics of future research into mutual funds. As was done in this study with financial institutions, a comparison with other classes of investors such as non-financial corporate investors and HNIs would be useful in revealing further investor behaviours. It is clear that the industry needs to hand hold retail investors, improve their trust and confidence in fund management, raise their awareness of mutual funds as long-term investments and address the perils of excessive trading, thereby achieving secular growth and investor wealth.

References

Agarwalla, S.K., Jacob, J., & Varma, J.R. (2013). Four factor model in Indian equities market. *SSRN* 1–22. https://doi.org/10.2139/ssrn.2334482.

AMFI. (2017). Association of Mutual Funds Industry. Retrieved from https://www.amfiindia.com/indian-mutual

Anagol, S., Marisetty, V., Sane, R., & Venugopal, B. (2017). On the impact of regulating commissions: Evidence from the Indian mutual funds market. *World Bank Economic Review* 31 (1), 241–270. https://doi.org/10.1093/wber/lhv065.

Arora, R.K. (2016). The relation between investment of domestic and foreign institutional investors and stock returns in India. *Global Business Review* 17 (3), 654–664. https://doi.org/10.1177/0972150916630830.

Barber, B.M., Lee, Y.-T., Liu, Y.-J., & Odean, T. (2006). How much do individual investors lose by trading? *Review of Financial Studies* 22 (2), 609–632.

Barber, B.M., & Odean, T. (2005). Individual investors. In: Thaler, R.H. (Ed.), Advances in Behavioral Finance Vol II. Russell Sage Foundation, pp. 543–569.

Bose, S. (2012). Mutual Fund Investments, FII Investments and Stock Market Returns in India. *SSRN*. https://doi.org/10.2139/ssrn.2204418.

Carhart, M.M. (1997). On persistence in mutual fund performance. *The Journal of Finance* 52 (1), 57–82.

Chevalier, J., & Ellison, G. (1997). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy* 105 (6), 1167–1200. https://doi.org/10.1086/516389.

Chhabra, R., De, S., Gondhi, N.R., & Pochiraju, B. (2011). Is zero return a natural benchmark for investors? An investigation with individual trading records. *SSRN*. https://doi.org/10.2139/ssrn.1846474.

De, S., Gondhi, N.R., & Sarkar, S. (2012). Behavioral biases, investor performance, and wealth transfers between investor groups. *SSRN*. https://doi.org/10.2139/ssrn.2022992.

Del Guercio, D., & Tkac, P.A. (2002). The determinants of the flow of funds of managed portfolios: mutual funds versus pension funds. *The Journal of Financial and Quantitative Analysis* 37 (4), 523–557. https://doi.org/10.2139/ssrn.166431.

Feng, X., Zhou, M., & Chan, K.C. (2014). Smart money or dumb money? A study on the selection ability of mutual fund investors in China. *North American Journal of Economics and Finance* 30, 154–170. https://doi.org/10.1016/j.najef.2014.09.004.

Ferreira, M.A., Keswani, A., Miguel, A.F., & Ramos, S.B. (2012). The flow-performance relationship around the world. *Journal of Banking and Finance* 36 (6), 1759–1780. https://doi.org/10.1016/j.jbankfin.2012.01.019.

Frazzini, A., & Lamont, O.A. (2008). Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics* 88 (2), 299–322. https://doi.org/10.1016/j.jfineco.2007.07.001.

Friesen, G.C., & Sapp, T. (2007). Mutual fund flows and investor returns: An empirical examination of fund investor timing ability. *Journal of Banking and Finance* 31, 2796–2816 Retrieved from https://ssrn.com/abstract=957728.

Glode, V., Hollifield, B., Kacperczyk, M.T., & Kogan, S. (2009). Time-varying predictability in mutual fund returns. *SSRN* 1–44. https://doi.org/10.2139/ssrn.1364351.

Goetzmann, W.N., & Peles, N. (1997). Cognitive dissonance and mutual fund investors. *Journal of Financial Research* 20 (2), 145–158. https://doi.org/10.1111/j.1475-6803.1997.tb00241.x.

Griffin, J.M., Nardari, F., & Stulz, R.M. (2007). Do investors trade more when stocks have performed well? Evidence from 46 countries. *Review of Financial Studies* 20 (3), 905–951. https://doi.org/10.1093/rfs/hhl019.

Grinblatt, M., & Keloharju, M. (2001). What makes investors trade? *The Journal of Finance* 56 (2), 589–616.

Grinblatt, M., Titman, S., & Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *American Economic Review* 85 (5), 1088–1105. https://doi.org/10.2307/2950976.

Gruber, M.J. (1996). Another puzzle: The growth in actively managed mutual funds. *The Journal of Finance* 51 (3), 783–810.

Hausman, J.A. (1978). Specification Tests in Econometrics. *Econometrica* 46 (6), 1251. https://doi.org/10.2307/1913827.

Hsieh, S., Yang, T.-Y., & Tai, Y.Y. (2010). Positive trading effects and herding behavior in Asian markets: Evidence from mutual funds. *The International Journal of Business and Finance Research* 4 (2), 177–188.

Keswani, A., & Stolin, D. (2008). Which money is smart? Mutual fund buys and sells of individual and institutional investors. *The Journal of Finance* 63 (1), 85–118.

Naik, P.K., & Padhi, P. (2015). An empirical evidence of dynamic interaction between institutional fund flows and stock market returns in India. *Indian Journal of Finance* 9 (4), 21–32.

Narend, S., & Thenmozhi, M. (2016). What drives fund flows to index ETFs and mutual funds? A panel analysis of funds in India. *Decision* 43 (1), 17–30.

Oh, N.Y., & Parwada, J.T. (2007). Relations between mutual fund flows and stock market returns in Korea. *Journal of International Financial Markets, Institutions and Money* 17 (2), 140–151.

Sapp, T., & Tiwari, A. (2004). Does Stock return momentum explain the "smart money" effect? *Journal of Finance* 59 (6), 2605–2622.

Shu, P.-G., Yeh, Y.-H., & Yamada, T. (2002). The behavior of Taiwan mutual fund investors—performance and fund flows. *Pacific-Basin Finance Journal* 10 (5), 583–600.

Sirri, E.R., & Tufano, P. (1998). Costly search and mutual fund flows. *The Journal of Finance* 53 (5), 1589–1622.

Tayde, M., & Rao, S.V.D.N (2011). Do foreign institutional investors (FIIs) exhibit herding and positive feedback trading in Indian stock markets? *International Finance Review* (pp. 169–185), Emerald. https://doi.org/10.1108/s1569-3767(2011)0000012009.

Warther, V.A. (1995). Aggregate mutual fund flows and security returns. *Journal of Financial Economics* 39 (2), 209–235.

Zheng, L. (1999). Is money smart? A study of mutual fund investors' fund selection ability. *The Journal of Finance* 54 (3), 901–933.